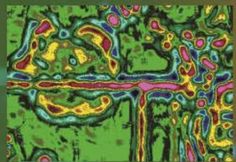

Functional classification of spatially heterogeneous environments: the Land Cover Mosaic approach in remote sensing

Marion Obbink 2011

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Functional classification of spatially heterogeneous environments: the Land Cover Mosaic approach in remote sensing

Martina Hendrika Obbink

Thesis

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Martina Hendrika Obbink

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To Renée, Malou, Yvonne & Han

PREFACE

My experience with remote sensing begun halfway the former century when I, as a student (like Marion in tropical forestry), started a sequential, long lasting, series of photographs with a "self-made" camera, from a 50 meter high tension line pillar, of a few hectares pioneer (fresh)water tidal accretion underneath. The next half of the century I had the chance to actively practice and follow the development of stereo airborne remote sensing by black and white, later also color photography and finally the modern digital satellite imagery, in all major biomes, from the Tropics up to the Arctic's, from the marches and forests to the deserts. So I had the privilege to become aware that the human brain, when concentrated in that "magic" three-dimensional photographic stereo image, creates, (even often in óne flash) in the brain an image of a "whole", a "unit of land", naturally classified by convergence of evidence. This image initiated by electromagnetic radiance (in wavelengths) and geometric (spatial) information, enhanced with knowledge about the relevant earth sciences, and amended by experience in the real ***FIELD*** ("ground-truth") partly even un-consciously, stored in the interpreter's memory. It is the proper base for a preliminary "land unit" map, base of stratified sampling of ground-truth data. The interpretation of the image in thematic terms (landform, soils, vegetation, land use etc.) is done by surveyors in these fields. General photo interpreters cannot exist (although administrators are not always aware of that). Photo interpretation ought to be one of the skills of the thematic surveyor, be it a vegetation, soil, geology, geomorphology or other thematic scientist etc., just as the sampling methodology etc. ought to be. How should otherwise the features in the photo image be merged with the thematic ones, obtained by study and field experience, if not one and the same person does the photo-interpretation as well as the field sampling? The holistic character of the stereo photo image is even at the base of the Trans disciplinary discipline "Landsschaftsoecologie", land (scape) ecology that developed since airborne aerial photographs became available for civil, scientific use. In land (scape) ecology one distinguishes three "dimensions" to study land: the topological dimension (emphasis on vertical relations, thematic and using semantics), the chorological dimension (emphasis on horizontal/spatial relations including semantics), and the geospherical dimension.

Remote sensing, as a discipline had its own development, driven by ICT technique, demand for automatic processing, especially for reconnaissance surveys over large areas. The observation using satellites opened better possibilities for sequential observation (seasonal pictures, monitoring). But the "magic" of the stereo image got lost by this, because the parallax, causing the stereo effect, becomes smaller with the altitude of observation. Airborne photography for land use, soils, vegetation, land use, vegetation surveys, has commonly scales of 1:20 000 to 40 000. Interpretation is done on these scales. Afterwards photos are combined to mosaics on scale 1:100 000 (comparable with the presently usual satellite imagery size) as base for the final cartography.

From the time on that military, political and administrative restrictions had been eliminated, we users were more and more forced to use the cheaper (!), hardly marginally overlapping, satellite images without the major feature the detailed stereovision, and exclusively based on 2-D represented radiographic information (wavelength), on a size of our former photo mosaics. So it happened that we looked compassionate to the propagandists for the modern method: "RS specialist", who never had used common stereo photos before; and proud did show us how they could indirectly derive the approximate relief, from the flat (two dimensional) image features like curvature of paths, roads, railways, rivers. And how they used sophisticated algorithms about the radiation (wavelength) mixtures to distinguish forest from grass land or shrub land, a difference that via the classic stereo photo image interpretation would directly register faultless in our brains, even unconsciously.

However the RS train was quickly rumbling on. Thousands of publication appeared since about the technique of image preparation for thematic photo interpretation. Most of these deal with subdivision of the wavelength spectrum as a base for parameterization of thematic expert knowledge and semantics, and monitoring. I got some times the impression that the technical methodology seemed for individual thematic surveyors even to compete with sound scientific and functional, ecological semantics. A main trend in the development is the endeavor for more details (resolution) in the RS-images. A popular reason is the well-known ideal of geometers / surveyors to "strive after the Micron" the ultimate accuracy. More practically, it may come forth from the hope that the smaller pixels will yield more clear parameters. It appears however that the land units, tend to be not homogeneous but are generalizations made by the brains of the interpreter, of more detailed information at the real earth surface, too small to be mapped individually. The main fault of inexperienced stereo photo interpreter, of the human "extreme splitter" type, is that he/she cannot resist copying these details.

Not only human splitters, also automatic interpretation machines have difficulties with generalization. Features recognized by the human eye by their form (geometry) can, opposite to wavelength data not easily be generalized irrespective their size (being smaller or larger than a pixel). Compare the similar constraint met by the compilation of a hierarchy in the legend of thematic maps. In very detailed maps, the units represent ecotopes, belonging to the topological dimension, and may so also be homogeny as far as vegetation or soil type concerns. In listing the units in a legend one may follow the hierarchy of the thematic typification (e.g. soil classification, vegetation classification.). The units of more global (less detailed) maps tend to be complexes of ecotopes that are spatially (chorological) related but may differ in content as far as thematic classification is concerned and are by consequence heterogenic, demanding (spatial) upgrading. The more detailed (resolution), the higher the redundancy. Geometric heterogeneity can only be generalized by ***HUMAN INTELLIGENCE***. The earlier mentioned, partly unconscious interpretation of a stereo image is in fact the same process: generalization (upgrading) of heterogenic spatial units. Hence, for automatic (artificial) interpretation, where human intelligence is excluded, a kind of ***ARTIFICIAL INTELLIGENCE*** is required. ***THAT NOW IS THE SUBJECT OF THIS THESIS!*** Marion Obbink, has for this purpose selected and combined a number of concepts, methods and techniques from the still growing arsenal of RS methodology, added an original extension to it about patch-segmentation, patch-classification, patch-mosaic segmentation and patch-mosaic classification of the scanned radiation data, developed the aggregate-mosaic theory with its land cover mosaic classification based on spatial aggregation classes, integrated into a new original methodology of generalization (upgrading) in a heterogenic environment. Her approach is strictly functional, at the outset semantic driven, directed on the management, in decision-makers format. So this study is in the same time a contribution to the concept of ***INTEGRATED SURVEY***, a subject to which ITC since 1968 on special request of UNESCO, in a variety of approaches, much attention has been paying. (At WUR my main subject was survey techniques in vegetation and landscape ecological land evaluation with a strong pragmatic accent that I recognize also in Marion's approach). Her example object is relative simple. Only a limited number of interpretation classes had to be generalized, in her main examples, with clear structural differences in the tree-canopy of Tropical Rainforest in various stages of exploitation and devastation, ultimately until agriculture. As such it is an important contribution to sustainable management and conservation of Tropical Rainforest. It does not bring back the full integration of the third dimension in automated form. As the parallax (the difference) between two overlapping stereo photo's that causes the awareness of height and relief is absent in the brains. This awareness can, as surrogate, approximately be raised indirectly by height impression by shades, and especially on oblique photos (compare the popular Google earth 3-D images). Another possibility is to add (e.g. by GIS), height data recorded separately by laser. However, this makes the operation more complex and expensive and still is not equivalent to the spatial photographic image. Still the combination with Marion's heterogeneity approach like the spatial aggregation on different hierarchic levels gives her methodology a pragmatic holistic character.

Anyhow her introduction of a "***NEW RS PARADIGM OF HETEROGENEITY***" in order to replace the current strive after a homogeneity approach, may lead to efficient and objective classification that contributes to sustainable management as well as science and conservation.

Ies Zonneveld (Prof. Em. ITC and WUR)

March 2011

CONTENTS

CHAPTER 1

REMOTE SENSING OF TROPICAL RAINFORESTS

"Wees de verandering die je in de wereld wilt"

"Be the change you want to see in the world"

Mahatma Gandhi (1869-1948)

1.1 Introduction

The world's forest resources continue to be lost or degraded at an alarmingly high rate (e.g., Meyers, 1989; Bryant et al., 1997; FAO, 1997; Matthews et al., 2000; FAO, 2003a, 2006). Many studies show that the scale of deforestation is such that it not only affects local economy and society, but also impacts global concerns that include biodiversity loss and climate change (e.g., Watson et al., 2000; Dennis et al., 2004; GMES, 2005; Malhi et al., 2008). Current estimates suggest that deforestation accounts for about one fifth of human induced emissions of carbon dioxide worldwide (Holmgren et al., 2007). Tropical rainforests suffer most from deforestation. World-leading organisations like FAO, ITTO, UNEP, the World Bank, and IUCN repeatedly emphasize to secure the multiple roles of tropical rainforests and tropical forestlands. Wise decision-making requires, among others, comprehensive forest monitoring to ensure that forests and forestry significantly contribute to livelihoods, sustainable development and poverty reduction (Holmgren et al., 2007). National policy processes are striving to address such cross-cutting issues. However, as early as beginning of the nineties, UNEP (1992) indicated that in many cases even the most basic information related to the area and type of forest at national level is lacking. Despite huge efforts, this information problem is still not solved today (e.g., Tuomisto et al., 1994; Apan, 1997; Asner et al., 2002; Giri et al., 2003). On the contrary, problems of uncertainty such as inaccurate statistics and different deforestation figures between various sources remain reported (e.g., Sader & Joyce, 1985; Gilruth & Hutchinson, 1990; Malingreau, 1991; Lambin & Ehrlich, 1997; Powell et al., 2004). Today, the need to improve national forest monitoring is overwhelming as the demand for (geo)-information has never been greater (ENS, 2008).

Using remote sensing data is a common way to monitor tropical rainforests (CIFOR, 2004). Most often, *satellite* imagery is the only data source to supply forest cover information in a timely and cost-effective way. Satellite imagery can cover vast expanses of land, it can be acquired regularly over the same area, and it can be acquired without encountering administrative restrictions (FAO, 2003b). In the last twenty years, huge efforts have been made to improve remote sensing devices, sensors, and algorithms to collect, process and store satellite remote sensing data.

Recent advancements include in particular an increasing variety of sensors for earth observation, shorter time intervals, more spectral bands (from panchromatic, via multispectral to hyperspectral data), increasing spatial resolution (from 1 km resolution to less than 1 m), and improved algorithms and models to compute variables. In addition, computer technology has been enormously improved to handle large data sets. Although remotely sensed data theoretically offer many solutions and provide a wealth of geo-data, the many technological improvements did not yet lead to better indicators on forest cover, nor on its changes. The ultimate question is: *what is causing the current discrepancy between demand and supply for relevant geo-information when monitoring deforestation in tropical rainforest areas?*

The problem of mixed-pixels is often seen as a major contributor to this discrepancy. This way of thinking is a result of maintaining a basic assumption in remote sensing, namely that of spatial homogeneity of land cover classes. For tropical rainforest areas, however, this assumption is not valid (see section 1.3.1). This thesis presents, therefore, a new way of looking at this discrepancy addressing three fundamental bottlenecks for supplying relevant geo-information (Figure 1.1):

- Lack of understanding about the characteristics of spatial heterogeneity in tropical rainforest areas.
- Lack of understanding about the requirements of decision-making for geo-information at different spatial aggregation levels.
- Lack of understanding the impact of maintaining the homogeneity assumption in digital classification methods.

These shortcomings drastically reduce the use of current digital classification methods for digitally analysing imagery of spatially heterogeneous environments like tropical rainforest areas. The lack of understanding the characteristics of spatial heterogeneity leaded to developments of digital classification methods that handle spectral heterogeneity of remote sensing imagery. Most often, these methods neglect spatial heterogeneity (Chapter 2). The lack of understanding the need for different spatial aggregation levels led to a focus on improving classification accuracy at remote sensing data levels. Most often, these data levels neglect vegetation patterns at decisive spatial aggregation levels (UNEP, 1992; Mackay, 1999; Fuller et al., 2003). The lack of understanding the impact of maintaining the homogeneity assumption led to developments of digital classification methods that are purely technology-driven. These methods do not include semantic and ontological issues (Comber et.al., 2005) nor the involvement of users in a comprehensive way (Köhler, 2005).

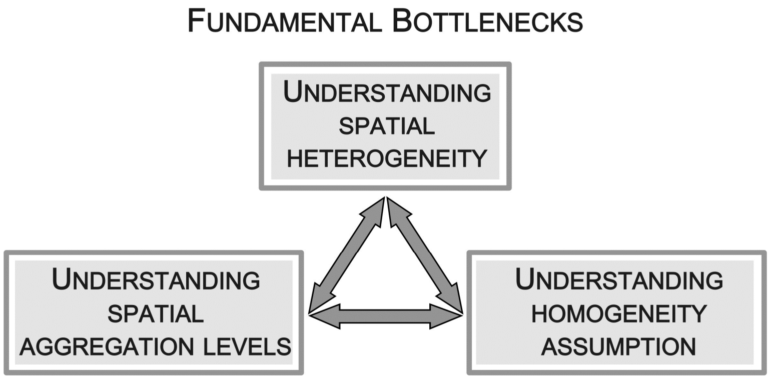

Figure 1.1: Three fundamental bottlenecks for supplying relevant geo-information.

This thesis provides, therefore, a new theoretical approach called *Aggregate-Mosaic Theory* to handle spatial heterogeneity besides spectral heterogeneity when digitally classifying remote sensing data of spatially heterogeneous environments. This theory explains and demonstrates how to *quantitatively* classify a spatially heterogeneous tropical peat swamp forest into functional spatial entities called *Land Cover Mosaics* (LCM). It incorporates functional heterogeneity of landscape ecology (Kolasa & Rollo, 1991; Reynolds et al., 1997) and the theory of spatial object modelling (Molenaar, 1998) to facilitate such a *LCM classification*. It formalizes the involvement of end-users to represent spatial heterogeneity as specific as required at different spatial aggregation levels. Accuracy estimates at these decisive levels are supportive of decision-makers at different administrative levels. Ultimately, they are committed to preserve the world's tropical rainforests for future generations.

Details on the rationale and underlying motivation of this thesis are described in this chapter, sections 1.2 to 1.4. Section 1.2 starts with background information on tropical rainforest areas, its major threats, and some highlights on the path of sustainable development. It also describes the need of decision-makers for relevant geo-information. Section 1.3 gives background information on the three fundamental bottlenecks causing the discrepancy between demand and supply for relevant geo-information. Section 1.4 elucidates two important responsibilities of remote sensing scientists in order to tailor geo-information to end-users. Following this, section 1.5

presents the research questions, objectives and methodology of this thesis. After that, section 1.6 describes details of the Pelangkaraya study area, the used remote sensing data, existing fieldwork data and other materials used. Finally, section 1.7 presents the outline of this thesis.

1.2 Tropical Rainforest Areas

1.2.1 Threats & impacts

Rainforests are the richest, oldest, most productive and most complex ecosystems on Earth (Morley, 2000). Although rainforests cover less than two percent of the Earth's surface, they are home to some 40 to 50 percent of all life forms on our planet - as many as 30 million species of plants, animals and insects (Whitmore, 1998). Currently, many investigations are still ongoing to acquire a better understanding of the structure, function, composition, biotic diversity and extent of such forests (e.g., Edwards et al., 1996; Cochrane, 2003; Dennis et al., 2004; Wijdeven et al., 2004; Stork, 2007). An increasing threat for tropical rainforest areas is, however, the impact of human activities (Figure 1.2).

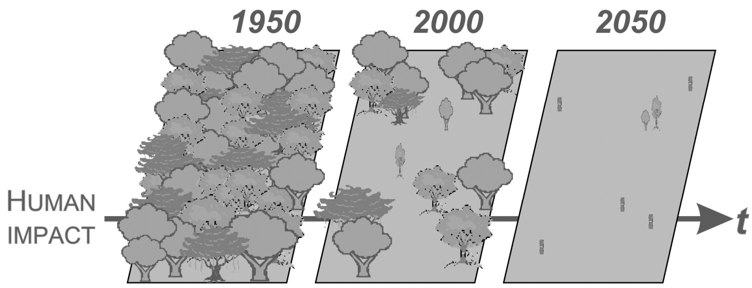

Figure 1.2: Impact of human activities in tropical rainforest areas.

Humans often uncontrollably degrade tropical forests and convert them to man-made types of land use (Sader & Stone, 1990; UNEP, 1992; Lambin, 1994; FAO, 1997,2003a,2003b,2006). Agricultural expansion like shifting cultivation, colonization, transmigration, cattle ranching and industrial forestry plantation increasingly demand agricultural land. Timber extraction for local house construction, for fuelwood and charcoal production, and for commercial logging still increases. Extensions of roads, railroads, settlements, hydropower developments, and mining activities all boast land speculation. Furthermore, indigenous people, local and international industries increasingly demand accessory forest products. Besides these growing demands of an expanding population and its (global) economy, natural catastrophes and forest fires also devastate large areas of tropical rainforests (Page et al., 2002). Consequently, the causes and drivers of deforestation cannot be reduced to a single variable, or to a few variables even. Generally, deforestation is a complex, multiform process as illustrated in Figure 1.3. Geist & Lambin (2001) compared five underlying causes of tropical deforestation: economy, policy and institution, technology, culture, and demography. They found that factors related to *policy and institution* emerge globally as the second most important underlying force after economy.

Soil erosion, loss of biological diversity, damage to wildlife habitats, degradation of watershed areas, global warming, deterioration of the quality of life, and reduction of the options for development including tourism all show the impact of loss and degradation of rainforests. The media frequently report loss of rainforests, most alarming in the number of football fields per second (e.g.: Meyers, 1989; Bryant et al., 1997; Matthews et al., 2000). This pressing situation calls for urgent and consistent action for conserving and sustaining tropical forest resources.

1.2.2 Sustainable development

The sustainable development of forests is increasingly recognised as an urgent challenge. Combating deforestation was even the working title of Chapter 11 in Agenda 21, the principal outcome of the 1992 United Nations Conference on. Environment and Development (UNCED) held in Rio de Janeiro, Brazil. This conference, popularly referred to as the Earth Summit or Rio Conference, presented Agenda 21, voted by 178 governments. This document is an action plan for the whole world at the brink of the 21st century and beyond, elaborating strategies and integrated programme measures to stop and reverse the effects of environmental degradation and to promote an environmentally sound and sustainable development in all countries. At the Rio Conference, the term *sustainable development* was adopted based on the report ‘Our Common Future’ of the World Commission on Environment and Development (WCED), also known as the Brundtland Commission (Brundtland, 1987). Sustainable development is defined most widely as ‘development that meets the needs of the present without compromising the ability of future generations to meet their own needs’ (Figure 1.4).

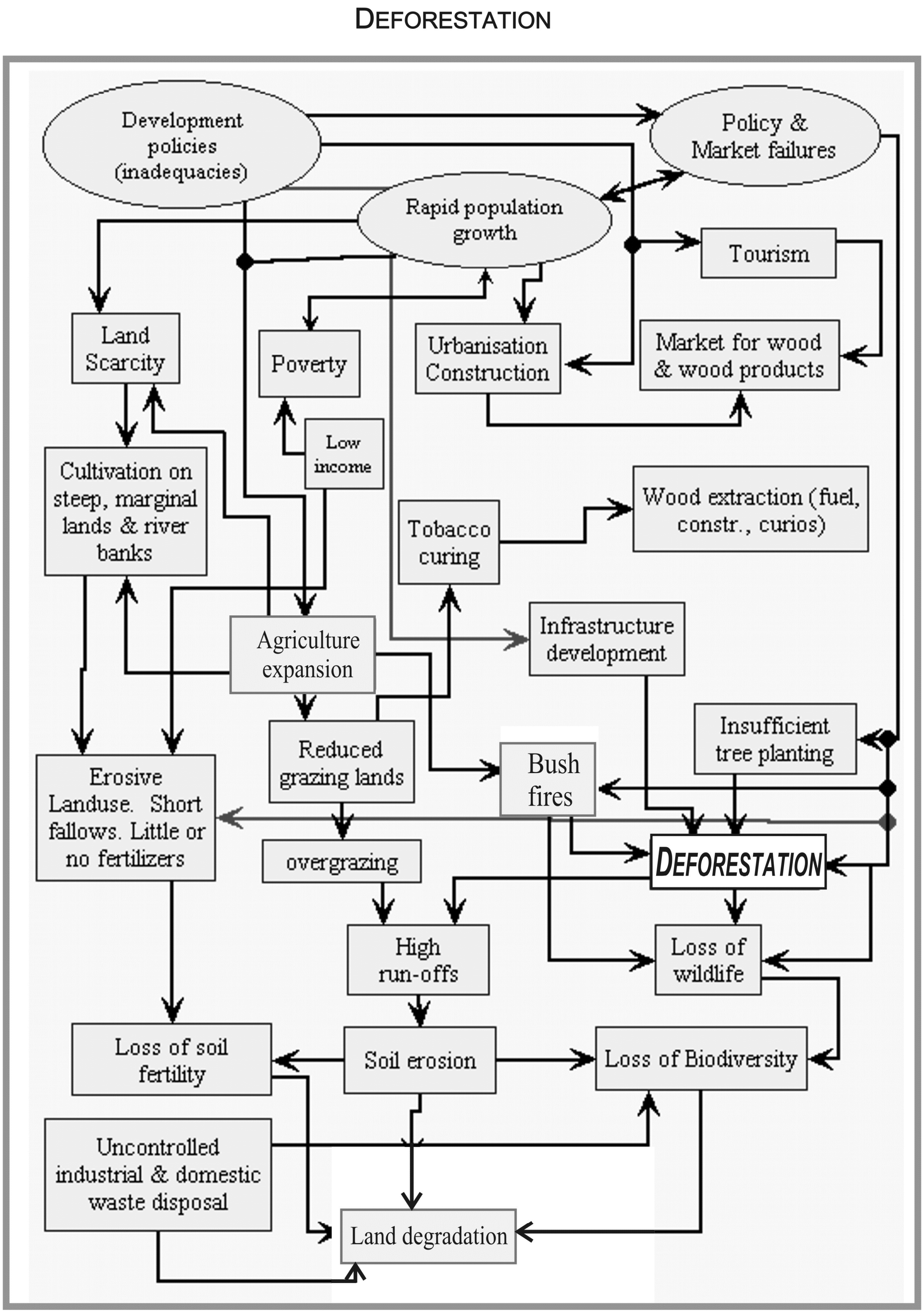

Figure 1.3: Deforestation is a complex multiform process; an illustrative example from Malawi (NSDP, 2004).

SUSTAINABLE DEVELOPMENT

 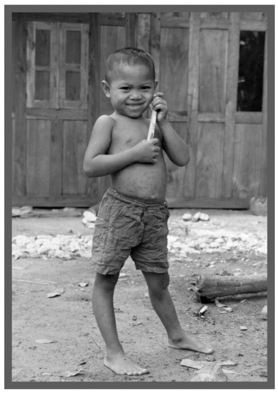

Figure 1.4: Sustainable development, meeting current needs (e.g. timber for house construction) without compromising future needs (e.g. growing population).

Chapter 11 of Agenda 21 states that there are major weaknesses in the policies, methods and mechanisms adopted to support and develop the multiple ecological, economic, social and cultural roles of trees, forests and forestlands. More effective measures and approaches are often required at the *national level* to improve and harmonize policy formulation, planning and programming (UNEP, 1992). The responsibility to report world progress on implementing Chapter 11 was given to the FAO. After 10 years on the path of sustainable development, the Executive Director of UNEP noted progress in achieving sustainability since Rio during the 2002 World Summit on Sustainable Development in Johannesburg, South Africa (UNEP, 2002). He stressed, however, that new scientific evidence of global environmental change necessitated a quantum increase in efforts to achieve sustainable development.

Although global commitment and public awareness of the impact of deforestation has increased in recent years, daily news is the still ongoing continuation of deforestation, especially in tropical rainforest areas (FAO, 1997, 2003a, 2003b, 2006). This continuation of deforestation is a strong signal that sustainable development of tropical rainforests is extremely difficult. Strengthened decision-making at *nationa-level* therefore is of prime importance, because national-level policies are striving to address cross-cutting issues such as poverty reduction and food security related to forests (ENS, 2008).

1.2.3 Decision-making

Focussing specifically on the information part of decision-making, today, the approach to the analysis of a problem, or a plan to deal with monitoring or managing areas for specific uses or (sustainable) development is based on *geo-information* (Figure 1.5). Geo-information describes the physical location of objects that has geographic, temporal, and spatial context, and the metric relationships between such objects (CRCSI, 2005). Often, this information is embodied in a Geographic Information System (GIS), and remote sensing is a major supplier of geo-information. End-users of geo-information, like decision-makers who are committed to preserve rainforests for future generations, are increasingly operating at different administrative or organizational levels (i.e., local, regional, national and global).

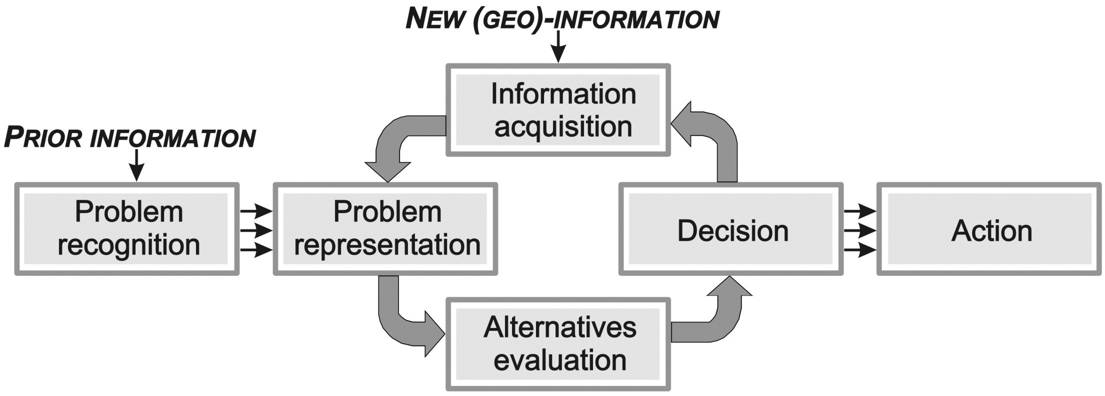

Figure 1.5: (Geo)information requirement in the decision-making process (after Timmermans, 1981).

Each decision-level requires its own *specific* geo-information on forest cover for setting rules and regulations on where and how to utilise tropical rainforests (Figure 1.6). An example at local level is a concession manager who needs to know concentrations of harvestable trees in forest stands for planning and managing logging activities. His need of geo-information for making such operational decisions is forest cover at tree level, meaning only trees should be counted as forest cover. An example at regional level is the head of a governmental forest province (in Indonesia the Kepala Pemerintah Provinsi abbreviated as PemProv) who needs to know distribution of above tree species over the diameter classes in forest types for regulating actual logging and agricultural use. His need of geo-information for making such *tactical* decisions is forest cover at stand level, meaning trees and small areas of grasses or shrubs should be counted as forest cover.

An example at national level is a forestry minister of a country who needs to know distribution of forests types in forest provinces for regulating *forest land use*[1] and *forest concession rights*[2]. His need of geo-information for making such *strategic* decisions is forest cover at forest type level, meaning trees and small areas of grasses, shrubs or even other land cover types should be counted as forest cover. A similar example of requiring specific geo-information at each decision-level is the information need on houses for making operational decision, cities for tactical decisions, and urban areas for strategic decisions when analyzing or planning urbanization.

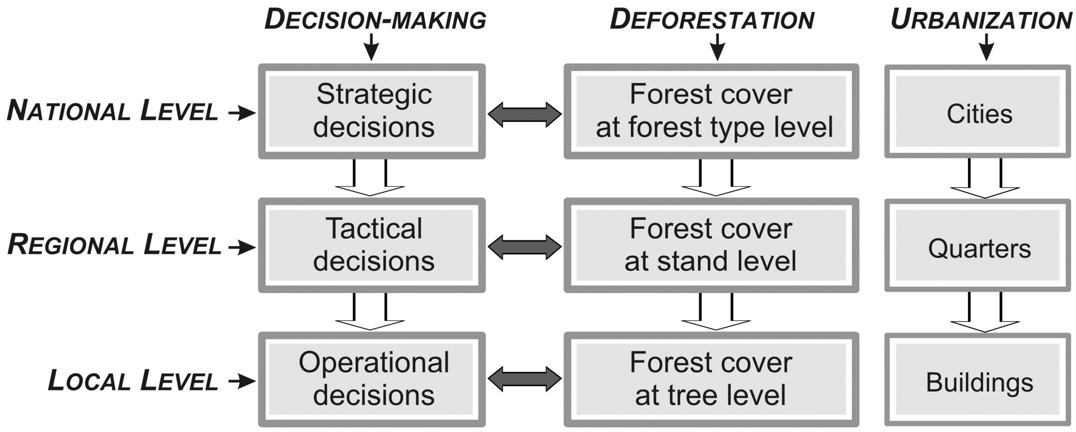

Figure 1.6: Levels in decision-making. Each level requires its own spatial specification on forest cover to analyze or plan deforestation (similarly to urbanization).

Generally, macro-policies are set at national level (i.e., central government), whereas micro-policies are set at provincial or district level (i.e., local government). As the examples on deforestation and urbanization show, setting such macro-rules requires less detailed geo-information than does setting such micro-rules. A major consequence is, however, that an area not identified as forest cover at micro-level could be forest cover at macro-level (i.e., upscaling is not a straight forward

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[1] Indonesian regulations concerning forest land use are specified in the Consensus of Forest Land Use or TGHK (*Tata Guna Hutan Kesepakatan*). Essentially, this law classifies the natural forest land into five forest land-use categories: protection forest, conservation forest including national parks and reservation forests, limited production forests, permanent production forests, and convertible production (conversion) forest.

[2] Indonesian regulations concerning forest concession rights are specified in the Bina Desa Program or HPH (*Hak Pengusahaan Hutan*).

process). Therefore, to suit macro-policies and micro-policies remote sensing should provide forest cover information at different levels of spatial detail, stated otherwise at different *spatial aggregation levels* (section 1.3.2). This spatial differentiation when monitoring deforestation will provide new (geo)-information on forest trends and new information on the drivers of deforestation and forest degradation. At each spatial aggregation level, the supplied geo-information should be accurate and up-to-date for predicting such trends and explaining underlying drivers (Lambin & Ehrlich, 1997).

1.3 Bottlenecks for relevant geo-information

1.3.1 Spatial heterogeneity

Many studies underline that in tropical rainforest areas both of the two key components of vegetation, *composition* and *structure*, are extremely heterogeneous (Whitmore, 1998; Morley, 2000). Generally, vegetation composition refers to floristic diversity, meaning the taxonomic classification into classes, orders, families, genera, species, varieties, etc. This, however, is not the only way to address the heterogeneity of vegetation composition. Species and individuals can also be grouped into classes of growth form or life form on the basis of their similarities in structure and function (Mueller-Dombois & Ellenberg, 1974). Examples of dominant growth forms are trees, shrubs and grasses. For primary tropical rainforests, the tree is the dominant growth form. With increasing human activities, this growth form loses its dominance and changes into a spatially heterogeneous mixture of trees, shrubs and grasses. Vegetation structure refers to both the horizontal and the vertical extent of vegetation. Vegetation structure is used as a concept complementary to vegetation function. Function entails physiological processes, whereas structure entails anatomy and morphology. Dansereau (1957) defines vegetation structure as ‘the organization *in space* of the individuals that form a stand, a vegetation type, or a plant association’. This definition comprises three generalization levels. Mueller-Dombois and Ellenberg (1974) define vegetation structure more generally as ‘the spacing and height of plants forming the matrix of a vegetation cover’. They interpret this spacing at least at five generalization levels. From the more detailed to the more general, these levels are: stand, floristic, life form, biomass and physiognomy. Finally, the horizontal extent of vegetation is also called the horizontal distribution, or the *pattern* (Küchler & Zonneveld, 1988).

For primary tropical rainforests, mainly environmental factors define vegetation pattern. With increasing human activities, this pattern becomes more *heterogeneous* and pattern borders show a variety of *transitions*. Both pattern heterogeneity (Figure 1.7) and border transition (Figure 1.8) occur at *any* spatial aggregation level in tropical rainforest areas. Pattern heterogeneity and border transition are the results of a complex interaction of social and environmental factors that has given rise to a dynamic mosaic of patches of deforestation and reforestation (Southworth et al., 2004; Zonneveld & Forman, 1990). Specifically in a human-induced transition of forest areas to non-forest areas such mosaics range between 'oceans of forest with scattered islands of human activity' and 'rainforest fragments in an ocean of man-made vegetation' (Whitmore, 1998 p. 224). Monitoring and classifying (i.e., defining extent and labeling) such spatially heterogeneous environments is very difficult, because pattern heterogeneity and border transition do not disappear when moving to spatially more detailed levels (i.e., from national to local decision level). Each spatial aggregation level shows pattern heterogeneity (Figure 1.7a) and border transition (Figure 1.8a). In fact, any pixel in a spatially heterogeneous environment is a mixed pixel. This in contrary to spatially more homogeneous patterns where patterns become more homogeneous when moving to a spatially more detailed level (Figure 1.7b). For such environments, border transitions are almost not existing (Figure 1.8b) and mixed pixels can only be found at boundary pixels. Consequently, for spatially heterogeneous environments a critical issue remains an explicit definition of thematic classes including their boundaries along transition zones (Powell et al., 2004) at each spatial aggregation level. This definition problem is in fact a modelling problem in conceptual generalization as will be discussed in Chapter 2.

1.3.2 Spatial aggregation levels

Spatial aggregation levels refer to levels of spatial detail at which vegetation pattern should be specified (c.q. classified) to be of significance for decision-making (Figure 1.9). For example, vegetation pattern can be specified at a very detailed spatial aggregation level like the arrangement of trees in a forest stand (required for operational decisions), at a more course spatial aggregation level like the arrangement of forest stands in a forest type (required for tactical decisions), and at a course spatial aggregation level like the arrangement of forest types in an ecozone (required for strategic decisions). An urban example of a comparable sequence of such different spatial aggregation levels are the arrangement of buildings in a quarter (operational decisions), the arrangement of quarters in a city (tactical decisions), and the arrangement of cities in an urban area (strategic decisions). Each decision-level requires its own spatial aggregation level. Generally, such levels are also restricted to a certain time period, for example, operational decisions yearly, tactical decisions for five year, and strategic decisions for 15 years.

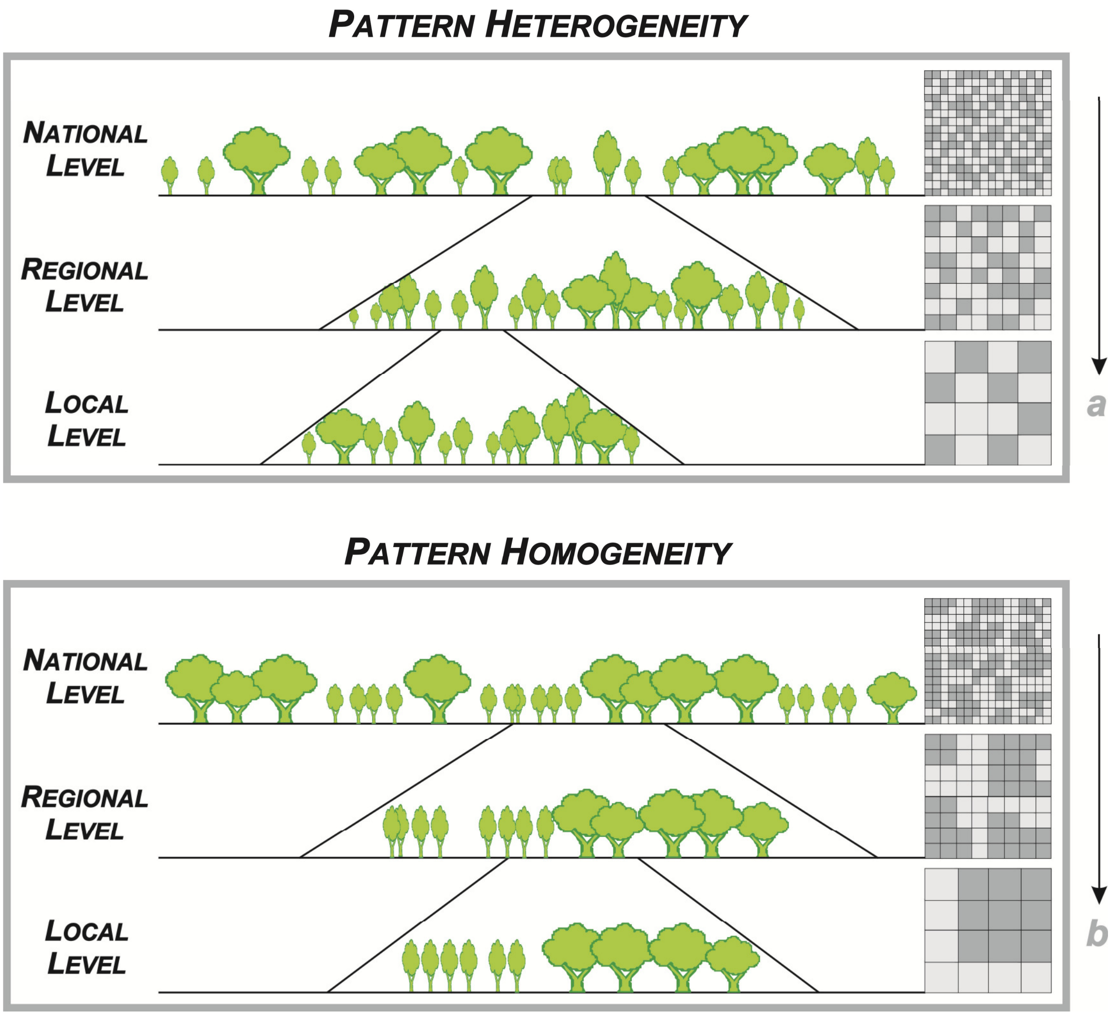


Figure 1.7: Pattern heterogeneity at different decision-levels; the pattern of forest and non-forest patches in Indonesia remains heterogeneous when moving to a spatially more detailed level (a). This in contrary to, for example, the Dutch situation where the pattern becomes more homogeneous when moving to a spatially more detailed level (b).

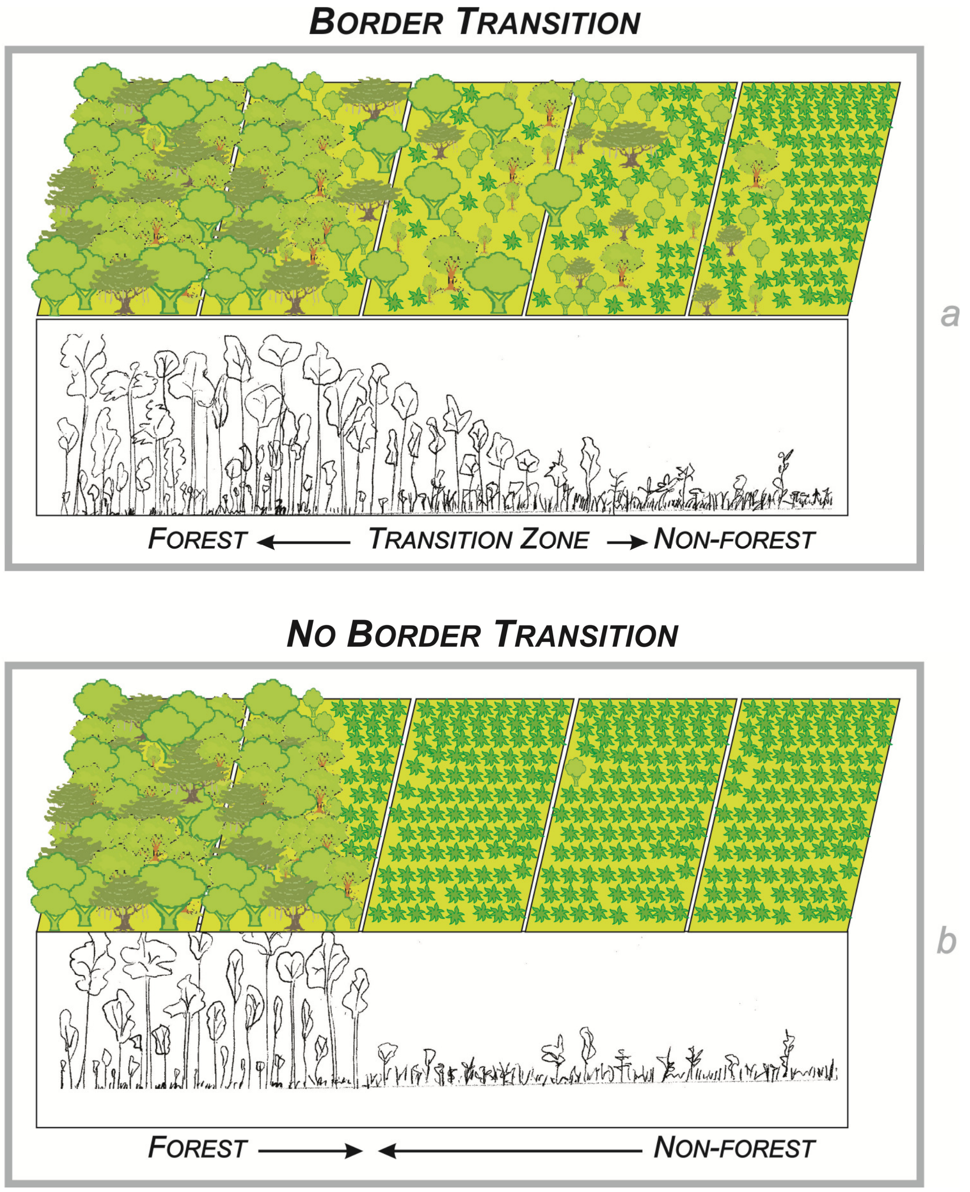


Figure 1.8: Border transition: the 'border' between forest and non-forest patches in Indonesia can span hundreds of meters and therefore called a transition zone (a). This in contrary to, for example, the Dutch situation where the border between forest and non-forest patches is a fairly distinct line (b).

Remote sensing images of spatially heterogeneous environments show vegetation pattern at different spatial aggregation levels. Applying pixel-based classifiers in such environments, these different vegetation patterns are classified at only one spatial aggregation level (i.e., at pixel-level). This spatial aggregation level does not necessarily address the vegetation pattern relevant for the decision-level at hand (Figure 1.10, land cover class C). Often, the supplied geo-information becomes too fragmented for adequate decision-making (UNEP, 1992; Beurden & Douven, 1999). In other words, apart from producing gross misclassifications, pixel-based classifiers failed to provide spatially crisp patterns (Tuomisto et al., 1994). Furthermore, increasing landscape heterogeneity lead to a decrease of thematic map accuracy (Smith et al, 2002; Powell et al., 2004). These problems remain existing with the introduction of object-based classifiers. These classifiers also supply geo-information at only one spatial aggregation level (i.e., at one object-level), and also failed to provide spatially crisp patterns because of classification constraints (i.e., spatial homogeneity). Consequently, current spatial aggregation levels at which vegetation patterns are being digitally classified do not match decision-making levels (section 1.2.3).

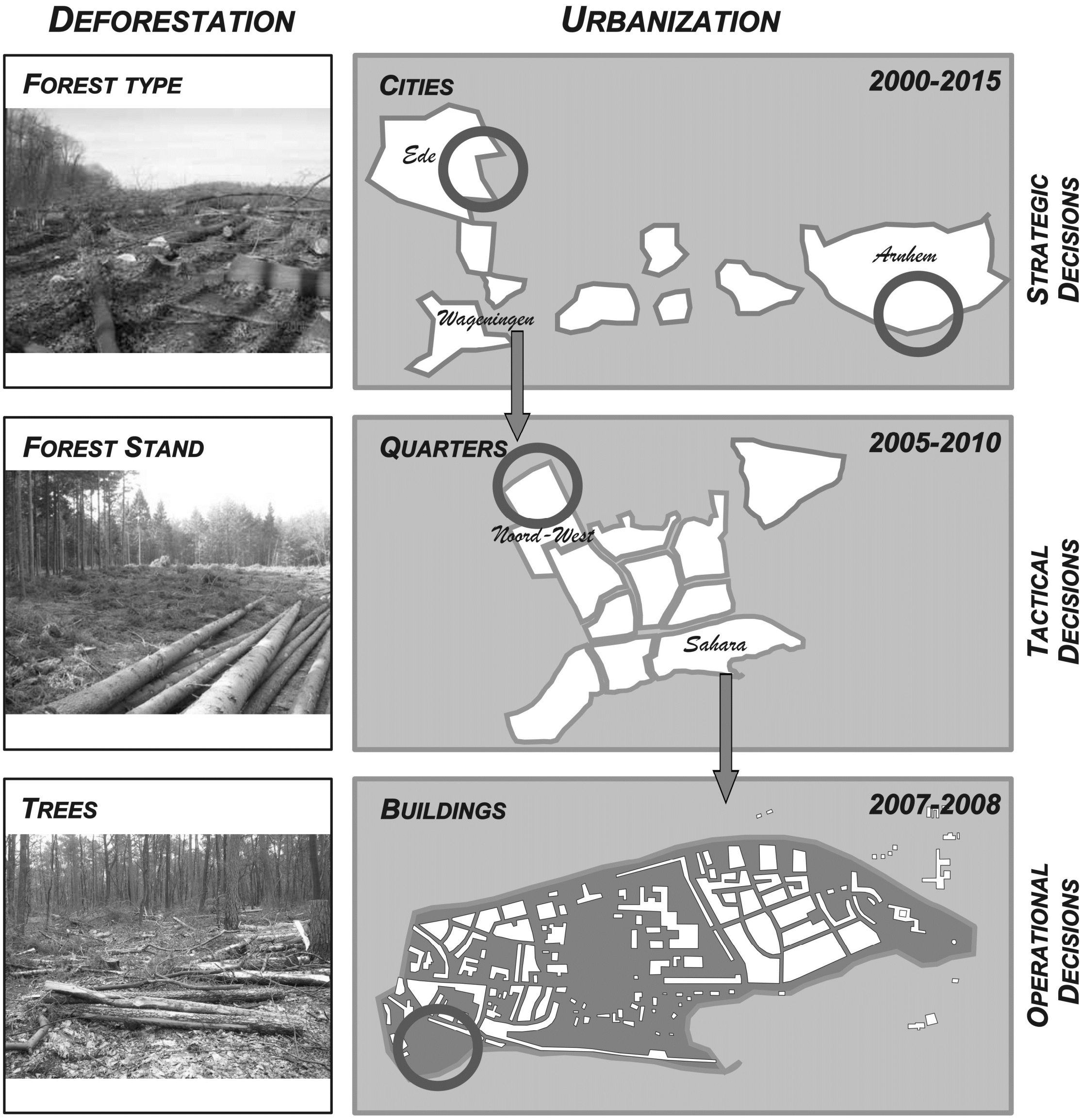


Figure 1.9: Spatial aggregation levels in deforestation processes to be of significance for decision-making similar to urbanization processes. The red circles address the different area(s) of interest at each decision level.

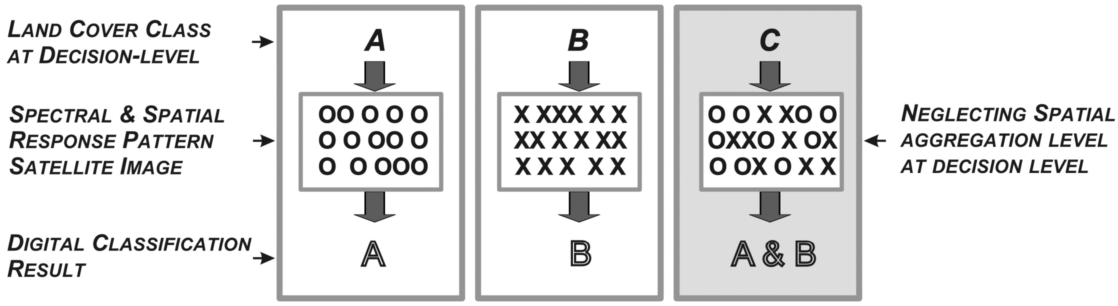


Figure 1.10: Digital mis-classification of land cover class C as a result of neglecting spatial aggregation level of its vegetation pattern at decision level (after Obbink, 1993).

This digital mismatch is the reason that in operational programmes, manual interpretations either on hardcopy or on screen remain daily practice (visited projects are the Indonesian National Forest Inventory/FAO project in 1990; the Nepalese Natural Resources Evaluation and Mapping/GTZ/World Bank project in 1993; and the yearly inventory programmes of Indonesian logging companies in 2003). The manual interpretations provide spatially crisp patterns at the required spatial aggregation levels, especially for spatially heterogeneous environments that are rapidly changing. Manual interpretations, however, face two problems: subjectivity causing inconsistency of the interpretation results, and lack of automation causing time constraints. These problems remain persistently although manual interpretation has a long tradition in aerial photography, even for highly skilled interpreters with extensive field knowledge. Therefore, expectations were high when digital sensors (airborne and satellite platforms) and digital analysis techniques emerged to solve these two problems. Digital methods enabled an opportunity to objectively and automatically classify remote sensing data.

1.3.3 Homogeneity assumption in digital methods

Digital classification methods (per-pixel or sub-pixel; supervised or unsupervised) are mostly based on the statistical analysis of the multi-spectral properties of image pixels in remote sensing. Conventionally, classification involves labeling image pixels as belonging to particular spectral classes that correspond to various land cover classes (Richards & Jia, 1999). A popular classifier in many operational remote sensing applications is the maximum likelihood classifier (per-pixel, supervised). Generally, this classifier provides spatially *crisp* patterns for spatially homogeneous environments, because many neighbouring pixels in the image contain the same land cover class (Figure 1.10, land cover class A & B). Applying this classifier to spatially heterogeneous environments, however, this classifier provides spatially *noisy* patterns, because many neighbouring pixels in the image do not contain the same land cover class (Figure 1.11) These noisy patterns are generally referred to as 'salt and pepper noise'. Digital classification results become noisy because of the inherently underlying homogeneity assumption in digital classification methods that neglects spatial heterogeneity of land cover classes.

In fact, any pixel-based classification method (unsupervised or supervised; per-pixel or sub-pixel) would produce noisy patterns for spatially heterogeneous environments, because of its *exclusive* focus on the multi-spectral properties of image pixels. Such a focus only refers to vegetation composition (i.e., spectral heterogeneity), and not to vegetation pattern (i.e., spatial heterogeneity). This exclusive focus on the multi-spectral properties even leads to a practice to zooming-in to details.

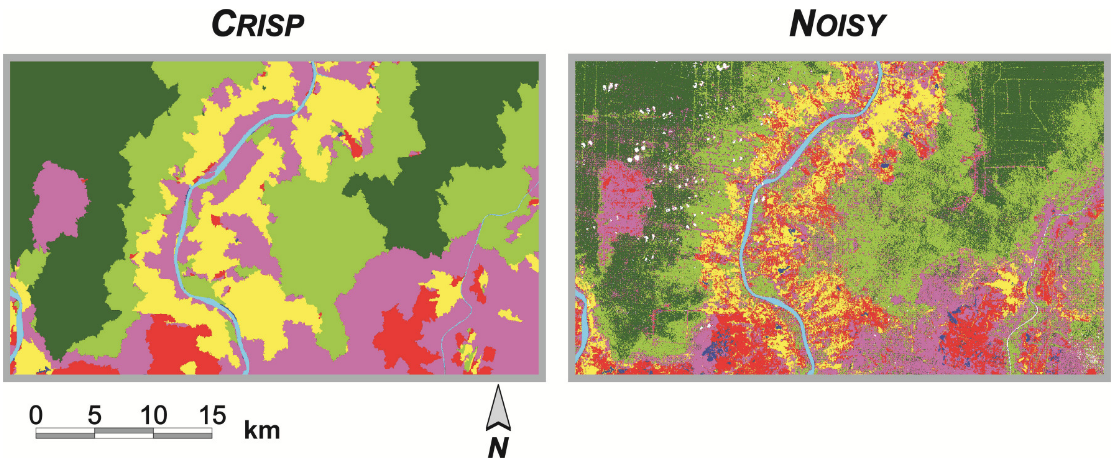


Figure 1.11: Spatial patterns considered as 'crisp' versus 'noisy', the latter as a result of the spatial homogeneity assumption in digital methods. (maps show p1990 image of the Pelangkaraya study area; Crisp is the result of a LCM classification (Chapter 6, section 6.2.2); Noisy is the result of a per-pixel maximum likelihood classification (Chapter 4, section 4.5.2).

The purpose of such a zooming-in to details is that the ability to quantify forest vegetation at a detailed level is supposed to enable a coherent quantification of forest vegetation at courser levels. For spatially heterogeneous environments, however, this purpose fails because of its affiliation with the two other bottlenecks for relevant geo-information (i.e., spatial aggregation levels and spatial heterogeneity). From the point of spatial aggregation levels, the supposed coherent quantification does not account for the specific requirements on forest cover in the decision-making process at courser spatial aggregation levels (i.e., micro-level it is not forest cover, macro-level it is forest cover). From the point of spatial heterogeneity, pattern heterogeneity and border transition do not disappear when zooming-in to details. Two examples of these facts are presented in Figure 1.12. Despite a huge increase in spatial resolution, the Ikonos images with 4 m resolution show a *similar* vegetation pattern (for both pattern heterogeneity and border transition) compared to the Landsat TM images with 30 m resolution. In fact, the Ikonos images only show more details on vegetation composition (e.g., single trees can be distinguished).

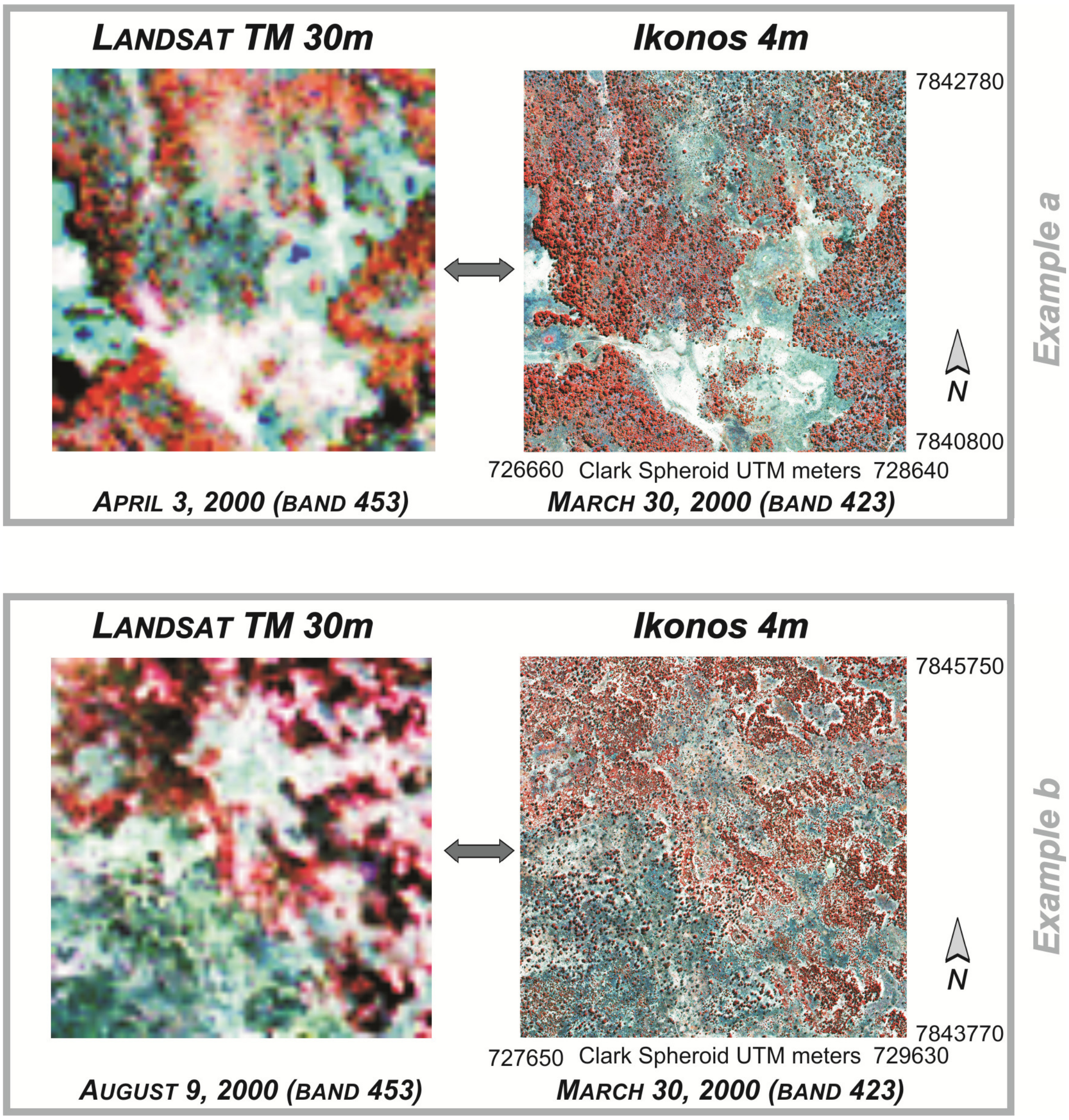


Figure 1.12: Two examples of a similar appearance of vegetation pattern comparing Landsat TM imagery with 30 m data resolution and Ikonos imagery with 4 m data resolution (imagery from Okavango delta, Botswana).

Moving to sub-pixel classifiers is another practice to zooming-in to details in order to solve the problem of resulting noisy patterns. Classification at sub-pixel level in the case of spatially heterogeneous environments only provides additional information on vegetation composition. In other words, at sub-pixel level only more detailed spectral classes can be defined. Defining more spectral classes neglects the spatial properties that a raster of image pixels comprises, and thus neglects vegetation pattern. Conversely, the presence of vegetation patterns lead to difficulties for defining suitable spectral classes. Often two or more spectrally dissimilar classes are needed to resemble forest cover classes (Wharton, 1982). The problem is that these spectrally dissimilar classes may belong to several forest cover classes (Figure 1.10; the spectral class **O** belongs to both land cover class A and C, and the spectral class **X** belongs to both land cover class B and C). As a consequence, defining such relationships involves additional *spatial* information besides the thematic information of forest cover classes. This refers to a modeling problem in conceptual generalization (Chapter 2, section 2.3.1).

Digital classification methods that are developed because of zooming-in to details (i.e., increasing spatial resolution and moving to sub-pixel level) do not solve the problem of resulting noisy patterns for spatially heterogeneous environments like tropical rainforest areas. Since the early 1980s, therefore, many other innovative approaches and techniques have been published to handle the problem of spatial heterogeneity when digitally classifying remote sensing data (e.g., contextual classifiers, hybrid classifiers, cover-frequencies, segmentation, and wavelet transformation, see Chapter 2). Reviewing this literature reveals that many such approaches and techniques either address vegetation composition or vegetation structure. Classifying spatially heterogeneous environments, however, requires input on both vegetation composition and vegetation pattern. The latter is often neglected in general vegetation typologies, but in image interpretation, vegetation pattern is most important because of its link with scale (Küchler & Zonneveld, 1988). Consequently, it should not be that surprising that current digital classification methods can not yet solve the discrepancy between demand and supply for relevant geo-information related to tropical rainforest cover and its changes (section 1.1). This appeals for a critical review on the responsibility of remote sensing being the main supplier of geo-information on world’s tropical forest resources.

1.4 Responsibilities of remote sensing specialists

1.4.1 Definition task

A first important responsibility of remote sensing specialists towards spatial heterogeneity is to convince end-users the importance of specifying spatial context in forest definitions and thresholds, and to demonstrate the impact that specification has on the use of supplied geo-formation (Figure 1.13). This definition task is necessary because forest cover needs to be quantified at different spatial aggregation levels to supply geo-information relevant for decision-making (see previous section). Two additional prerequisites for such a quantification are a clear definition and meaning of the term *forest*[3] and a clear understanding of its use.

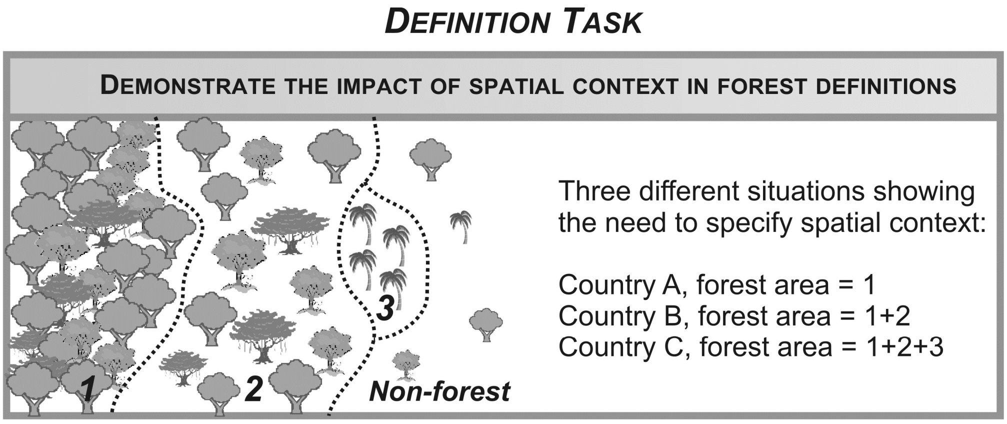


Figure 1.13: Definition task of remote sensing scientists (after Lund, 1999).

Lund (1999, 2000) has done intensive investigations in various countries (i.e., at national level) on *definitions* of forest terms. He found that, if defined at all, forest definitions and thresholds (i.e.,: *area*, *crown cover*, and *tree height*) vary from country to country. The minimum area of tree covered lands to be considered as forest varied from 0.01 ha for the Czech Republic to 100 ha for Papua New Guinea (Lund, 1999). The most common threshold for the minimum areas was 0.4 to 0.5 ha (i.e., 4-5 Landsat TM pixels). The minimum crown cover varied from 10% for Malaysia to 80% for Malawi, whereas the minimum tree height varied from 1.3 meters for Estonia to 15 meters for Zimbabwe. An example of a complete forest definition, he found, is the definition used by the FAO and the UN/ECE in the context of the remote sensing

[3] Literally, forest comes from the Latin word *foris* that means 'out of doors', in this case 'out of civilisation' (Le Goff, 1967; Makkonen, 1974; Lund, 2000).

component of FAO's Global Forest Resources Assessment (FRA) series. In this series, forest cover is defined as land with a tree crown cover of more than 10 % and with a minimum tree height of 5 meters covering an area of more than 0.5 ha (for complete definition see FAO, 2000). This definition is, however, defined to monitor and to assess forest at global level. Such a definition cannot simply be implemented for decision-making at national level, because at national level in the Indonesian context, even Jakarta becomes a forest.

There is also considerable variation in the *use* of the term forest. For example, while the global FRA definition appears to be one of land cover, it actually is a *land use* definition, because lands without trees can be considered forest (land) for the assessment (Lund, 1999). Understanding such differences is fundamental for a discussion of assessment methods, ecosystem status, and sustainability. Generally, four broad categories are distinguished: administrative unit, land cover, land use, and land capability. Thus, speaking about forests can refer to areas that include lands that never had and never will have tree cover (administrative), areas that currently have tree cover (land cover), areas that currently have no tree cover but probably will have in future (land use), or land areas that could support tree cover (land capability) regardless of owner intent. For Indonesia, Lund (2000) found three national definitions for the term forest:

- As a declared, legal or administrative unit: a forest is an area growing trees, which as a whole forms a living natural community and natural living environment, and which is designated by the government as being forest (MOF, 1998).
- As a land cover type: a unit of ecosystem in the form of lands comprising biological resources, dominated by trees in their natural forms and environment, which can not be separated from each other (MOF, 1999).
- As a land use type: a forest is a spread out area filled (or planned to be filled) with trees, other living (biological) and non-living elements that as a whole form an ecosystem unit (MOF, 1998).

Using remote sensing data, only forest areas categorized 'as a land cover type' can be assessed and monitored, because these areas should have tree cover. In this definition, however, no explicit reference is made to a spatial context. The latter is needed in order to tailor geo-information to end-users (i.e., decision-makers). Therefore, additional information of end-users on spatial context is required to enable quantification of forest cover at relevant spatial aggregation levels when using remote sensing data.

1.4.2 Monitoring task

A second important responsibility of remote sensing specialists towards spatial heterogeneity is to expand their monitoring tools from monitoring vegetation cover at pixel level towards deforestation scenario's at different spatial aggregation levels (Figure 1.14a; Figure 1.14b). This monitoring task is necessary because deforestation processes leave spatial patterns or *footprints* in forest cover due to specific sequences of events (Geist & Lambin, 2001 p. 66). Within the context of environmental conditions (i.e., flora and fauna) and preconditions (e.g., politics, economics, and culture), decision-makers have to take decisions based on questions like 'which management strategy would be most suitable where in the area', 'when do I what', and 'what are the consequences of my decisions'? Addressing these questions without spatial context is hardly possible. For example, selective logging results in a mixture of old remaining trees and young regenerating trees, with some areas dominated by shrubs or grasses. The number and area of small trees is related to the intensity of regeneration; the number and area of remnant trees, shrubs or grasses are related to the intensity of logging. With spatial context, the intensity at which forests are logged can be monitored. Generally, events are natural or human-induced, but whether it is felling, clearing, fire, reforestation, or regeneration to name a few, each of them occur at specific spatial aggregation levels. Monitoring events related to spatial aggregation levels provide knowledge on actors. Once actors can be identified, models on actors' behavior can be developed and scenarios of impact of actors can be forecasted.

An additional prerequisite for such a monitoring task is to bridge the conflicting interests between remote sensing specialists and decision-makers concerning spatial aggregation levels (Beurden & Veen,1999). Generally, the remote sensing specialists need fairly detailed data to meet the necessary classification accuracy. This high resolution (or detailed spatial aggregation level) often does not provide the geo-information what decision-makers need for policy evaluation or planning (i.e., strategic or tactical decisions). For them the obvious aim of thematic classifications is to obtain geo-information that enhances the quality of the decisions. Such a presentation should match the level of detail that is relevant to the decision-maker (Beurden & Douven, 1999). Nowadays, geo-information has many forms to be presented ranging from traditional paper maps to interactive 3D visualizations on the internet. These new forms are excellent opportunities to stimulate interactions between remote sensing specialists and decision-makers (Bouma, 1999).

1.5 Research objectives, questions & methodology

The previous section addressed two responsibilities of remote sensing specialists towards tropical forestry applications: improvement of spatial entity definition (definition task), and development of monitoring tools at different spatial aggregation levels (monitoring task). These responsibilities call for an underlying remote sensing theory and for digital classification methods that can deal with forest cover classes in spatially heterogeneous environments. Therefore, the ***main objective*** of this thesis is to develop a remote sensing theory and related digital classification methods that allow quantifying spatially heterogeneity at different spatial aggregation levels tailored to end-user needs for decision-making. As a start for such a comprehensive theory, two main research questions are investigated in this thesis:

1. What is an effective classification framework to digitally classify spatially heterogeneous environments at different spatial aggregation levels?
2. How to implement this classification framework in remote sensing applications?

From the main objective of this thesis, four specific objectives are formulated:

1. To find and define information units for effectively monitoring deforestation processes for management at different decision levels.
2. To formulate a theoretical basis for digitally classifying such information units using remote sensing data.
3. To develop digital classification methods for classifying the newly defined information units using remote sensing data.
4. To assess in a case study the use of the new digital classification methods, and compare their results to a conventional per-pixel classification method.

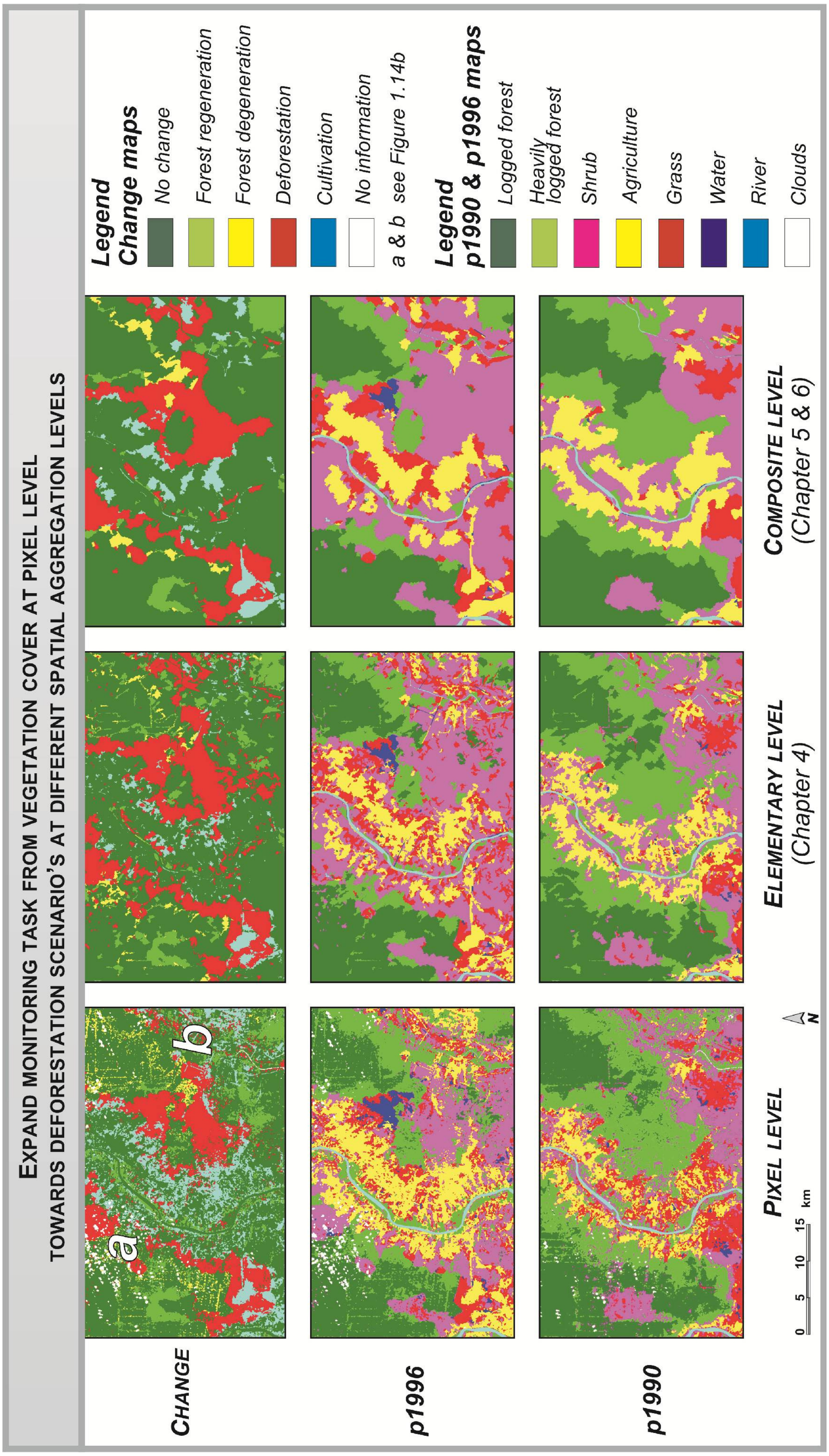


Figure 1.14a: Monitoring task of remote sensing scientists.

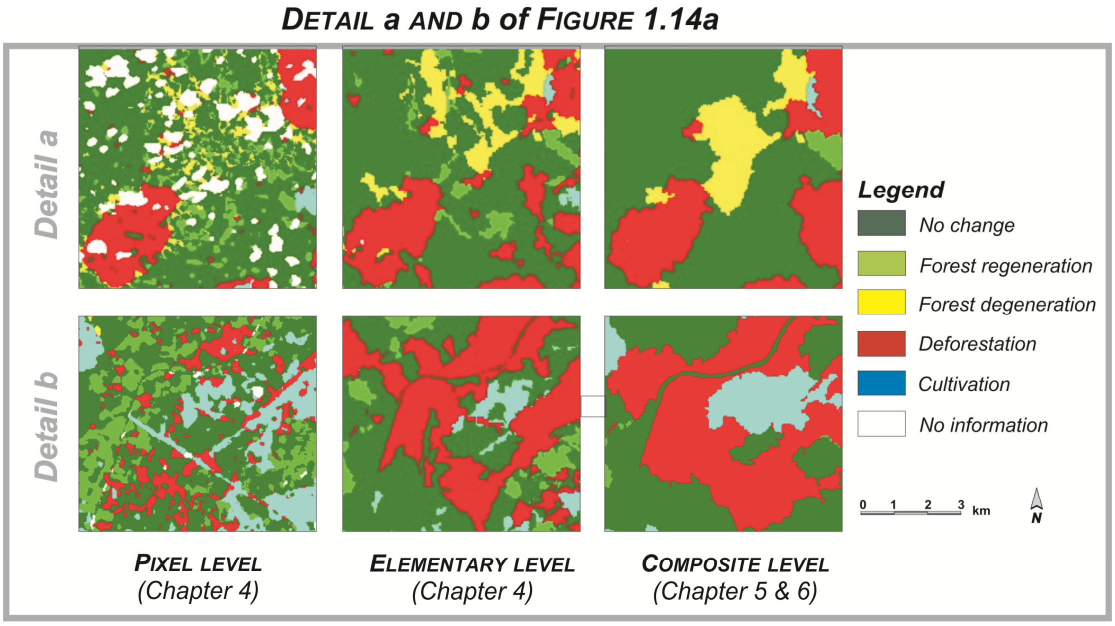


Figure 1.14b: Deforestation at different spatial aggregation levels.

To achieve these four specific objectives the following research questions have been investigated:

1. Can the field of landscape ecology be supportive to find and define effective information units to monitor deforestation processes in spatially heterogeneous environments?
2. Can the abundant spectral and spatial diversity of remote sensing data of spatially heterogeneous environments be reduced into a diversity of functional spatial objects at distinct levels of information detail?
3. Can digital classification methods make use of both the geometric aspects and the thematic aspects of spatial objects when classifying remote sensing data?
4. Can landscape pattern metrics be useful indicators to assess digital classification results besides accuracy assessment metrics conventionally used in remote sensing?

For answering both levels of research questions and for achieving the objectives, the research methodology followed in this thesis consisted of five operational steps (Figure 1.15):

- Reviewing literature to analyze how spatial heterogeneity is dealt with in both the field of remote sensing and the field of landscape ecology.

- Developing a remote sensing theory to quantify spatial heterogeneity at different spatial aggregation levels tailored to the end-users need for decision-making.
- Developing digital classification methods to quantify spatial heterogeneity at different spatial aggregation levels (i.e., elementary objects and composite objects).
- Digitally classifying two temporal Landsat TM images for the Pelangkaraya study area located in Kalimantan, Indonesia.
- Evaluating digital classification results using thematically oriented metrics used in remote sensing *(KHAT and Z-statistic)* and descriptively oriented metrics used in landscape ecology (i.e., composition and configuration metrics).

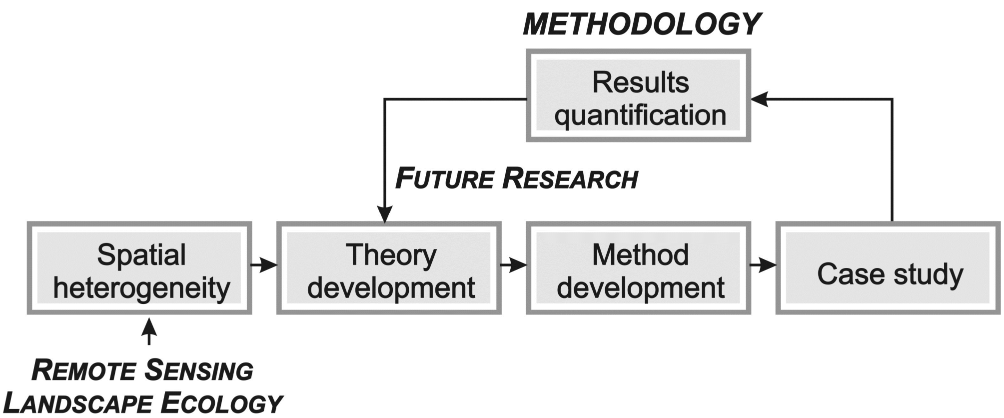


Figure 1.15: Methodology: five operational steps to achieve the objectives.

1.6 Pelangkaraya study area

A peatswamp forest near Pelangkaraya city, Central Kalimantan, Indonesia (Figure 1.16) has been selected as study area because of its many deforestation processes: shifting cultivation, logging, clear cut, drainage, permanent agricultural practices and fire. These processes changed the original *(spatial homogeneous)* peatswamp forest into a *(spatial heterogeneous)* mosaic of logged forest, heavily logged forest, patches of original forest, agricultural fields (trees and crops), fields covered mainly with grasses, abandoned fields covered mainly with shrubs, and water areas (section 1.6.1). Such patchy landscapes typically occur in many tropical rainforest areas in South-East Asia. From 1997 till 1999, the study area became part of a large project area known as the One Million Hectare Mega Rice Project (MPR) or *Proyek Pengembangan Lahan Gambut* (Notohadiprawino, 1998). This project became a failure. Nowadays, the Dutch government has amended to finance in the order of €5 million in 2005 and €10 million of structural funding a year for the conservation and restoration of this area currently known as the Ex-Mega Rice Project (EMRP) area, integrated with poverty reduction (Silvius, 2004). Furthermore, the study area has been indicated as one of the areas offering major classification problems using conventional digital classification methods (Pala, 1990). Besides this, temporal remote sensing images (section 1.6.2), extensive field knowledge and field data (section .6.3) are available.

1.6.1 Deforestation processes

The Pelangkaraya study area covers roughly 115.000 ha (45 by 25 km). Three rivers, *Barito*, *Kahayan* and *Kapuas*, meander through the flat area. The main vegetation of this area was natural peatswamp forest. Such forests are significant stores of carbon because of their considerable peat layers that can be up to 20 meters thick. Peatswamp forests in Southeast Asia contain almost 70%, or about 30 million ha, of the world's total tropical peatland area (Rieley et al., 1996; Radjagukguk, 2004). They contain at least 25% of the carbon globally fixed in peat (Immirzi & Maltby, 1992). Peatswamp forests have also been recognized as important reservoirs of biodiversity (Rieley et al., 1996; Page et al., 1997). Particularly, they contain a large number of tree species (Shepherd et al., 1997) and several rare and endangered animals, including the orang utan (Page et al., 1997; Meijaard, 1997).

For centuries, shifting cultivation has been the main agricultural activity of local people leaving the peatswamp forest intact as it was only practiced along the rivers. Since the eighties, however, numerous logging firms have obtained large concessions, and large transmigration projects have entered the area (Figure 1.17). The logging companies have exploited the peatswamp forest practicing selective logging based on a cycle of 35 years. They constructed railroad systems to extract and transport commercial species like ramin *(Gonystylus bancanus)*, bintangor *(Calophyllum spp.)*, kumpang *(Gymnacranthera farguhariana)*, and rattan (*Calamus tetradactylus*). The transmigration projects have been developed to release population pressure from densely populated areas like Java and Bali. They cleared the peatswamp forest through burning and additional draining by constructing several large canals and many small ones. The transmigrants were selected under the authority of the resettlement programmes of the Indonesian government. The goal of the government to provide the transmigrants with agricultural land, however, was (and is) hardly possible on peat soils. Instead, only shifting cultivation has become the main agricultural activity for transmigrants. The many constructed railroad systems of the logging firms drastically increased accessibility into the forest. Both the local people and the transmigrants extended their shifting cultivation radius. They also started logging activities in logged-over areas to increase their income.

Drainage and forest clearing, however, make peatlands susceptible to fire specifically in dry years (Watson et al., 2000). This process has been aggravated when the Indonesian Government started the Mega Rice Project in 1995. This project was an attempt to convert over one million ha peatswamp forest into rice fields in order to make Indonesia self-sufficient. Permits were issued to remove the peatswamp forest by clear-felling and to prepare the land for rice cultivation. The large-scale land clearing activities in combination with peat drainage for land preparation (making the area unusually dry) were responsible for the fact that during the 1997 El niňo event forest fires uncontrollably destroyed large areas of peatlands (BAPPENAS/ADB, 1999; Siegert et al., 2001). These fires contributed for about 13-40% of the mean annual global carbon emissions from fossil fuels (Page et al., 2002). The Mega Rice Project was stopped officially in 1999. It devastated, however, most of the project area having a huge impact not only on the environment, but also on the more than 15,000 inhabitants living in the Mega Rice Project area (Zain Muhamad, 2001).

Nowadays, many efforts are taken to rehabilitate the destructed peatland landscape and to restore the rights of local people in this area (e.g., Wösten, 2004).

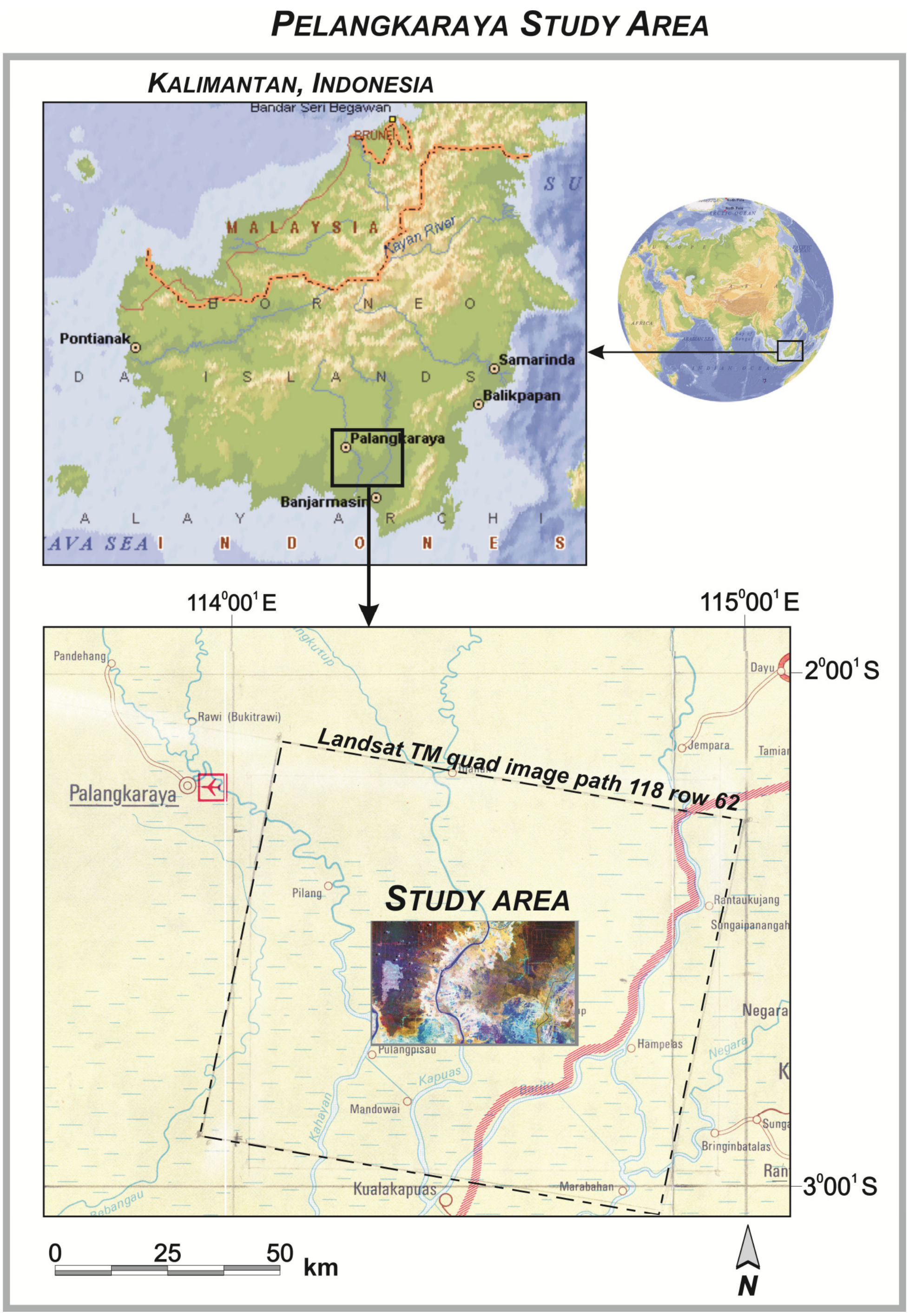


Figure 1.16: Location of the Pelangkaraya study area.

Figure 1.17: Tropical rainforest and the increasing impact of humans; natural peatswamp forest (a),commercial logging (b and c), agricultural encroachment (d and e), and transmigration (f, g and h) – Pelangkaraya study area, Kalimantan, Indonesia.

1.6.2 Remote sensing data

Landsat Thematic Mapper (TM) imagery has been selected for studying the new digital classification methods because this remote sensing data has been operationally used in the National Forestry Inventory Project of Indonesia (Revilla & Djwa Hui Liang, 1989; Pala, 1990; Obbink, 1993. A total of 175 full scene Landsat TM images are required to fully cover entire Indonesia (size of imagery 183 km wide, 170 km long). Digitally classifying such a number of images is important, specifically for spatially heterogeneous environments that are rapidly changing. The Landsat TM sensor consists of seven spectral bands: six reflective-optical bands (band 1-5 and 7) each with a pixel size of about 30m, and one thermal band (band 6) with a pixel size of about 120m (Landsat 5) or about 60m (Landsat 7). Wavelength details of each band are given in Table 1.1. Figure 1.18 shows the position of the Landsat TM bands in the electromagnetic spectrum.

Table 1.1: Details of Landsat Thematic Mapper Sensor.

Landsat 5 and 7	*Wavelength (μm)*	*Colour range*	*Resolution (m)*	*Sensitiveness (Jensen, 2007)*
Band 1	*0.45-0.52*	*Blue*	*30*	*Smoke*
Band 2	*0.52-0.60*	*Green*	*30*	*aquatic vegetation, turbidity and sediment*
Band 3	*0.63-0.69*	*Red*	*30*	*chlorophyll absorption; soils*
Band 4	*0.76-0.90*	*Near IR*	*30*	*vegetation varieties; water in soils and vegetation*
Band 5	*1.55-1.75*	*Middle IR*	*30*	*leaf-tissue water content; ferric/hematite rocks; discriminates between ice/snow & clouds*
Band 6	*10.40-12.50*	*Thermal*	*120 L5 60 L7*	*radiant surface temps –100C to +150C*
Band 7	*2.08-2.35*	*Middle IR*	*30*	*hydrous minerals (clay mica, some oxides, and sulfates)*

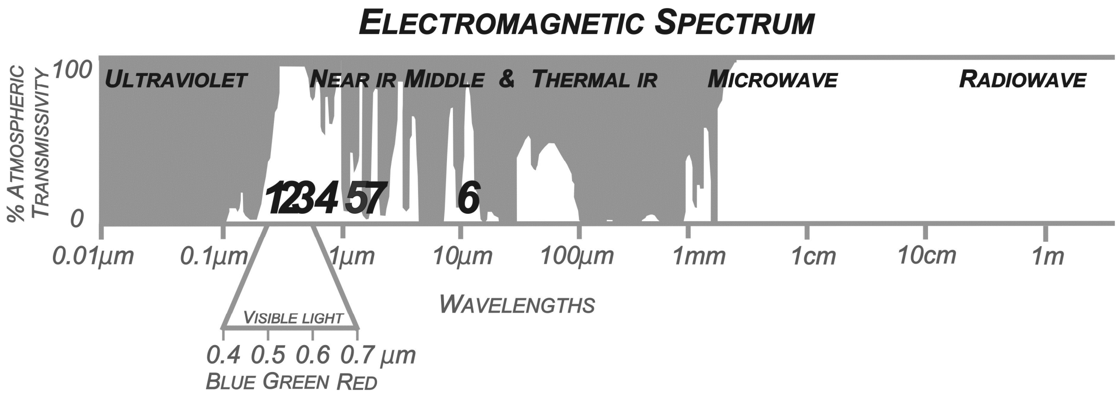


Figure 1.18: Position of Landsat TM bands (1234576) in the electromagnetic spectrum.

Although remote sensing images covering the Pelangkaraya study area were scarce because of persistent cloud-cover, three images of Landsat Thematic Mapper (TM) could be selected (Figure 1.19). Their acquisition dates are September 30, 1990 (further referred to as *p1990 image*); May 10, 1996 (*p1996 image*); and July 16, 2000 (*p2000 image*). The three images were georeferenced using a cubic-convolution resampling to relate the images to field data. A set of 1:50,000 topographic maps, UTM projected on the IND 1974 datum, were used to georeference the p1990 image. The p1990 image was used to georeference the p1996 and p2000 images. The spatial ground resolution after geo-correction was set at 30 meters. Details of acquisition dates, sensor platform, georeferencing accuracy, and UTM coordinates of the study area are given in Table 1.2.

Table 1.2 : Details of the remote sensing data for the Pelangkaraya study area.

Landsat TM imagery	*p1990 image*	*p1996 image*	*p2000 image*
Acquisition date	*30/08/1990*	*10/05/1996*	*16/07/2000*
Sensor platform	*Landsat 5*	*Landsat 5*	*Landsat 7*
Geo-accuracy in RMS error	*1.5 pixels*	*0.4 pixels*	*0.3 pixels*
UTM coordinates	*Lower Left point (m)*	*Upper Right point (m)*	
X	*196482.000*	*239922.000*	
Y	*9698835.000*	*9725055.000*	

After a preliminary analysis, the p2000 image was not further analyzed in this thesis because no forest cover classes were left as a consequence of the Mega Rice Project (see previous section). Principally, two historical images have been used to illustrate the developed theory and digital classification methods. Regarding the main objective of this thesis, however, the actual acquisition dates of remote sensing imagery are not relevant as long as the remaining temporal images cover a significant part of the deforestation problems as presented in the previous section. Obviously, both images show a destructive peatswamp forest area with abundant spatial heterogeneity.

Finally, four optical bands (i.e., band 1345) have been selected because Landsat TM band 2 was highly correlated with Landsat TM band 3, and Landsat TM band 5 was highly correlated with Landsat TM band 7 (correlation coefficient ≥ 0.85). Both band 2 and band 7 showed lowest variance, and thus were excluded. In addition, the information content of the thermal band is negligible for thematic applications.

Similar results were found in literature (Atkinson et al., 1985; Kenk et al., 1988; Karteris, 1990).

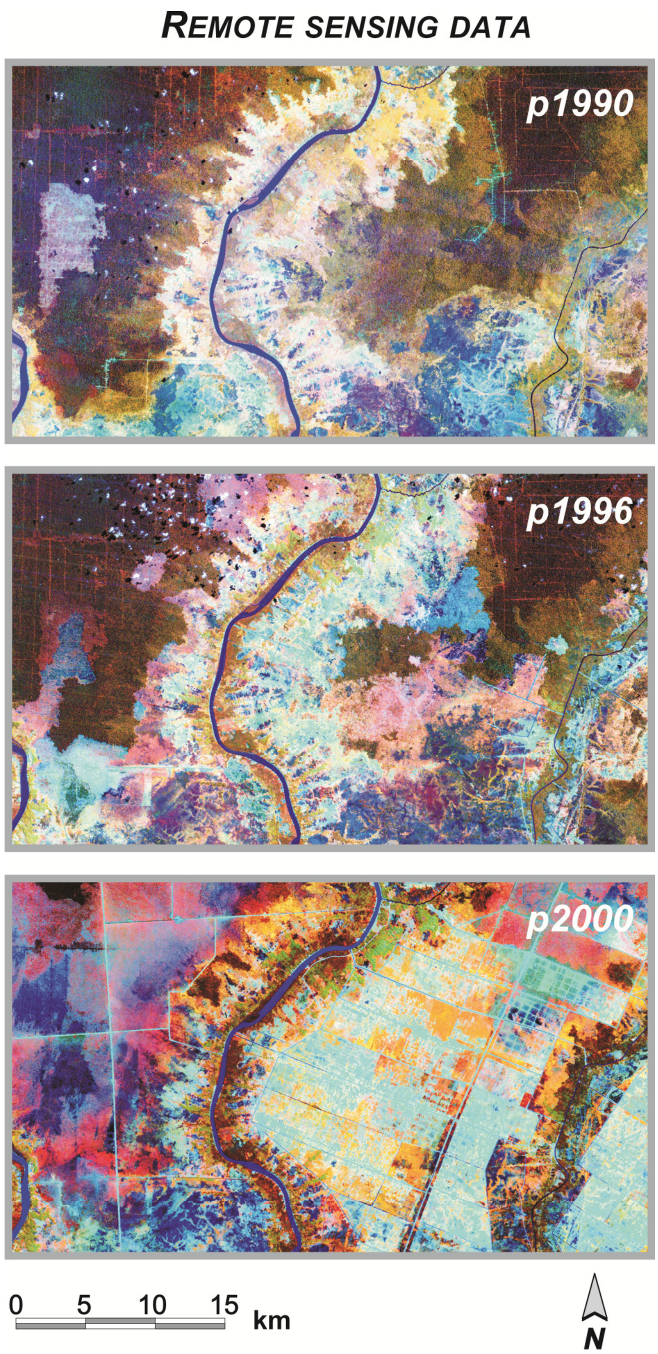


Figure 1.19: Three Landsat TM images covering the Pelangkaraya study area (color composite TM band 453, histogram equalization)

1.6.3 Field data

Field data have been collected within the framework of the National Forest Inventory (NFI) Project of the Indonesian Ministry of Forestry in cooperation with the Food and Agriculture Organization (Obbink, 1992). The field survey was part of a series of extensive Forests Resource Monitoring ground surveys together with two additional air surveys covering two areas in Sumatra, three areas in Kalimantan, and two areas in Irian Jaya. Each area was about one million ha. From central and local government, available land cover/land use maps derived from previous projects (e.g., RePPProT series) and the NFI project were acquired, as well as other remote sensing data sources (e.g., SPOT, Landsat MSS, Landsat TM, NOAA, Radarsat). Stratified random sampling was applied to locate a total of 28 ground survey plots in the Pelangkaraya study area. These plots represented the full range of spectral colours and textures of the pre-processed Landsat TM imagery. The coordinates of the plot centre and the approximate diameters of the ground survey plots were registered. The minimum radius of every plot was 1 km, considering the geometrical correction error, the map datum error, and the GPS position error. The maximum radius varied up to 2.5 km as a result of spatial heterogeneity. A 5 km grid was superimposed on the pre-processed Landsat TM image to ease map position while travelling in a very inaccessible and heterogeneous environment. Only river streams, a few canals, and the available logging railroad system could be used for travelling. The area was visited from November 23 till December 3, 1992. The ground survey data consisted of a description of site characteristics (e.g., land system, water level), land use/land cover information and their coverage, major tree species, a transect sketch providing the vertical structure of the vegetation, and an overview sketch providing the horizontal structure (texture) of the vegetation. Representative pictures were taken for each ground survey plot.

1.6.4 Classification software

Three remote sensing software packages were used to digitally classify the two Landsat TM images: ILWIS Academic 3.1, ERDAS Imagine 8.7, and eCognition Standard 3.0. The ILWIS Academic 3.1 was used for geo-correction, per-pixel based image classification, wavelet transformation, and all necessary GIS related processing. The Erdas Imagine 8.7 was used to create sample points for accuracy assessment and to convert images into required formats (signed-8-bits, unsigned-8-bits). The eCognition Standard 3.0 was used for image segmentation and image classification, both at elementary level and at composite level. Four additional software packages were used to assess the classification results: SPSS 10.0, Microsoft Excel 2003, IQM 6.5.2 and Fragstats 3.3. The statistical software package SPSS 10.0 was used for calculating the discrete multivariate analysis technique *KHAT*. The spreadsheet software package Microsoft Excel 2003 was used for calculating the test *Z*-statistics. The image quality software package IQM 6.5.2 was used for quantifying the performance of wavelet transformed images. Finally, the spatial pattern analysis software package Fragstats 3.3 was used for calculating four Landscape Pattern Metrics (*PLAND*, *NP*, *SIDI*, *LSI; details provided in Chapter 4*).

1.7 Outline thesis

This thesis consists of seven chapters. The chapters are grouped into three parts, the *Problem & Answer* part, the *Theory* part and the *Implementation* part (Figure 1.20).

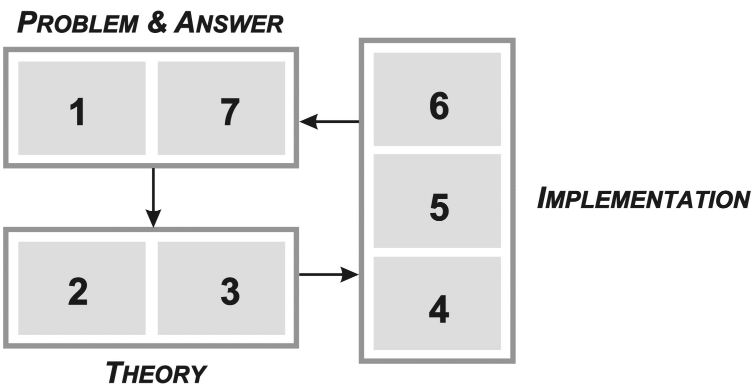


Figure 1.20: The three main parts of this thesis (numbers indicating related chapters).

Chapter 1 and Chapter 7 constitute the **Problem & Answer** part. Chapter 1 describes current problems when digitally classifying spatially heterogeneous environments using remote sensing data, and the necessity to improve digital classification methods in order to tailor geo-information to the need of end-users. The ultimate goal is to enhance sustainable development in tropical rainforest areas. Chapter 7 provides the synthesis of this thesis, focussing on the development and implementation of the so-called *Aggregate-Mosaic Theory*. The developed theory presents a functional generalization framework - called a LCM classification - to digitally classify remote sensing data into *Land Cover Mosaics* (LCMs). A LCM classification uses both the geometric and the thematic aspects of spatial entities. The implementation presents four digital methods of LCM classification. Chapter 7 also evaluates the digital classification results of the implementation chapters, presents the limitations of the research, and provides the recommendations for future research to quantify spatial heterogeneity at different spatial aggregation levels.

Chapter 2 and Chapter 3 constitute the **Theory** part of this thesis. Chapter 2 elucidates what is provided in literature on quantifying spatial heterogeneity. The first part of this chapter starts with presenting some models and theories used in the field of landscape ecology. A major issue found was the patch-mosaic, because it divides the landscape into functional spatial entities without compromising on their structural heterogeneous nature. The patch-mosaic addresses both vegetation composition and vegetation structure. The second part of Chapter 2 reviews innovative processing techniques in remote sensing related to their support to this patch-mosaic concept. Chapter 3 introduces the Aggregate-Mosaic Theory for modeling quantitatively spatial heterogeneity at different spatial aggregation levels (i.e., patches, patch-mosaics and landscapes). It provides a general model for functionally generalizing geo-information from (conventional) land cover classes to (functional) LCM classes. Essential in this model is that LCM classes at composite level are created based on the mixture and area of land cover classes at elementary level. This entire process is called LCM classification.

Chapter 4, Chapter 5 and Chapter 6 constitute the **Implementation** part of this thesis. Chapter 4 deals with creating elementary objects. Specifically, it studies the impact of segmentation parameters on classification results related to forest cover and forest cover pattern. This chapter also describes several thematic and descriptive evaluation methods that have been used throughout the implementation part. Chapter 5 deals with creating composite objects. Specifically, it deals with the *thematic* upscaling of elementary objects into composite objects using a multi-scaled classification method (i.e., patch-mosaic classification). It also investigates the impact of the two LCM upscaling parameters 'mixture' and 'area' on classification results related to forest cover and forest cover pattern. Chapter 6 also deals with creating composite objects, but this chapter deals with the *geometric* upscaling of elementary objects into composite objects. Specifically, it studies the impact of four different segmentation methods (i.e. patch-mosaic segmentation) on classification results related to forest cover and forest cover pattern.

Finally, this thesis ends with summaries in English, Dutch and Indonesian, and the curriculum vitae of the author.

References

Apan, A.A. (1997). Land cover mapping for tropical forest rehabilitation planning using remotely-sensed data. *International Journal of Remote Sensing* 18(5):1029-1049.

Asner, G.P., Keller, M., Pereira R. & Zweede, J.C. (2002). Remote sensing of selective logging in Amazonia. *Remote Sensing of Environment* 80(3):483-496.

Atkinson, P., Cushnie, J.L., Townshend, J.R.G., & Wilson, A. (1985). Improving Thematic Mapper land cover classifcation using filtered data. *International Journal of Remote Sensing* 6(6):955-961.

BAPPENAS/ADB (1999). Causes, extent, impact and costs of 1997/1998 firest and drought. Planning for Fire Prevention and Drought Management Project. Asian Development Bank (ADB) TA 2999-INO. Final Report, Annex 1 and 2 (BAPPENAS is National Development Planning Agency of Indonesia).

Beurden, A.U.C.J. van & Douven, W.J.A.M. (1999). Aggregation issues of spatial information in environmental research. *International Journal of Geographical Information Science* 13(5):513-527.

Beurden, A.U.C.J. van & Veen, A.A. van der (1999). Areal units for environmental decision support, revisited. Proceedings, Joint European Conference and Exhibition on Geographical Information (JEC-GI), Volume 1, 292-297.

Bryant, D., Nielsen, D. & Tangley, L. (1997). The last frontier forests: Ecosystems and economies on the edge. World Resources Institute, Washington D.C. At http://www.wri.org/wri/ffi/lff-eng/, accessed July 10, 2004.

Bouma, J. (1999). Land evaluation for landscape units. In: Sumner, M.E. (ed), Handbook of Soil Science, CRC Press, Boca Raton, Florida, E393-E412.

Brundtland, G.H. (1987). Our Common Future. World Commission on Environment and Development (WCED). At: http://www.are.admin.ch/are/en/nachhaltig/international_uno/unterseite02330/, accessed June 15, 2004.

CIFOR (2004). Remote sensing and forest governance in Indonesia: Increasing transparency and accountability, Bogor, Indonesia. At http://www.as.miami.edu/geography/assets /docs/ remote_sensing.pdf, accessed August 18, 2005.

Cochrane, M.A. (2003). Fire science for rainforests. *Nature* 421, 913-919.

Comber, A., Fisher, P. & Wadsworth, R. (2005). You know what land cover is but does anyone else?...an investigation into semantic and ontological confusion. *International Journal of Remote Sensing* 26(1):223-228.

CRCSI (2005). About spatial information. Cooperative Research Centre for Spatial Information (CRCSI), Carlton, Australia. At http://spatialinfocrc.org/pages/about.aspx, accessed December 19, 2005.

Dansereau, P. (1957). Biogeography, an ecological perspective. Ronald Press, New York.

Dennis, C. & Aldhous, P. (2004). Biodiversity: A tragedy with many players. *Nature* 430, 396-398.

Edwards, D.S., Booth, W.E., Choy, S.C. (eds) (1996). Tropical Rainforest Research – Current Issues. Kluwer Academic Publisher, Dordrecht.

Ens (2008). Global forest survey aims to stem deforestation. Environmental News Services, Washington, D.C. At http://www.ens-newswire.com/ens/jul2008/2008-07-16-01.asp, accessed September 15, 2008.

FAO (1997). State of the World's Forests 1997. Food and Agriculture Organization of the United Nations, Rome.

FAO (2000). Global Forest Resources Assessment 2000. Main Report. FAO Forestry Paper 140. Food and Agriculture Organization of the United Nations, Rome. At www.fao.org/forestry/site/7949/en, accessed November 5, 2003.

FAO (2003a). State of the World's Forest 2003. Food and Agriculture Organization of the United Nations, Rome. At ftp://ftp.fao.org/docrep/fao/005/y7581e/y7581e00.pdf, accessed June 15, 2004.

FAO (2003b). Satellite imagery to assist forest management - Pilot study in Morocco. Remote Sensing for Decision-makers Series, No. 15. Food and Agriculture Organization of the United Nations, Rome. At http://www.fao.org/sd/EIdirect/EIre0069.htm, accessed August 18, 2005.

FAO (2006). Global Forest Resources Assessment 2005. Progress towards sustainable forest management. FAO Forestry Paper 147. Food and Agriculture Organization of the United Nations, Rome. At www.fao.org/forestry/site/fra/en/, accessed January 14, 2008.

Fuller, R.M., Smith, G.M. & Devereux, B.J. (2003). The characterisation and measurement of land cover change through remote sensing: problems in operational applications? *International Journal of Applied Earth Observation and Geoinformation* 4:243-253.

Geist, H.J. & Lambin, E.F. (2001). What drives tropical deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence. LUCC report series, No. 4. CIACO, Louvain-la-Neuve.

Gilruth, P.T. & Hutchinson, C.F. (1990). Assessing deforestation in the Guinea Highlands of West Africa using remote sensing. *Photogrammetric Engineering & Remote Sensing* 56(10):1375-1382.

Giri, C., Defourny, P. & Shrestha, S. (2003). Land cover characterization and mapping of continental Southeast Asia using multi-resolution satellite sensor data. *International Journal of Remote Sensing* 24(21):4181-4196.

GMES (2005). Forest Monitoring Services, Global Monitoring for Environment and Security (GMES), initiative of European Commission and the European Space Agency (ESA). At http://www.esa.int/esaLP/SEM36I2IU7E_LPgmes_0.html, accessed December 15, 2005.

Goff, J. Le (1967). Le désert-forêt. In: Diderot & D'Alembert (eds), Forêt: La grande encyclopédie, 65-66.

Holmgren, P., Marklund, L-G., Saket, M. & Wilkie, M.L. (2007). Forest Monitoring and Assessment for Climate Change Reporting: Partnerships, Capacity Building and Delivery. Forest Resources Assessment Working Paper 142, FAO, Rome. At www.fao.org/forestry/fra, accessed January 14, 2008.

Immirzi, C.P. & Maltby, E. (1992). The global status of peatlands and their role in the carbon cycle. Wetlands Ecosystem Research Group, Report 11, University of Exeter, UK.

Jensen, J.R. (2007). Remote Sensing of the Environment: An Earth Resources Perspective, 2nd Ed., Upper Saddle River, NJ. Prentice-Hall, Inc.

Karteris, M.A. (1990). The utility of digital Thematic Mapper data for natural resources classifcation. *International Journal of Remote Sensing* 11(9):1589-1598.

Kenk, E., Sondheim, M. & Yee, B. (1988). Methods for improving accuracy of thematic mapper ground cover classifications. *Canadian Journal of Remote Sensing* 14(1):17-31.

Köhler, P. (2005). User-oriented provision of geo-information in disaster management. Potentials of Spatial Data Infrastructures considering Brandenburg/Germany as an example, GFZ, Potsdam. At http://www.gdmc.nl/events/gi4dm/presentations/03-Koehler.pdf, accessed December 15, 2005.

Kolasa, J. & Rollo, C.D. (1991). The heterogeneity of heterogeneity: A glossary. In: Kolasa, J. & Pickett, S.T.A. (eds), Ecological heterogeneity, Ecological Studies 86, Springer-Verlag, New York, 1-23.Küchler, A.W. & Zonneveld, I.S. (1988). Vegetation mapping. Handbook of vegetation Science, Volume 10. Kluwer, Dordrecht.

Lambin, E.F. (1994). Modelling deforestation processes: A review. TRopical Ecosystem Environment observations by Satellites, TREES Series B, Research Report No. 1. European Commission, Directorate-General XIII, Information Technologies and Industries, and Telecommunications, L-2920, Luxembourg.

Lambin, E.F. & Ehrlich, D. (1997). The identification of tropical deforestation fronts at broad spatial scales. *International Journal of Remote Sensing* 18(17):3551-3568.

Lund, H.G. (1999). Forest classification: A definitional quagmire. In: The world's natural forests and their role in global processes, Khabarovsk, Russia, 17 p.At http://home.att.net/~gklund/quagmire.htm, accessed November 7, 2003.

Lund, H.G. (2000). Definitions of forest, deforestation, afforestation, and reforestation. Unpublished report. Manassas, VA: Forest Information Services. At http://home.att.net/~gklund/DEFpaper.html, accessed November 5, 2000.

Mackay, S.C. (1999). Semantic integration of environmental models for application to global information systems and decision-making. *SIGMOD Record* 28(1):13-19.

Makkonen, O. (1974). Forst-sanan alkuperä. Summary: On the origin of the word Forst (Forest). The society of forestry in Finland, Helsinki. Silva-Fennica 8(1):10-19.

Malhi, Y., Roberts, J.T; Betts, R.A.; Killeen, T.J.; Wenhong Li; Nobre, C.A. (2008). Climate Change, Deforestation, and the Fate of the Amazon, Review. *Science* 319(5860):169-172.

Malingreau, J.P. (1991). Remote sensing for tropical forest monitoring: An overview. In: Belward, A.S. & Valenzuela, C.R. (eds), Remote sensing and geographical information systems for resource management in developing countries. Kluwer Academic Publishers, Dordrecht.

Matthews, E., Payne, R., Rohweder, M. & Murray, S. (2000). Pilot analysis of global ecosystems: Forest ecosystems. World Resources Institute, Washington D.C.

Meijaard, E. (1997). The importance of swamp forest for the conservation of the orang utan (Pongo pygmaeus) in Kalimantan, Indonesia. In: Rieley, J.O. & Page, S.E. (eds), Biodiversity and sustainability of tropical peatlands. Samara Publications, Cardigan, UK, 243-254.

Molenaar, M. (1998). An introduction to the theory of spatial object modelling for GIS. Taylor & Francis, London.

MOF (1998). Decision of the Indonesian Minister of Forestry and plantations on social forest(ry) / Keputusan Menteri Kehutanan dan Perkebunan tentang hutan kemasyarakatan (Number 677/Kpts-II/1998).

MOF (1999). Decision of the Indonesian Minister of Forestry as declared in the Forestry Law of 1999, Chapter 1, Article 1, Point 2. At http://www2.bonet.co.id/dephut/41-99-1.htm, accessed November 5, 2000.

Morley, R.J. (2000). Origin and evolution of tropical rainforests. John Wiley & Sons, Chichester.

Mueller-Dombois, D. & Ellenberg, H. (1974). Aims and methods of vegetation ecology. John Wiley & Sons, New York.

Myers, N. (1989). Deforestation rates in tropical forests and their climatic implications. Friends of the Earth, London.

Notohadiprawiro, T. (1998). Conflict between problem solving and optimizing approach to land resources development policies - the case of Central Kalimantan wetlands. Proceedings of the International Peat Symposium "The Spirit of Peatlands", International Peat Society, Jyvaskyla, Finland, 14-24.

NSDP (2004). The National Environmental Action Plan of Malawi. Chapter Four: Environmental Issues, Figure 4.1.At http://www.sdnp.org.mw/enviro/action_plan/fig_4_1.html, accessed June 15, 2004.

Obbink, M.H. (1992). PODINS Ground Survey I and II. National Forest Inventory UTF/INS/066/INS, Back to Office Report (BTOR6). Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Obbink, M.H. (1993). Manual on operational digital image analysis for land cover/land use mapping. National Forest Inventory UTF/INS/066/INS, Working Document No. 6. Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Page, S.E., Rieley, J.O, Doody, K., Hodgson, S., Husson, S., Jenkins, P., Morrogh-Bernard, H., Orway, S. & Wilshaw, S. (1997). Biodiversity of tropical peatswamp forest: A case study of animal diversity in the Sungai Sebangau catchment of Central Kalimantan, Indonesia. In: Rieley, J.O. & Page, S.E. (eds). Biodiversity and sustainability of tropical peatlands. Samara Publications, Cardigan, 243-254.

Page, S.E., Sieger, F., Rieley, J.O. Goehm, H.-D.V., Jaya, A. & Limin, S. (2002). The amount of carbon released from peat and forest firest in Indonesia during 1997. *Nature* 420:61-65.

Pala, S., (1990). Pilot project and training of Indonesian scientists in operating digital image analysis. National Forest Inventory, UTF/INS/066/INS, Field Document No. 8. Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Powell, R.L., Matzke, N., Souza, C. de, Clark, M., Numata, I., Hess, L.L. & Roberts, D.A. (2004). Sources of error in accuracy assessment of thematic land-cover maps in the Brazilian Amazon. *Remote Sensing of Environment* 90:221-234.

Radjagukguk, B. (2004). Developing sustainable agriculture on tropical peatland: Challenges and prospects. Proceedings of the 12th International Peat Congress, Tampere, Finland, Volume 1, 707-712.

Revilla, J.A.V. & Djwa Hui Liang (1989). The National Forest Inventory (NFI) Project of Indonesia. National Forest Inventory UTF/INS/066/INS, Field Document No. 3. Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Reynolds, J.F, Virginia, R.A. & Schlesinger, W.H. (1997). Defining functional types for models of desertification. In: Smith, T.M., Shugart, H.H. & F.I. Woodward (eds), Plant functional types, their relevance to ecosystem properties and global change, International Geosphere-Biosphere Programme Book Series, Cambridge University Press, Cambridge, 195-216.

Richards, J.A. & Jia, X. (1999). Remote sensing digital image analysis. Third edition. Springer, Berlin.

Rieley, J.O., Ahmad-Shah, A.A. & Brady, M.A. (1996). The extend and nature of tropical peat swamps. In: Maltby, E., Immirzi, C.P. & Safford, R.J. (eds), Tropical lowland peatlands of Southeast Asia, Gland, Switzerland, IUCN, 17-53.

Sader, S.A. & Joyce, A.T. (1985). Global tropical forest monitoring. Advance technology for monitoring and processing global environmental data. Proceedings of the International Conference of the Remote Sensing Society and the Center for Earth Resources Management, 9-12 September, London.

Sader, S.A. & Stone, T.A. (eds) (1990). Special Issue: Remote sensing for monitoring tropical moist forests. *Photogrammetric Engineering & Remote Sensing* 56(10):1341-1401.

Siegert, F., Ruecker, G., Hinrichs, A. & Hoffmann, A.A. (2001). Increased damage from fires in logged forests during droughts caused by El Nino. *Nature* 414:437-440.

Silvius, M. (2004). Good news for the peatswamp Forests of Central Kalimantan, Indonesia. At http://www.imcg.net/imcgnl/nl0404/Kap10.htm, accessed December 23, 2004.

Shepherd, P.A., Rieley, J.O. & Page, S.E. (1997). The relationship between forest vegetation and peat characteristics in the upper catchment of Sungai Sebangau, Central Kalimantan. In: Rieley, J.O. & Page, S.E. (eds), Biodiversity and sustainability of tropical peatlands, Samara Publications, Cardigan, 191-210.

Smith, J. H., Wickham, J. D., Stehman, S. V., & Yang, L. (2002). Impacts of patch size and land cover heterogeneity on thematic image classification accuracy. Photogrammetric Engineering and Remote Sensing 68: 65-70.

Southworth, J., Munroe, D. & Nagendra, H. (2004). Land cover change and landscape fragmentation – comparing the utility of continuous and discrete analysis for a western Honduras region. *Agriculture, Ecosystems and Environment* 101:185-205.

Stork, N.E. (2007). Biodiversity: World of insects. *Nature* 448: 657-658.

Timmermans, H.J.P. (1981). Consumer choice of shopping centre: An information integration approach. *Regional Studies* 16:171-182.

Tuomisto, H., Linna, A. & Kalliola, R. (1994). Use of digitally processed satellite images in studies of tropical rainforest vegetation. *International Journal of Remote Sensing* 15(8):1595-1610.

UNEP (1992). Agenda 21, United Nations Environment Programme. At http://www.unep.org /Documents/ Default.asp?DocumentID=52, accessed June 18, 2004.

UNEP (2002). Statement by Klaus Toepfer, Executive Director United Nations Environment Programme, World Summit on Sustainable Development, 26 August 2002 Johannesburg, South Africa. At http://www.unep.org/wssd/Documents/ED%20Stmt.doc, accessed June 18, 2004.

Watson, R. T., Noble, I. R., Bolin B., Ravindranath, N. H., Verardo, D.J., Dokken, D.J. (eds) (2000). Land use, land-use change, and forestry. A special report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge.

Wharton, S.W. (1982). A contextual classification method for recognizing land use patterns in high resolution remotely sensed data. *Pattern Recognition* 15(4):317-324.

Whitmore, T.C. (1998). An introduction to tropical rainforests – 2nd edition. Oxford University Press, Oxford.

Wijdeven, M.J., Meer, P.J. van der, Chai, F.Y.C., Tan, S., Mohizah, M. & Liam, D. (2004). Sustainable management of Peat Swamp Forest of Sarawak with special reference to Ramin (Gonystylus bancanus). Development of a monitoring system. Wageningen, Alterra-rapport 1123, 40p.

Wösten, J.H.M. (2004). Project coordinator of the EU funded project entitled 'Strategies for implementing sustainable management of peatlands in Borneo (STRAPEAT)'.At http://www.alterraresearch.nl/pls/portal30/docs/folder/strapeat/strapeat/p_frameset.htm, accessed August 17, 2004.

Zain Muhamad, N. (2001). Management of tropical peatlands: mega reclamation project in Central Kalimantan. At http://www.geocities.com/kopitubruk/Report2.html, accessed December 23, 2004.

Zonneveld, I.S. and Forman R.T.T. (eds.) (1990). Changing landscapes: an ecological perspective. Springer-Verlag, New York, p. 285.

CHAPTER 2

SPATIAL HETEROGENITY

“*Wij verblijven zo graag in de vrije natuur omdat deze geen oordeel over ons heeft”*

“We are so fond of being out among nature, because it has no opinions”

Friedrich Wilhelm Nietzsche (1844 - 1900)

2.1 Introduction

Digitally analyzing remote sensing imagery at different spatial aggregation levels of spatially heterogeneous environments requires an approach that addresses both vegetation composition and vegetation structure, the latter in terms of horizontal structure or *pattern* (Chapter 1, section 1.3). The specific focus of ecology on spatiality in relation to functionality could provide useful concepts or theories to the field of remote sensing to define information units for effectively monitoring deforestation processes for management at different decision levels as stipulated in the first objective of this thesis (section 1.5). Therefore, a review on handling spatial heterogeneity in landscape ecology is presented in section 2.2. This section starts with some key definitions in landscape ecology. After that it describes the backbone of this thesis: a bottom-up approach using *patch-mosaics* that are based on ecosystem functional types (EFTs) to divide the landscape into *functional* spatial objects without compromising on their heterogeneous structural nature (Reynolds et al., 1997; Reynolds & Wu, 1999). The remainder of this section describes underlying models, approaches, and developments in landscape ecology leading to the approach of using patch-mosaics. It therefore discusses three structural models and two functional approaches to handle two distinctive heterogeneities: structural heterogeneity and functional heterogeneity. Related to this, it also presents the modifiable areal unit problem (MAUP) that arises when defining structural areal units, specifically in thematically complex landscapes. Section 2.2 ends with discussing two developments in landscape ecology (i.e., the Hierarchical Patch Dynamics Paradigm or HPDP, and the Ecotissue Model), both addressing the necessity to link the structural and the functional properties of landscapes when modeling spatial heterogeneity.

Section 2.3 moves to remote sensing in its broadest sense of spatial object modeling. It starts with presenting spatial generalization besides thematic generalization as a key conceptual generalization operation for digitally analyzing spatially heterogeneous environments. Related to this, it explains the need for defining aggregation hierarchies besides classification hierarchies. Therefore, it discusses three types of relationships for building aggregation hierarchies and presents functional generalization as the most appealing conceptual generalization strategy to model spatial heterogeneity. After that, it describes two major limitations when implementing functional generalization in remote sensing using either the field approach or the object approach. Related to this, it discusses why current digital analysis techniques do not overcome these two limitations. Section 2.3 ends with describing two innovative digital techniques, multi-scale segmentation and wavelet transformation, which were used in this thesis to implement functional generalization in remote sensing. Last but not least, section 2.4 summarizes two major implications when implementing patch-mosaics in categorical image analysis using remote sensing data.

2.2 Handling spatial heterogeneity in Landscape Ecology

Landscape ecology is a relatively new scientific branch of ecology. It deals with the detection, measurement, and interpretation of pattern, the relationship between patterns and ecological processes, and the dependency of pattern and process on spatial scale (Forman & Godron, 1986; Turner, 1989). Therefore, two key aspects of landscape ecology are the emphasis on the role of *spatial* pattern in ecological processes and the focus on spatial extents of ecological processes that are much larger than those studied in ecology (Turner et al., 2001). While ecology views systems in the 'vertical' perspective, highlighting their internal processes and functions, landscape ecology views systems in the 'horizontal' perspective, highlighting their spatial distribution and interactions (Rowe 1961; Reynolds & Wu, 1999). Consequently, landscape ecology expands the scope of ecology to specifically address the role of spatial heterogeneity in ecological processes (Picket & Cadenasso, 1995). In fact, in landscape ecology, the *spatial* approach of the geographer is combined with the *functional* approach of the ecologist (Naveh & Lieberman, 1984; Forman & Godron, 1986, Turner et al., 2001).

2.2.1 Definitions in Landscape Ecology

The tendency of scientists to seek order in nature has led to assumptions concerning uniformity, homogeneity and constancy (McIntosh, 1991). The significance of both homogeneity – the absence of variation or lack of pattern – and its converse heterogeneity – the presence of variation or abundance of pattern – has led to disputes during the late nineteenth century and entire twentieth century. Homogeneity by its very nature requires little descriptions. Addressing heterogeneity, however, has lead to pluralism of theories and approaches to handle spatial heterogeneity (McIntosh, 1991). To give the reader a flavor of this pluralism, a title to describe the conceptual foundation of spatial heterogeneity gives '…the heterogeneity of heterogeneity…' (Kolasa & Rollo, 1991). Moreover, definitions in landscape ecology suffer from the common problem of new sciences: they are principally defined using terms that are usually poorly defined, or are based on a group of similar, but not identical, definitions (Eng, 1997). This section only attempts to introduce some of the more important terms and concepts using the most generic definition in the landscape ecology literature.

Spatial heterogeneity is generally defined as the quality or state of being composed of different elements that may assume many forms and combinations (Kolasa & Rollo, 1991). Examples of such 'different elements' are mixed habitats or vegetation types occurring in a ***landscape*** (Turner et al., 2001). The vegetation types can vary in plant form as well as in species composition, creating a ***mosaic*** of definable alternatives of, for instance, basic woodland/shrubland/grassland themes (Gilbert & Plowes, 2004). Spatial heterogeneity relates explicitly to structure being the spatial relationship among landscape elements. A more extensive definition of structure is the distribution of energy, materials, and species in relation to the sizes, shapes, numbers, kinds, and ***configuration*** of components (Turner & Gardner, 1991). Reference to configuration is important, because it is a main characteristic of pattern (Li & Reynolds, 1995). It refers to the arrangement of the landscape, or 'how things are distributed' (Forman, 1995; Gustafson, 1998). This is complementary to ***composition*** that refers to variability of the landscape, or 'how different things are'.

Spatial and temporal aspects are conventionally used to describe spatial heterogeneity. For spatial aspects a static descriptor suffices. For instance, vegetation cover is spatially heterogeneous if a chosen quantitative or qualitative descriptor assumes different values at different locations. Temporal heterogeneity is similar to spatial heterogeneity, except that it refers to one point (location or site) in space and many points in time (Kolasa & Rollo, 1991). Li and Reynolds (1995) extended the given definition on spatial heterogeneity to make explicitly an operational distinction between qualitative and quantitative descriptors. They defined spatial heterogeneity as the *complexity* and/or *variability* of a *system's property* in space and/or time. ***Complexity*** refers to a qualitative or categorical description of a system's property (composition of parts of different kinds). Consequently, complexity measures are applicable for categorical maps. ***Variability*** refers to a quantitative or numerical description of a system's property (different values of a variable of one kind). Consequently, variability measures are applicable for numerical maps. A ***system's property*** can be anything that is of ecological interest (e.g. soil nutrients, plant biomass, and vegetation cover), and that we wish to measure in the landscape (Reynolds & Wu, 1999). Figure 2.1 provides a schematic overview of the two descriptive approaches. Both approaches are traditionally used in remote sensing analysis and called respectively the *object approach* and the *field approach* (section 2.3.3). As such, complexity concerns the object approach, sometimes also called the cartographic approach, using classification to subdivide the image into homogeneous mapping units (Gustafson, 1998). Variability concerns the field approach, sometimes also called the direct image approach, using reflectance or vegetation indices to measure image variance on a pixel-to-pixel basis (Goodchild & Quattrochi, 1997).

Structural heterogeneity refers to the complexity and variability of a structural property, for example, vegetation cover, soil nutrients, and elevation (Reynolds & Wu, 1999). This heterogeneity is sometimes called measured heterogeneity to directly link to the observer's perspective. Structural measures of heterogeneity are tempting and popular, but their ability to reflect the relevant properties of the system of interest is often unclear and questionable because such measures are often uni-dimensional (i.e., across infinite spatio-temporal scales; Kolasa & Rollo, 1991).

Functional heterogeneity refers to the complexity and variability of a functional property, for example, gas flux and primary productivity (Reynolds & Wu, 1999). It is the heterogeneity an ecological entity perceives and responds to. Functional heterogeneity is an organizational (or systemic) aspect of heterogeneity and is necessarily multi-dimensional (Kolasa & Rollo, 1991). Functional heterogeneity arises from the interaction between scales relevant to the ecological entity and its environment.

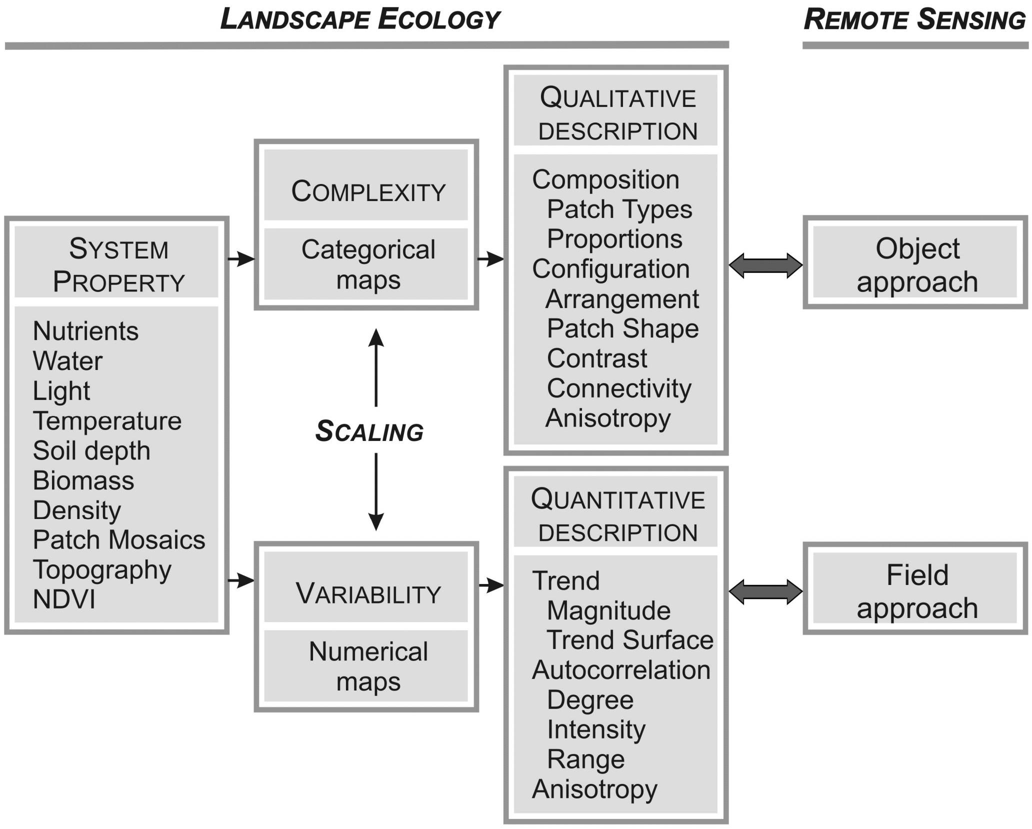


Figure 2.1: Describing spatial heterogeneity in Landscape Ecology (after Li & Reynolds, 1995) linked to Remote Sensing; a qualitative object approach versus a quantitative field approach.

Moreover, functional heterogeneity is heterogeneity from the perspective of participating ecological entities. It has many dimensions and many potentially important interactions amongst them. There are many functional heterogeneities in a system as simple as local population and many more in a system as complex as an ecosystem (Kolasa & Rollo, 1991). Figure 2.2 provides a schematic overview of the two heterogeneities in relation to patterns, processes and scales.

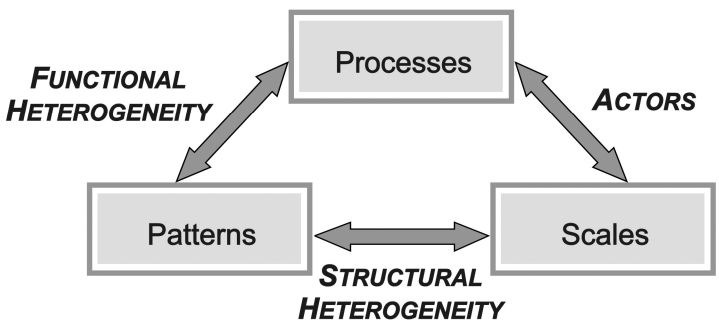


Figure 2.2: Functional heterogeneity and structural heterogeneity in relation to patterns, processes and scales.

The distinction between structural heterogeneity and functional heterogeneity may disappear as the knowledge of a system increases. For example, in cases where the scale of the study is small or where the choice of heterogeneity measures is strongly influenced by prior knowledge of the organisms involved, the structural and functional heterogeneities start to converge. Consequently, indices of heterogeneity become more and more functional, while interpreting them as if they were entity-independent, or 'objective' (Kolasa & Rollo, 1991). Whatever heterogeneity is measured (complexity or variability), spatial heterogeneity emerges and disappears with alteration of ***scale***. As Kolasa and Pickett (1991) formulated: '…scale is the window, heterogeneity is the characteristic of the view in it…'. Therefore, from a data analysis point of view, rescaling (including transformation, reduction and aggregation) modifies spatial heterogeneity (Reynolds & Wu, 1999).

Scale refers to the spatial or temporal dimension of an object or a process, characterized by both grain and extent (Turner et al., 2001). Grain is the finest resolution of data, that is the pixel size (average dimension of an area) of image data or the minimum time step to which an organism perceives and responds to time series data (Kotliar & Wiens, 1990). Extent is the coarsest resolution of data, that is the total dimension of an area or the duration at which organisms react (Farina, 1998; Reynolds & Wu, 1999). Scale represents the window of perception and is the filter or measuring tool with which a system is viewed and quantified (Hay et al., 2001; Burnett & Blaschke, 2003). This concept of scale differs from the cartographic context; landscape ecologists are using the terms fine scale and broad scale, while cartographers are using the terms small scale and large scale. However, to landscape ecologists *fine scale* refers to a minute resolution or a small study area, and *broad scale* refers to a coarse resolution or a large study area, while to cartographers *small scale* (i.e., a small fractional scale of display) refers to a large area of little detail and *large scale* (i.e., a large fractional scale of display) refers to a small area of great detail (Withers & Meentemeyer, 1999). Kolasa & Pickett (1991) stated that scale is not a property of nature, but rather specified by the decision of the observer. The latter should be based on the research objective and the nature of the phenomenon of interest. Finally, the scale of a process is fixed only once the observer has specified the actors in the system (Allen & Hoekstra, 1991).

Landscape is defined as a spatial mosaic of interacting natural elements at various spatial scales (Zonneveld, 1995). The ***mosaic*** refers to a pattern of patches, corridors and matrices, each composed of similar aggregated objects (Forman, 1995). A ***patch*** is a relatively homogeneous nonlinear (surface) area that differs from its surroundings in nature or appearance; a corridor is a narrow strip of a particular type that differs from the areas adjacent on both sides; a matrix is the background cover type in a landscape, characterized by extensive cover, high connectivity, and/or major control over dynamics (Forman, 1995; Turner et al., 2001). In addition, Wiens (1976) defined a patch as a relatively discrete area of a relatively homogeneous environmental condition at a particular scale. Both ***composition*** and ***configuration*** of a landscape mosaic explicitly affect ecological systems in ways that would be different if the mosaic composition and arrangement were different (Wiens, 1995). Therefore, a landscape exhibits the same three fundamental characteristics of all living systems as an organism, a vegetation stand, or an agricultural system (Ingegnoli, 2002). These three characteristics are structure, function, and transformation. ***Structure*** relates to, as mentioned before, the spatial relationship among landscape elements, ***function*** relates to the interactions among the landscape elements, and ***transformation*** concerns the evolution and alteration in the structure and function of the landscape elements. ***Landscape elements*** represent each of the relatively homogeneous units or spatial elements recognized at the proper range of scales of the landscape mosaic (Forman, 1995), named ***patch*** (Forman & Godron, 1986), ecotope (Naveh & Lieberman, 1994), or land unit (Zonneveld, 1995).

2.2.2 Patch-mosaic EFTs

Ecosystem Functional Types (EFTs) are biotic components of ecosystems that respond similarly to the same environmental factors or disturbances, and are based on a context-dependent classification or context-specific simplification of the real world to deal with predictions of the dynamics of complex systems or any of their components (Gitay & Noble, 1997). The grouping of species into EFTs is necessary, because it will not be feasible to develop models for every ecosystem of the globe nor represent every species within those ecosystems (Steffen et al., 1992). Globalization requires, for example, prediction of the effects of changing climate and carbon dioxide on plants at the global scale. A major stumbling block, however, is the little information, in many cases none, about how plants will respond in the future (Shugart, 1997). In order to overcome this problem, and until more information on species accumulates, the diversity of species is reduced to a diversity of functions and structures. The structures may be trees, shrubs, herbs and grasses. The functions may be types of photosynthetic processes, the capacity to minimize water loss, and the timing of growth (Smith et al., 1997).

For an arid ecosystem in southern New Mexico, EFTs were used to compose hierarchically a (heterogeneous) landscape from Patch EFTs, to Patch-Mosaic EFTs, up to a Regional EFT (Figure 2.3). The patch EFT represents a fine-scale unit of land (ca. 1-10 m^2) that is internally consistent for the purpose at hand (context dependent). In the example as given in Figure 2.3, three patch EFTs are distinguished: grass, shrub island, and bare soil. The patch-mosaic represents a medium-scale unit of land (ca. 1 ha – 1 km^2) consisting of contiguous patch EFTs, of which patch EFTs can consist of one type of patch EFT, or a mixed type of patch EFTs. In Figure 2.3, three types of patch-mosaic EFTs are distinguished: grass, mixed, and shrub islands. The grass EFT is composed solely of grass patch EFTs. The mixed EFT is composed of all three patch EFTs. The shrub island EFT is composed of shrub island patch EFTs and bare soil patch EFTs. The landscape represents a broad-scale unit of land (ca. 50 – 100 km^2) consisting of many complex patch-mosaic EFTs. Following this general bottom-up hierarchical approach, landscape EFTs can form regions, and regional EFTs can form biomes according to the geosperic dimensions described by Zonneveld (1989,1995). A complete description and background of the described landscape hierarchy is given in Reynolds et al. (1997).

The behavior of a patch-mosaic EFT is a function of the composition (number and proportion) ánd configuration (spatial distribution, shapes, etc.) of patch EFTs. Subsequently, the behavior of a landscape is a function of the composition (number and proportion) and configuration (spatial distribution, shapes, etc.) of patch-mosaic EFTs. The patch, patch-mosaic, and landscape EFTs possess heterogeneity at different spatial and temporal scales, of which the dominant structural and functional characteristics of these EFTs should represent *distinct* degrees of heterogeneity (Reynolds et al., 1997).

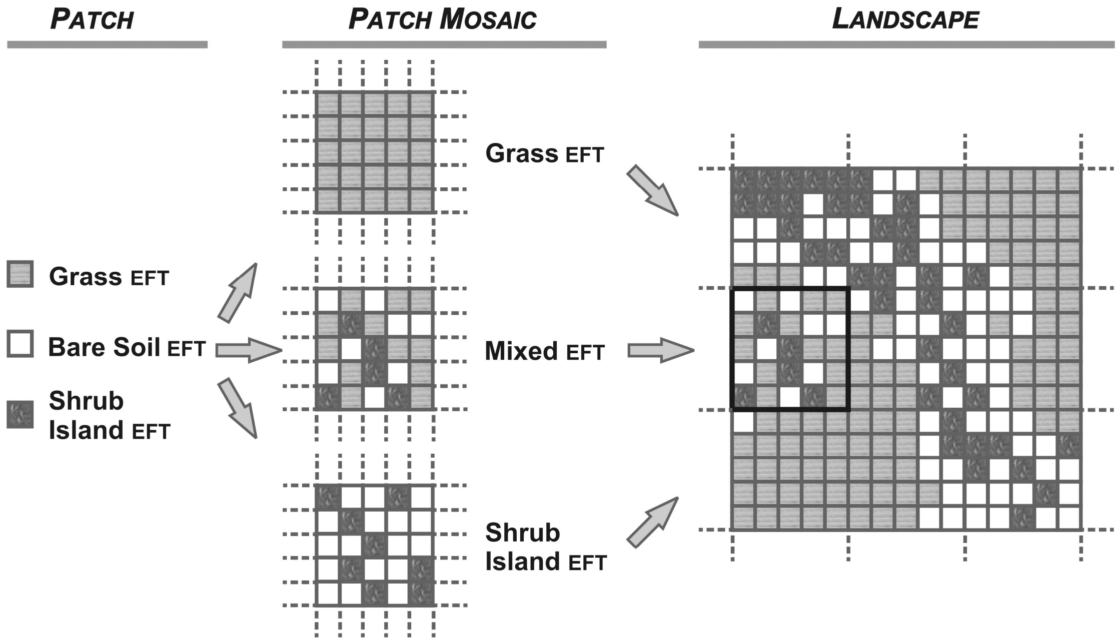


Figure 2.3: Landscape hierarchy based on Patches and Patch-Mosaics using Ecosystem Functional Types (EFTs), after Reynolds et al. (1997).

For landscape ecologists, the distinction of patch-mosaic EFT is directly relevant to the understanding and predicting of ecosystem behavior at different scales (Kolasa & Rollo, 1991). In addition, an important concept from hierarchy theory (section 2.2.4) is the importance of considering at least three hierarchical levels in any study: the upper level, the focal level and the lower level (O'Neill et al., 1986). The focal level is the (intermediate) level of interest. It is identified as a function of the question or objective of the study. The upper level constrains and controls the lower levels, providing context for the focal level. The lower level provides the details needed to explain the behavior observed at the focal level (Turner et al., 2001). Consequently, for a given case, patch-mosaic EFTs can be considered as the focal level, landscape EFTs as the upper level and patch EFTs as the lower level according to hierarchy theory (Figure 2.4).

For remote sensing scientists, patch-mosaic EFTs can be a viable strategy for digital image analysis to handle spatial heterogeneity, because it (spatially) enables the digital analysis of both vegetation composition and vegetation structure at different spatial aggregation levels (i.e., patch, patch-mosaic, and landscape). This is an important requirement to tailor geo-information to end-users as discussed in Chapter 1.

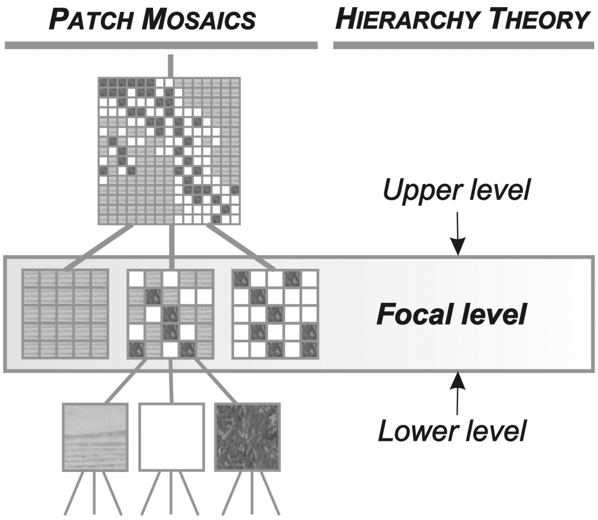


Figure 2.4: Patch-mosaic EFTs considered as the focal level according to hierarchy theory. The upper level (landscape EFT) constrains the focal level and provides significance; the lower level (patch EFTs) provides details required to explain the response of the focal level (see Figure 2.7 for details on Hierarchy Theory).

2.2.3. Structural models

Structural models are used in landscape ecology to study structural heterogeneity. Ingegnoli (2002) discerns three structural models:

- The ecosystem model
- The mosaic model
- The variegation model

The ecosystem model considers the landscape as a homogeneous spatial (ecological) unit within a given scale of interest such as, for example, a forest area in an agricultural environment (Figure 2.5a). It refers to a traditional ecosystem model, emphasizing spatial homogeneity, which was generally used in ecology before 1960 (McIntosh, 1991; Ingegnoli, 2002). Outside this spatial (forest) unit, there was an indistinct (heterogeneous) environment. A more complete model considers the boundaries of the ecological unit as edge belts.

The mosaic model considers the landscape as a combination of patches, corridors and a matrix (Figure 2.5b). Patches are formed by the types of ecological communities at a given scale of interest. Corridors are composed of natural or human-made elements. A matrix is the main element of the landscape and exerts the most control over landscape function. Both patches and corridors are embedded in the matrix. This model has been extensively described at the beginning of the 1980s (Forman &

Godron, 1981,1986). A more complete model emphasizes the entire landscape mosaic, the elements being the principal types of ecosystems and constituting a sort of geographic map, but with an ecological sense (Ingegnoli, 2002).

The variegation model considers the landscape as a fuzzy-edged ecological mosaic consisting of many different landscape elements (Figure 2.5c). It comprises an overlapping series of different patch-matrix mosaics, with ecological elements having a variable constitution (e.g., fuzzy-edged boundaries). A more complete model recognizes habitat mosaics proportional to the main groups of habitats (Farina, 1998).

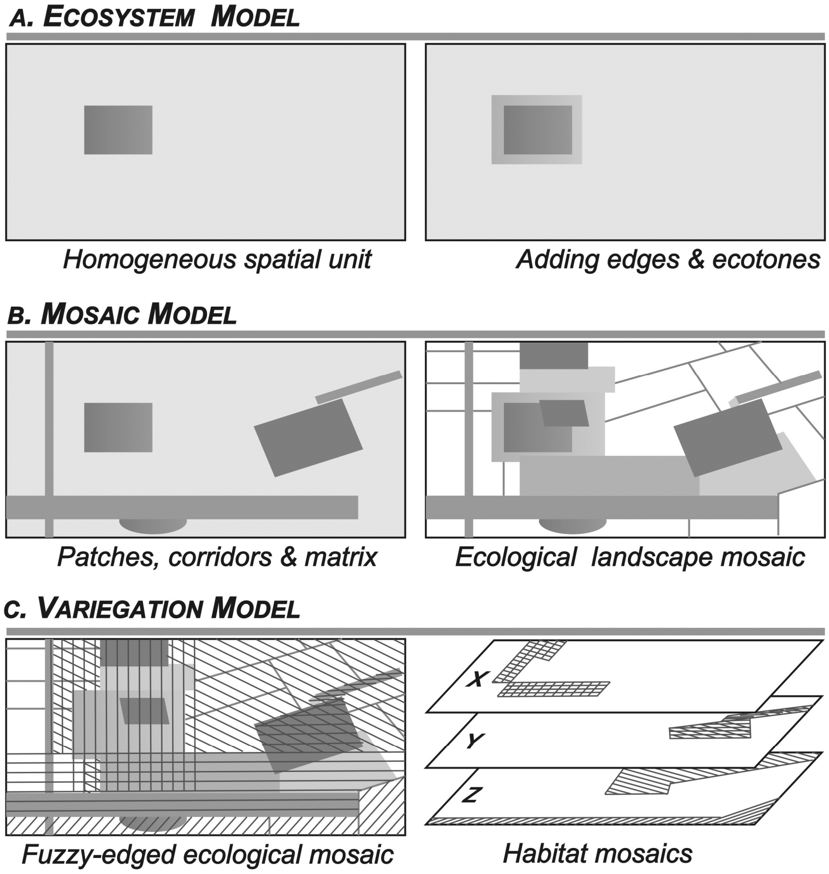


Figure 2.5: Main structural models of a landscape; Ecosystem model (a), Mosaic model (b), and Variegation model (c). Each model may be represented in two versions, of which the second one is more complete (after Ingegnoli, 2002).

The mosaic model and variegation model are two divergent new models of the simplified and unrealistic ecosystem model (Forman & Godron, 1981; Farina, 1998). The mosaic model is a static model of non-overlapping landscape (ecological) elements. Its main limitation is that differently scaled entities may be forced together in a rigid mosaic. The variegation model is otherwise a dynamic model of overlapping species-specific habitat mosaics with variable geometry. This model becomes, however, inconsistent as a scaled unit if species on the same spot respond to differently scaled patches of a landscape (Ingegnoli, 2002). Each system shows a structure made by well-defined functional groups that is changeable in space and time. The landscape elements of these functional groups are not only adjacent, but also overlapping and intersecting (Naveh & Lieberman, 1994). Therefore, diverse hierarchies of ecological factors are needed to describe the spatial heterogeneity of the landscape, some of them depending on the mosaic model, others on the variegation model. This diversity requires knowledge on functional relationships.

2.2.4 Functional relationships

Functional relationships are used in landscape ecology to study functional heterogeneity. Two important methods to describe functional relationships are:

- Landscape graphs
- Hierarchy theory

Landscape graphs is a modeling method to describe functional relationships between objects (Wilson, 1979). A graph consists of a finite set of nodes called vertices (or dots) connected by linkages called edges (or arcs). The World Wide Web is a nice example of a graph; the files are the nodes, and the linkage from one file to another is a directed edge (Caldwell, 1995). Cantwell and Forman (1993) introduced the concept of landscape graphs to describe landscape structure; the nodes represent landscape elements (i.e., patch, matrix, and corridor), and linkages represent common boundaries between elements. Their main objective was to identify and compare patterns produced by different processes of landscape change, including connectivity and direction of flow. They found that landscape graphs contain a limited number of repetitive graph patterns of which the *spider*, *necklace*, and *graph cell* predominate (Figure 2.6). The spider represents a matrix area surrounding or adjoining many patches. The necklace represents a corridor bisecting a heterogeneous area. The graph cell represents a unit in a network of intersecting corridors. Consequently, the landscape graph may be used as a skeletal structure, because landscape structure of any scale and any landscape can be compared in time (e.g., deforestation, desertification, and suburbanization throughout the world). A main limitation of landscape graphs is defining the structural units upon which to build the functional organization. This problem is called the modifiable areal unit problem (MAUP), which is discussed in section 2.2.5.

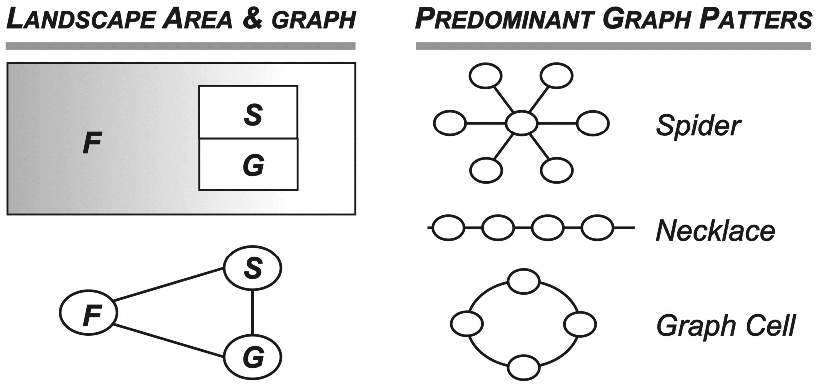


Figure 2.6: An example of a landscape area with corresponding landscape graph (F-forest, S-shrub, and G-grass), and the three predominant graph patterns (after Cantwell & Forman, 1993).

The hierarchy theory considers a landscape as a functional multi-scaled system (systems, sub-systems, etc.). It is a theory of the role of the observer and the process of observation in science (Ahl & Allen, 1996). It is also a holistic theory that closely examines issues of definition, measurement scale, and purpose in scientific models (Figure 2.7). One of the most significant contributions of the hierarchy theory is its role in making researchers aware of the importance of scale (O'Neill, 1996). Hierarchy theory has been developed primarily in the context of general systems theory studying complexity (Simon, 1962,1969). Simon (1962) noted that complexity frequently takes the form of a hierarchy, whereby a complex system consists of interrelated subsystems that are in turn composed of their own subsystems, and so on. Such systems tend to evolve faster, allow for more stability, and are favored by natural selection (Simon, 1962).

A central property of the hierarchy theory in landscape ecology is that many ecological systems are hierarchically structured based on differences in process rates (Allen & Star, 1982; O'Neill et at., 1986). Process rates (expressed by, for example, cycle time, response time, or occurrence of frequency) are fundamental characteristics of most ecological systems. Consequently, very slow behaviors and very rapid behaviors are vertically isolated in hierarchy theory (O'Neill et al., 1986). Therefore, a hierarchically organized ecosystem can be seen as a system with on top levels that correspond to progressively slower behavior, while levels reflecting successively faster behavior are seen lower in the hierarchy (Wu & Loucks, 1995). Higher levels impose constraints on lower levels. They often are treated as constants. On the other hand, the dynamics of the lower levels can be so fast that their signals are smoothed at higher levels. They often are treated as averages.

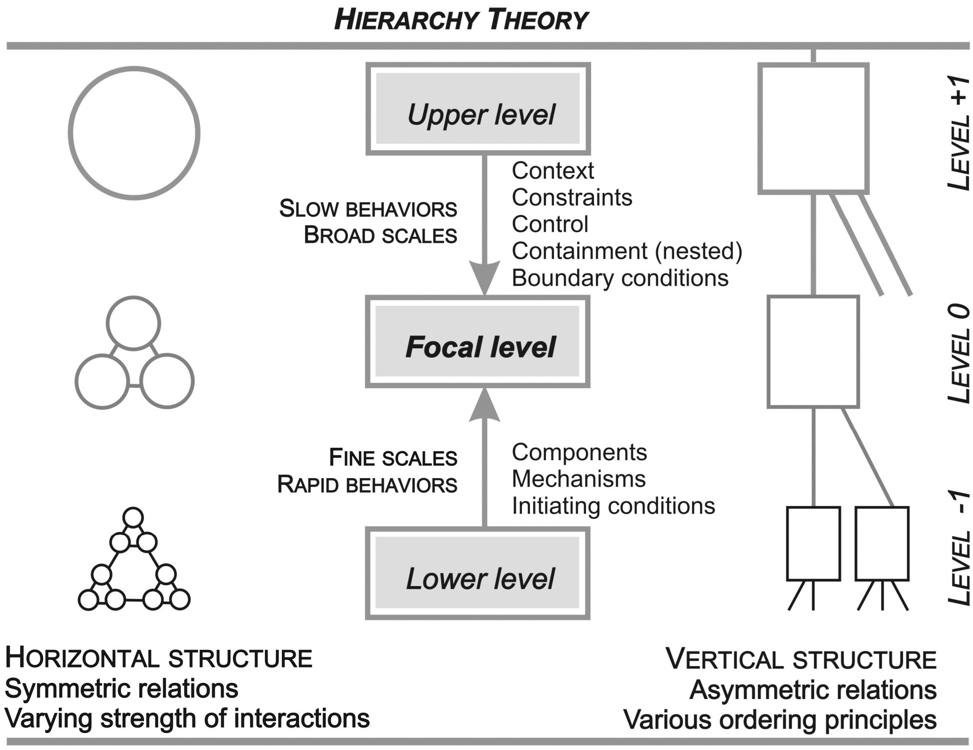


Figure 2.7: Illustration of hierarchy theory with its major concepts (after Wu, 1999).

Ecosystem organization appears as a system of constraints (O'Neill et al., 1986). Structural constraints that operate on organisms, and functional constraints that operate on processes. Differences in process rates result from differences in structuring processes exerting the influence of ecological systems over defined ranges or domains of scale (Wu & Loucks, 1995). This means that process rate and spatial scale are interrelated (O'Neill et al., 1986). Therefore, hierarchy theory predicts that each level in a hierarchy functions at rather distinct temporal and spatial scales (Withers & Meentemeyer, 1999). Fine-scaled spatial phenomena appear to possess high rates of change while broad-scaled phenomena appear to change over long time scales (Figure 2.8). Moreover, hierarchy theory considers the process-functional viewpoint when dividing multi-scaled systems (such as a forested landscape) into an ordered progression of interrelated spatial scales or levels (Eng, 1997). How ecological systems are arranged in space at each scale level, however, requires knowledge of landscape structure. This means that describing spatial heterogeneity should include both landscape structure and landscape function. This issue is further discussed in section 2.2.6.

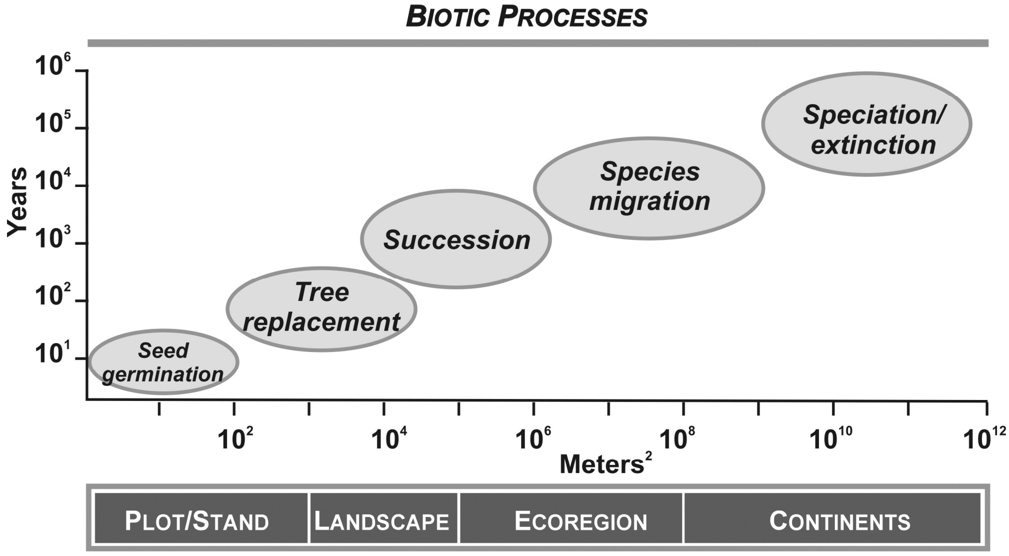


Figure 2.8: Interrelation of spatial and temporal scales for biotic processes in a subalpine forest (after Eng, 1997).

2.2.5 The modifiable areal unit problem (MAUP)

The modifiable areal unit problem, or *MAUP,* (Openshaw, 1984; Jelinski & Wu, 1996; Marceau, 1999; Hay et al., 2001) originates from the fact that a significant number of different ways exists by which a landscape can be divided into non-overlapping areal units for spatial analysis and upscaling (Hay et al., 2001). The choice of such basic areal units is often arbitrary (Meentemeyer, 1989) or dictated by the resolution of available spatial data like remotely sensed data (Jelinski & Wu, 1996). The MAUP represents the sensitivity of analytical results related to two distinct components when choosing basic areal units: the *scale* problem and the *aggregation* problem. The scale problem refers to variation in results that can be obtained when areal units are progressively aggregated into fewer, larger units. The aggregation problem refers to variation in results that can be obtained when using other aggregation strategies (see section 2.3.2) at equal or similar resolutions (Openshaw, 1984). Both problems are getting renewed attention because of an increasing ecological research towards large spatial scales (i.e., landscape dynamics, biodiversity, and global change). Currently, much knowledge on scale-dependent phenomena is derived from the aggregation of area-based information obtained from small areas, represented by even smaller plots (Burke et al., 1991; Jelinski & Wu, 1996). Therefore, increasing knowledge on both the scaling and aggregation problem is necessary.

Remote sensing data represent a particular case of the MAUP (Marceau, 1994a,1994b). Its importance, however, remains poorly recognized and understood (Wu et al., 2000). Basically, two main solutions for the MAUP are described in literature when classifying remote sensing data:

- Overcome MAUP (Hay et al., 2001)
- Explore MAUP (Jelinski & Wu, 1996)

Overcome MAUP means that the MAUP should be made non-existing. Hay et al. (2001) argued that the MAUP does not exist when identifying basic entities at each level in a hierarchy. For example, leaves and branches are basic entities of a tree-crown; tree-crown and stem are basic entities of a tree, etc. These basic entities overcome the MAUP, because the related structural units are spatially discrete rather than arbitrarily defined areal units (Hay et al., 2001). This is only true, however, if all basic entities spatially follow their *thematic* description when aggregated. In geo-science, this is also called the geometric condition of containment (Droesen, 1999). Such a condition is valid in what Droesen (1999) calls *nested* aggregation (Figure 2.9a). For definition transparency, this thesis prefers to introduce ***thematic generalization*** in stead of using nested aggregation to refer to this geometric condition (see section 2.3.1 for definition on aggregation and thematic generalization). The MAUP remains, however, in what Droesen (1999) calls non-nested aggregation. Again, for definition transparency, this thesis prefers to introduce ***functional generalization*** (section 2.3.2) to refer to cases that dropped this geometric condition of containment. For example, woodland is an aggregate of clusters of trees and grasses, and grassland is an aggregate of grasses and some trees. Depending on the scale of the areal units and the applied aggregation rules (both constituting the MAUP), grasses and trees can be aggregated into woodland ánd grassland (Figure 2.9b).

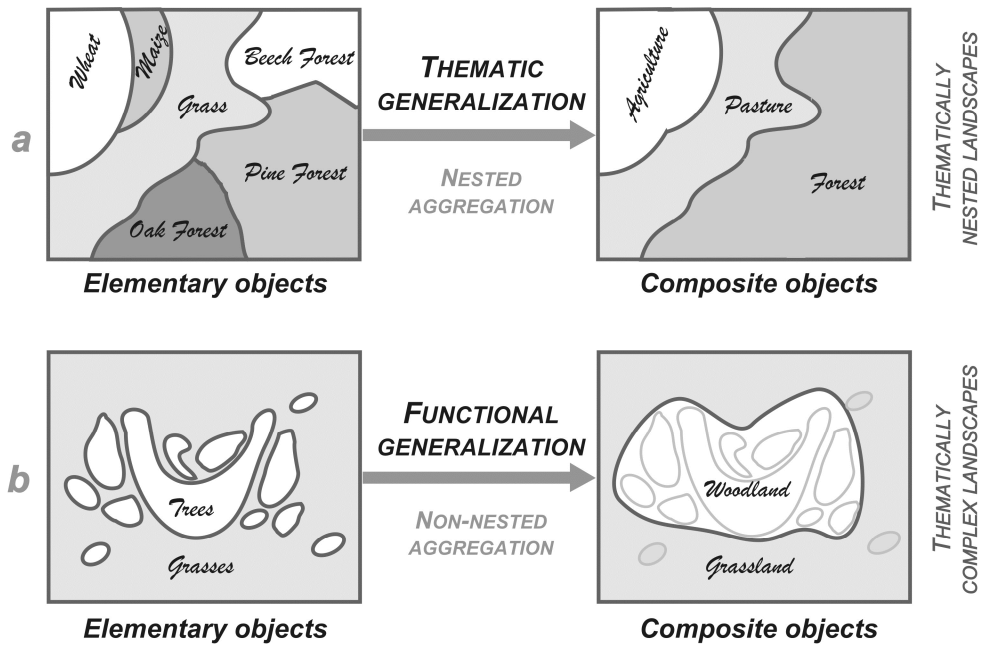


Figure 2.9: Definition transparency: thematic generalization instead of nested aggregation (a) and functional generalization in stead of non-nested aggregation (see also section 2.3.1 and 2.3.2).

Explore MAUP means that the MAUP should be made explicitly. The MAUP can be made explicitly when identifying the sensitivity of the results of a spatial analysis to the definition of units for which data are collected (Jelinski & Wu, 1996). Exploring MAUP is useful, because it can reveal critical information for understanding the structure, function and transformation of a landscape (Jelinski & Wu, 1996). Especially, from a hierarchical point of view, the MAUP should not be regarded as a problem, but instead it provides a means to support multi-scale analysis. In addition, part of the challenge to recognize the MAUP is the fact that there is no unique 'MAUP statistic' (Hay et al., 2001). Recognizing the sensitivity of the results of a spatial analysis to the definition of units for which data are collected (i.e., the MAUP) is critical to characterizing landscapes with a minimum of bias and to avoid spurious relationships (Jelinski & Wu, 1996). Advancing our understanding and predictability of spatio-temporal patterns and processes in nature is especially necessary, since the need for up-scaling and down-scaling in ecological studies on both landscape levels and global levels has never been greater.

2.2.6 Linking structural models and functional relationships

Handling spatial heterogeneity should include both landscape structure and landscape function (section 2.2.4 & 2.2.5). Two important developments in landscape ecology to describe spatial heterogeneity based on both structural and functional properties of a landscape are:

- The Hierarchical Patch Dynamics Paradigm (HPDP)
- The Ecotissue Model

The HPDP includes landscape structure when defining functional relationships. The Ecotissue Model includes landscape function in a structural model. Both developments consider a multi-scale approach, and thus explore MAUP, which makes them useful to characterize heterogeneous environments. Only the HPDP, however, provides a valuable approach for classifying spatially heterogeneous vegetation using remote sensing data. The reason is given hereafter when describing both developments.

The hierarchical patch dynamics paradigm (HPDP) perceives the landscape as near-decomposable nested hierarchies in which hierarchical levels correspond to structural and functional units at distinct spatial and temporal scales (Wu & Loucks, 1995; Wu, 1999; Reynolds & Wu, 1999). It explicitly integrates hierarchy theory (section 2.2.4) and the patch dynamics perspective (Forman & Godron, 1981,1986) to enhance understanding of the pattern-process-scale relationship in landscapes by providing both an organizational and an operational framework (Figure 2.10). The basic premise is that the hierarchical nature of a landscape structure can be used to model its function, because landscape structure affects function (and visa versa). Each object in a functional hierarchy has relevant factors that are important in functioning at each particular scale (Reynolds & Wu, 1999). As an example, land use and fire history are important at the forest stand level, light availability is critical at the individual tree level, and carbon dioxide concentration affects photosynthesis at the leaf level (Reynolds & Wu, 1999).

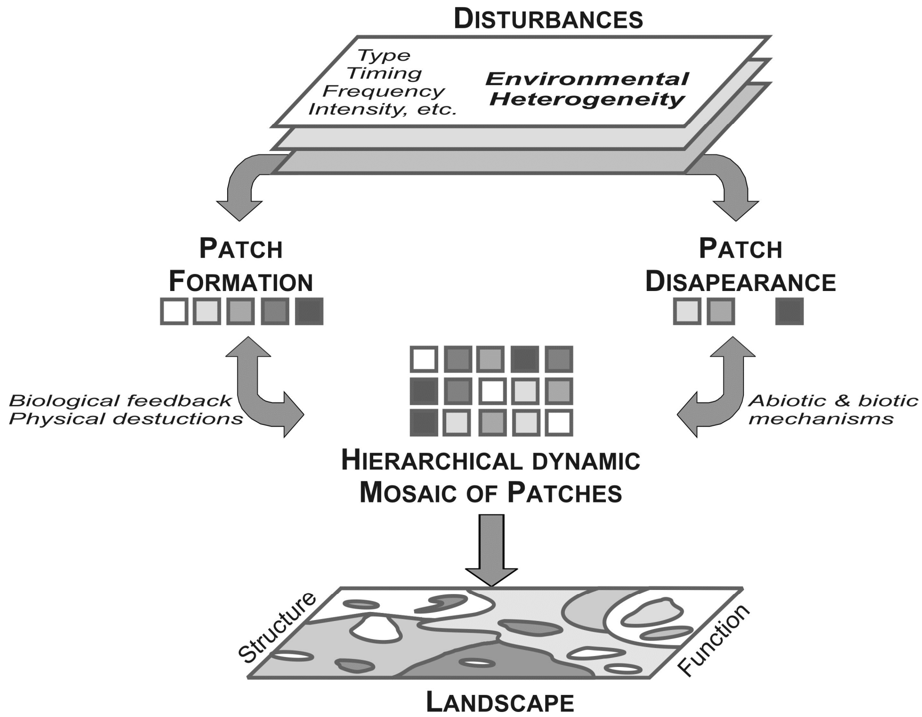


Figure 2.10: A hierarchical patch dynamics modeling framework (after Wu & Levin, 1997; and Reynolds & Wu, 1999).

Explicitly identifying these hierarchical levels is essential in order to simplify and understand ecological functioning in complex environments. The structural detail considered at each level dictates how landscape function can be modeled. Three types of structural models are distinguished: n*on-spatial*, q*uasi-spatial, and spatially explicit* (Baker, 1989; Reynolds & Wu, 1999). Non-spatial, or patch implicit, models ignore structural detail. An example is the use of traditional point models in ecology. Quasi-spatial, or patch explicit, models include more structural detail. An example is the relative contribution of each patch type to the modeled variable of interest. Spatially explicit models are structurally most detailed, because they consider explicit spatial locations and configurations of the patches. An example is remote sensing imagery. Both non-spatial and quasi-spatial models may be sub-models of the spatially explicit models when scaling-up to a landscape level following a general bottom-up hierarchical approach, that ranges from local patches, to patch aggregates, to landscape (Wu & Levin, 1994,1997). As an example of a HPDP, Reynolds & Wu (1999) refer to a landscape hierarchy based on *Ecosystem Functional Types* (EFT) as presented in section 2.2.2 (see also Reynolds et al., 1997). Its spatial explicitness to enhance landscape structure at interrelated spatial scales makes it an interesting approach for digitally analyzing remote sensing data of spatially heterogeneous environments like tropical rainforest areas.

The ecotissue model is a complex multi-dimensional structure represented by a basic 'main mosaic' and a hierarchic succession of correlated 'thematic mosaics' and attributes (Ingegnoli, 2002; Figure 2.11). The basic main mosaic is generally formed by the vegetation (or landscape) elements, because processes pertain to it (control of the flux of energy and matter, and the capacity to create the proper environment). Trying to detect organisms outside this main scale is generally nonsense, because of the hierarchic organization theory (Ingegnoli, 2002). The other correlated thematic mosaics and attributes are correlated to the basic main mosaic, and compatible with its main scale. They are related to landscape function (i.e., projections and sections of a self-organizing system) integrating spatial scales ranging from local to regional, and temporal scales ranging from past to future. The ecotissue model includes an 'operative chart of integration' to elaborate plans. This means that the ecotissue model attempts to provide a conceptual structure to represent the hierarchical relation between biological levels at the bottom (i.e., organisms, populations, ecosystems) and biological levels at the top (i.e., ecoregions), as well as their relationships in the landscape (Ingegnoli, 2002). Although scale dependency of biological levels (i.e., landscape function) is a major issue in the ecotissue model, only *cartographic* scales are provided as examples to enhance landscape function at each level. Cartographic scales consider only the cartographic abstraction or *cartographic generalization* of landscape elements (section 2.3.1). Such a scaling does not necessarily divide landscapes into an ordered progression of interrelated spatial scales or spatial aggregation levels conform hierarchy theory (i.e., a functional multi-scaled system, section 2.2.4). It enhances only structural properties, and not functional properties of a system. Therefore, the ecotissue model needs extension before it can be applied in remote sensing to handle spatial heterogeneity.

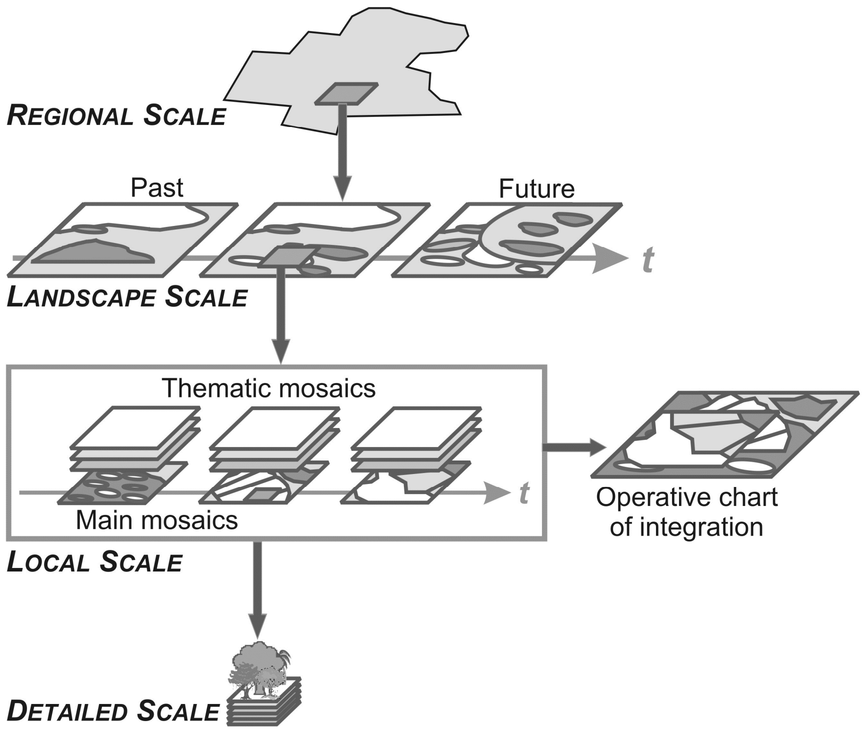


Figure 2.11: Abstract version of the Ecotissue Model (after Ingegnoli, 2002).

2.3 Handling spatial heterogeneity in remote sensing

Upscaling geo-information during classifying remote sensing images into functional landscape entities is important (Iverson et al., 1994). One of the main sources of systematic change on local, regional, or global scale is variations in the composition *and* distribution of vegetation. The ability to detect these variations using remotely sensed data is of the utmost importance for both environmental researches and management activities (Hall et al., 1995). Fully digital analysis of remotely sensed data should not remain an elusive goal, because it offers a staggering potential for landscape ecology over a wide range of spatial scales (Withers & Meentemeyer, 1999). Therefore, remote sensing needs to be considered in its broadest sense of spatial object modeling, where image classification relates to a modeling problem in conceptual generalization (Molenaar, 1998).

2.3.1 Conceptual generalization

Although generalization originated from the field of cartography, with the advent of digital geographic information a distinction is made between cartographic generalization and conceptual generalization (Figure 2.12).

Cartographic generalization is the process of abstracting the *representation* of geographic information when changing the scale (i.e., its areal unit or detail) of a map (Kilpeläinen, 1999; Smaalen, 2003). This is related to a *visualisation problem*, because geometric simplification is needed when deriving small scale, less detailed, maps (e.g., 1:1000.000) from larger scale maps (e.g., 1:250.000). Traditionally, this type of generalization is performed by cartographers and entails processes of selection, simplification, amalgamation, symbolization and displacement of map features (Müller et al., 1995).

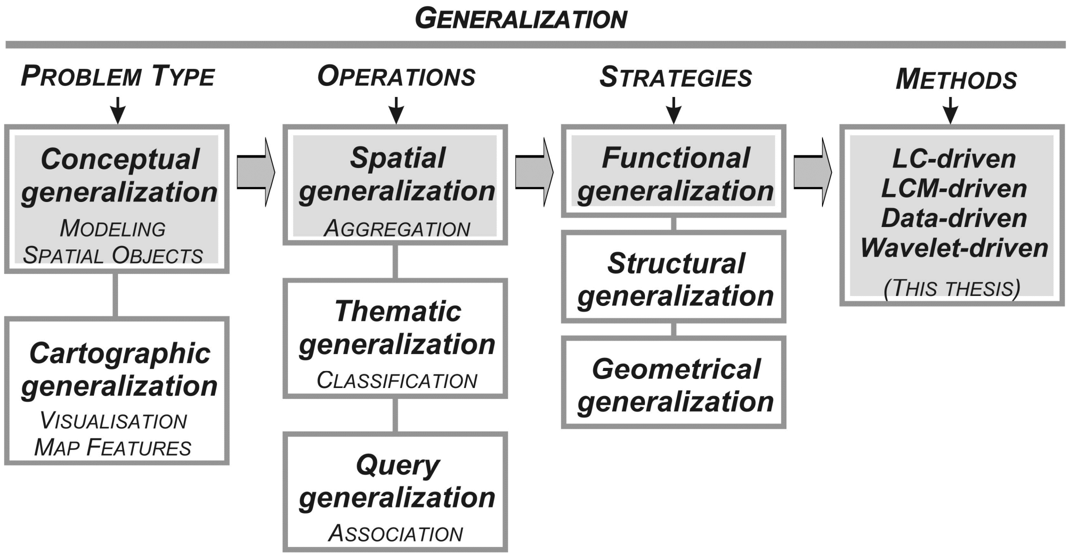


Figure 2.12: Generalization in geo-information.

Conceptual generalization concerns the process of abstracting *the actual content* of geographic information (Kilpelaïnen, 1992; Molenaar, 1998; Smaalen, 2003). This is related to a *modeling problem* (i.e., spatial object modeling), because both *thematic* abstraction ánd *geometric* abstraction is needed when expressing a complex world according to a particular view that suits specific user and application needs. In such a conceptual generalization, different levels of information detail correspond to different conceptual descriptions of attributes, as well as to relations of landscape entities that are represented as spatial objects in databases (Panopoulos et al., 2003).

This type of generalization is performed by geo-specalists and entails three operations: classification, aggregation and association (Nyerges, 1991; Molenaar, 1998). To avoid confusion because of a too general use of these terms in literature, and to embed these three operations in the context of conceptual generalization, this thesis refers to three generalization-based terms that each relate specifically to one of these operations:

- Thematic generalization (classification)
- Spatial generalization (aggregation)
- Query generalization (association)

Thematic generalization generalizes solely *thematic* aspects of spatial objects in order to obtain spatial objects at different thematic levels. Thematic generalization follows a ***classification hierarchy***, a hierarchy that is based on inheritance. This means that objects are related by *'is a'* links. For example, a peatswamp forest 'is a' tropical rainforest 'is a' tropical forest 'is a' forest (Figure 2.13). The generalized class *forest* is called a ***superclass*** of the more detailed class *tropical forest*. Subsequently, the more detailed class *tropical forest* is called a ***subclass*** of the more generalized class *forest*. Such a relationship between superclasses and subclasses is called a taxon (Uitermark, 2001; Smaalen, 2003). Therefore, a classification hierarchy is also called a ***taxonomy***. Thematic generalization is moving up in the taxonomy, whereas thematic specialization is moving down the taxonomy. Using taxonomies, the spatial distribution of major classes (i.e., superclasses) can be studied (Richardson, 1993; Rigaux & Scholl, 1995; Molenaar, 1996). Taxonomies are frequently used in categorical image analysis. An example is, for instance, the production of the Global Land Cover 2000 database of the European Commission and Joint Research Centre (Steffen et al., 2003). The relationship between subclasses and superclasses is 'many to one', or shortly m:1 in thematic generalization (Molenaar, 1998). Despite such a relation, the number of spatial objects does not necessarily reduce because object adjacency is not required in taxonomies. What often hampers, especially in fragmented environments, is that after thematic generalization spatial objects are still not adjacent. Fragmented environments remain fragmented, although the thematic classes themselves are not bound to any geometrical restrictions. For example, the (super)class *forest* can occur on areas of 1 ha up to $1x10^5$ ha, or even larger. Consequently, thematic generalization can only be used for a limited spatial range (Smaalen, 2003). Therefore, it is by itself not a powerful operation to describe spatial heterogeneity.

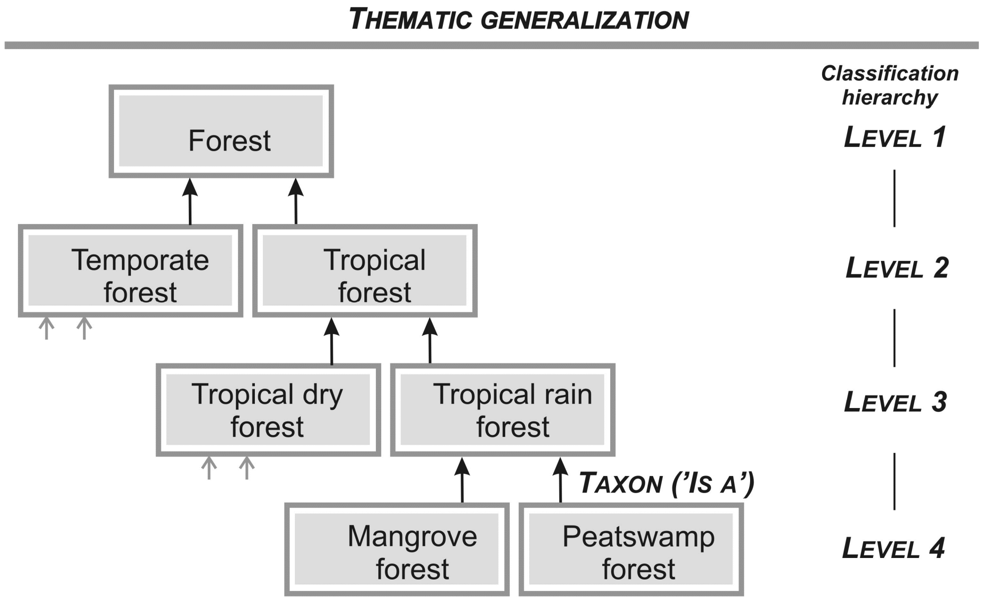


Figure 2.13: Thematic generalization; moving up in the classification hierarchy.

Spatial generalization generalizes both thematic and geometric aspects of spatial entities to obtain spatial objects at different spatial aggregation levels. Spatial generalization follows an ***aggregation hierarchy*** (Richardson, 1993; Molenaar, 1998). An aggregation hierarchy is based on relationships (e.g., functional, structural, and geometrical, see section 2.3.2). This means that spatial objects are related by *'part of'* links. For example, a tree is 'part of' a forest stand is 'part of' a forest type is 'part of' a biome, etc. (Figure 2.14). The generalized spatial object *forest stand* is called a ***composite object*** of the more detailed spatial object *tree*. Subsequently, the more detailed spatial object *tree*[4] is called an ***elementary object*** of the more generalized spatial object *forest stand*. Such a relationship between composite objects and elementary objects is called a parton (Uitermark, 2001; Smaalen, 2003). Therefore, an aggregation hierarchy is also called a ***partonomy***. In fact, spatial generalization is moving up in the partonomy, whereas spatial specialization is moving down the partonomy. The relationship between elementary objects and composite objects is 'many to many', or shortly m:n in spatial generalization (Molenaar, 1998). Each spatial object at a lower level may belong to several aggregated spatial objects of different context. For example, forest stands can be aggregated into forest types in the context of land use. The same forest stands can be differently aggregated into soil suitability units in the context of mineral content. In addition, a collection of

[4] But a tree in, for example, a pasture is not an elementary object of a forest stand.

aggregated spatial objects does not need to be exclusive or complete. This implies that not all elementary objects are necessarily part of an aggregated spatial object (Molenaar, 1998). Although the relation is many to many, the number of objects necessarily reduces because object adjacency is required in partonomy. Consequently, fragmented environments do not remain fragmented, although spatial objects in aggregation hierarchies are bound to geometrical restrictions. For example, the spatial entity forest type cannot occur on 10 m^2 as discussed in Chapter 1 (section 1.3). To be called a forest, among others, it should cover an area of more than 0.5 ha by definition. Although spatial entities themselves are limited to a certain spatial range (see also Figure 2.8), spatial generalization is not limited to a spatial range, as it can be applied nearly unlimited. Therefore, spatial generalization is a powerful operation to describe spatial heterogeneity. Table 2.1 summarizes main characteristics of thematic generalization versus spatial generalization.

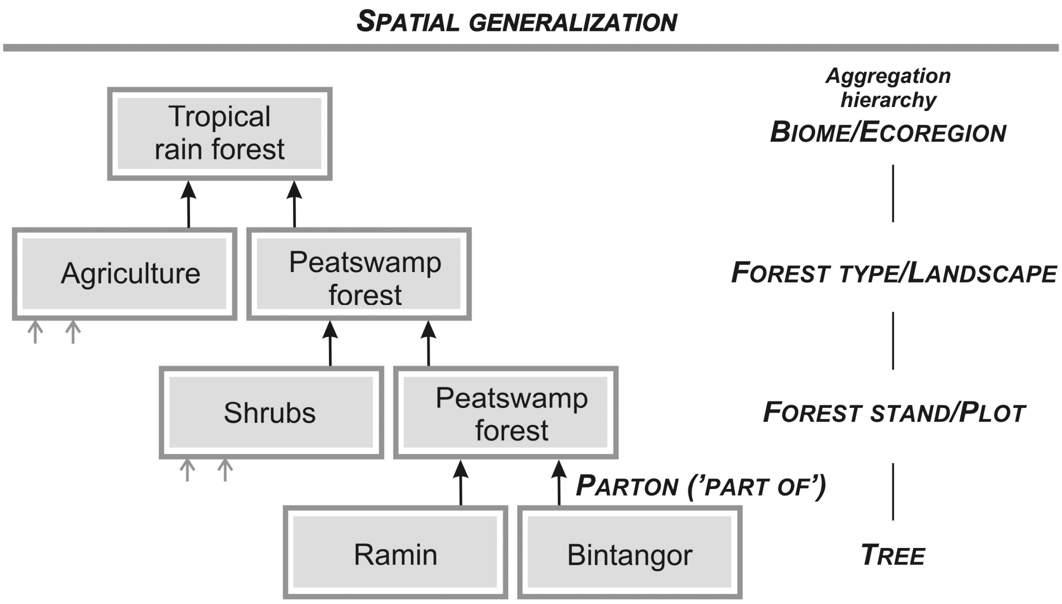


Figure 2.14: Spatial generalization; moving up in the aggregation hierarchy.

Despite fundamental differences between thematic generalization (with thematic classes as fundamental entities) and spatial generalization (with spatial objects as fundamentalentities), the underlying hierarchies (i.e., classification hierarchies and aggregation hierarchies) are related (Huising, 1993; Janssen, 1994; Molenaar, 1998). The classification hierarchy describes the thematic context, whereas the aggregation hierarchy describes the spatial context. This relation is illustrated in Figure 2.15. Both the elementary objects and the composite objects (the latter illustrated at two different spatial aggregation levels) clearly have their own subclasses and superclasses. Each spatial aggregation level requires its own classification hierarchy (Molenaar, 1998). Such a *recursive* relation enables the modeling of both thematic and geometric aspects of spatially heterogeneous environments (i.e., considered as functional multi-scaled systems).

Table 2.1: Main characteristics of thematic generalization versus spatial generalization.

Main Characteristics	*Thematic-Generalization*	*Spatial-generalization*
Fundamental entity	*Thematic class*	*Spatial object*
Generalization affects	*Thematic aspects*	*Thematic & geometric aspects*
Generalization mode	*Inheritance*	*Relationships*
Object link	*'is a'*	*'part of'*
Object relationship	*Taxon*	*Parton*
Hierarchy type and Synonym	*Classification hierarchy Taxonomy*	*Aggregation hierarchy Partonomy*
Object types	*Subclasses & Superclasses*	*Elementary objects & Composite objects*
Object relationship	*m:1*	*m:n*
Object adjacency	*Not required*	*Required*
Geometric restriction	*Not restricted*	*Restricted*
Describing spatial heterogeneity	*Limited*	*Unlimited*

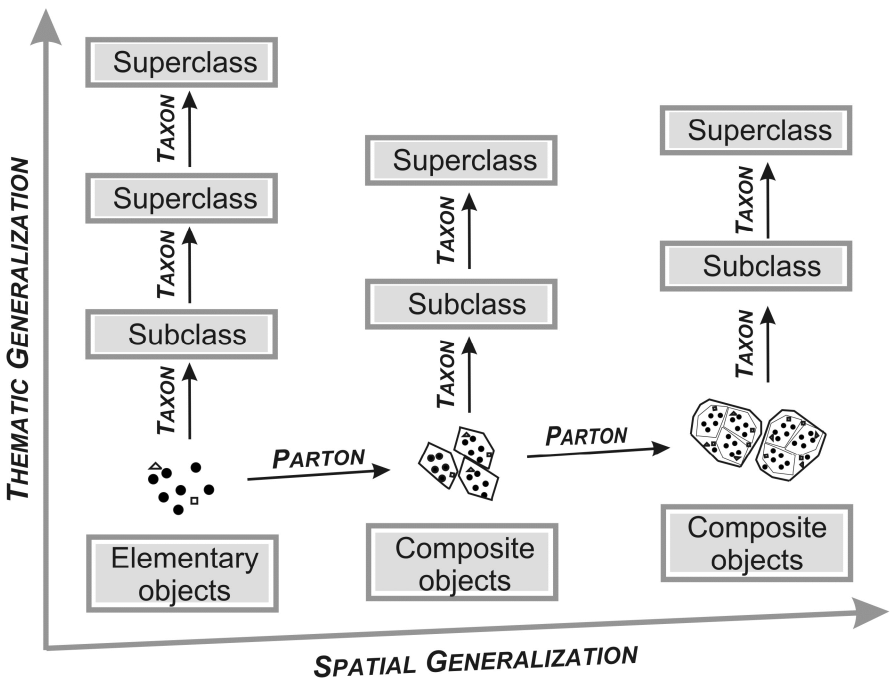


Figure 2.15: Relation between spatial generalization and thematic generalization in conceptual generalization.

Query generalization generalizes thematic and/or geometric aspects of objects following queries. Queries can be defined with and without geometric restrictions, or with and without topology. For example, an association of all trees near the river uses topology, but an association of all trees does not. Queries are based on common criteria that do not need any hierarchy. Without hierarchies, this generalization operation is not explicitly embedded in a data model (Droesen, 1999). Therefore, it is not a powerful operation to link different abstraction levels necessary for describing spatial heterogeneity.

2.3.2 Spatial generalization strategies

Functional, structural and geometrical relationships can be used to build aggregation hierarchies (Molenaar, 1998). Therefore, three different spatial generalization strategies are distinguished (see also Table 2.2):

- Functional generalization
- Structural generalization
- Geometrical generalization

Functional generalization is based on *functional* relationships. Spatial objects have functional relationships with respect to processes defined at higher spatial aggregation levels (see section 2.2.4). This strategy is occasionally mentioned in categorical image analysis. The major problem of applying functional generalization is to *quantitatively* define the functional relationships. Robinson (1995) described a top-down bottom-up approach where functional relationships were pragmatically based on the relative importance of certain *topologic* features over others. Smaalen (2003) described a bottom-up approach where functional relationships were based on spatial co-occurrence (i.e., class *topology*) of elementary object classes. Molenaar (1998) described a theoretical example in the context of agricultural land use where different fields were aggregated as a lot, and different lots as a farmyard, and different farmyards as a farm, and different farms as a farm district. These functional relationships were also based on class *topology* (i.e., specifying topologic relationships among spatial objects) using a bottom-up approach. In a landscape ecological context, however, approaches using (class) topology resemble only vegetation composition. They do not resemble vegetation structure, although topologic rules are commonly used to address geometric relationships among spatial objects (Molenaar, 1998; Droesen, 1999). Explicit geometric rules that resemble vegetation structure are necessary to model spatial heterogeneity in spatially heterogeneous landscapes like tropical rainforest areas (see also section 2.2.5). This thesis presents functional relationships using explicit geometric rules besides topology to address also geometric relationships among spatial objects (Chapter 3).

Structural generalization is based on *hierarchical* relationships. This strategy is not used in categorical image analysis. It is developed for numerical data only, and its suitability for categorical data is yet unclear (Smaalen, 2003). An example of structural generalization regarding catchment areas implies the elimination of lower-level stream elements to retain a constant flow at the outlet (Martinez Casasnovas, 1994; Molenaar, 1998).

Geometrical generalization is based on *geometric* relationships. This strategy is frequently used in categorical image classification for spatial data having a raster structure. An example is, for instance, increasing the pixel size from 30 to 120 meters. The generalization operation geometrically merges sixteen 30m cells into one 120m cell and then transferring the thematic information of the original cells into the new cell. If the thematic information is not the same for all the original cells, common procedures to transfer the thematic information are the numerical mean (Townshend & Justice, 1990; Jelinski & Wu, 1996; Beurden & Douven, 1999), the categorical majority or predominance (Turner et al., 1989; Moody & Woodcock, 1995; Benson & MacKenzie, 1995), and a random assignment (He at al., 2002). With respect to ecology, geometrical generalizations either cause distortions of cover type proportions (using mean, majority or predominance) or cause disaggregation of spatial patterns (using random assignment).

Molenaar (1998) distinguishes a fourth spatial generalization strategy called class-driven generalization, which is based on thematic relationships (i.e., taxonomy). This relationship does not require object adjacency (which is fundamental in partonomies). Therefore, it should not be considered a spatial generalization operation, but a thematic generalization operation. In addition, Smaalen (2003) regarded class-driven generalization as a special case of similarity-driven generalization. Similarity-driven generalization uses attribute values of thematic classes to drive the generalization process. Numerical attributes can use distances between attribute values, whereas nominal attributes can use similarity matrices. The latter is, however, labor intensive and case sensitive (Bregt & Bulens, 1996). Both similarity-driven generalization strategies are thematic generalization operations, because spatial objects are only related using taxonomy (see section 2.3.1).

Table 2.2: Main characteristics of three spatial generalization strategies.

Spatial generalization strategy	*Geometrical generalization*	*Structural generalization*	*Functional Generalization*
Driving relationship	*Geometrical (spatial resolution)*	*Structural*	*Functional*
Spatial data type	*Numerical & Nominal*	*Numerical*	*Numerical & Nominal*
Problem	*Distortion of cover types / spatial disaggregation*	*Only numerical data*	*Defining functional relationships with specific rules for class geometry besides class topology*
Describing spatial heterogeneity	*Limited*	-	*Most promising*

2.3.3 Fields and objects

Remote sensing data contain both thematic and geometric (spatial) information, and thus are useful to model spatially heterogeneous vegetation. The thematic information can address its composition and the geometric information its structure (pattern). Two principal approaches for linking thematic and geometric information in remote sensing data are the field approach and the object approach (Molenaar, 1998).

The field approach assumes that thematic aspects of the earth surface (e.g., vegetation) are a continuum in the spatio (-temporal) domain. These thematic aspects are represented in the form of attributes, of which their values are considered to be position dependent (Figure 2.16a). Modeling the attributes requires discretisation of the continuum (what entails the MAUP, see section 2.2.5). For remote sensing data, this discretisation is the raster format being a lattice of pixels. For each pixel, attribute values are evaluated, which are often based on reflectance or vegetation indices (measuring image variance). Therefore, the field approach is sometimes called the direct image approach (Goodchild & Quattrochi, 1997). With respect to landscape ecology, it quantitatively measures the *variability* of a system's property in space (see also section 2.2.1).

The object approach assumes that thematic aspects of the earth surface (e.g., vegetation) are discrete units (i.e., objects) in the spatio-(temporal) domain. Similar to the field approach, these thematic aspects are also represented in the form of attributes, but these attributes and their values are considered to be object dependent. Each object is, therefore, represented by means of an object identifier. The geometric aspects of each object are represented in the form of attributes (e.g., topology, size, shape, position and orientation), and their values (Figure 2.16b). Modeling the attributes requires identification of the objects (i.e., identification of the non-overlapping aerial units what entails the MAUP, see section 2.2.5). For remote sensing data, this identification is often based on image classification by grouping individual pixels or subdividing the entire image into homogeneous mapping units. Therefore, the object approach is sometimes called the cartographic approach (Gustafson, 1998). With respect to landscape ecology, it qualitatively measures the *complexity* of a system's property in space (see also section 2.2.1).

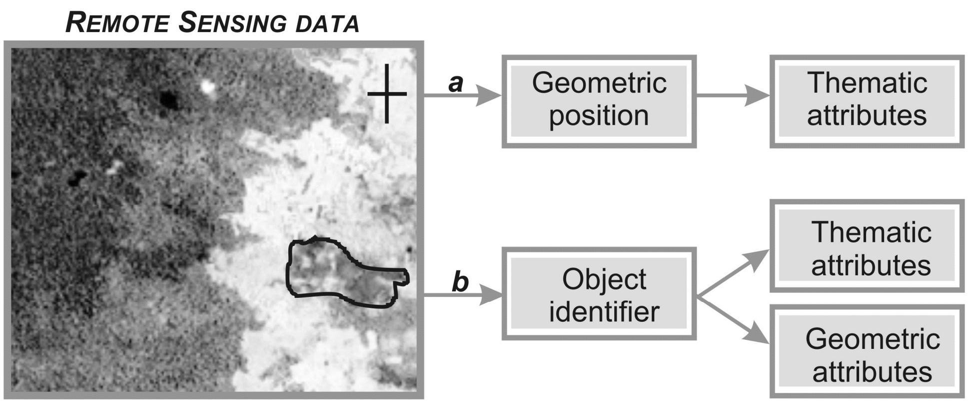


Figure 2.16: Linking thematic data and geometric data in geo-information; field approach (a) versus object approach (b).

Although both approaches, fields and objects, can be used for modeling spatial heterogeneity (i.e., composition and structure), they both face two major limitations:

LIMITATION 1 Both fields and objects assume spatial homogeneity; they consider landscapes either as a continuum or as discrete patches. This implies limitation in the modeling of vegetation composition.

LIMITATION 2 Both fields and objects are single-scaled; they measure landscapes at only one spatial aggregation level either at pixel level or at object level. This implies limitation in the modeling of vegetation structure (i.e., pattern).

From landscape ecology it was concluded that landscapes are functional multi-scaled systems (i.e., patches, patch-mosaics, and landscape). This understanding affects both limitations:

I

Functional multi-scaled systems cannot always be modeled either as a continuum or as discrete patches. Discrete boundaries hardly exist in natural environments, but a true continuum is also rare. Consequently, the precondition of spatial homogeneity limits a conceptual *thematic* representation of spatially heterogeneous vegetation (i.e., limiting the modeling of vegetation composition).

II

Functional multi-scaled systems cannot be conceptually represented at only one spatial aggregation level. At a single aggregation level only structural heterogeneity is considered, not functional heterogeneity (see section 2.2.1). In addition, single-scaled information suffers from the Modifiable Areal Unit Problem or MAUP (described in section 2.2.5). Consequently, a single-scaled spatial generalization limits a conceptual *geometric* representation of spatially heterogeneous vegetation (i.e., limiting the modeling of vegetation structure).

The remote sensing literature acknowledges both limitations and demonstrate many improvements (section 2.3.4 and 2.3.5). These improvements, however, only handle one of the two limitations. This means that the current improvements deal with improving the modeling of either vegetation composition – related to limitation 1, or vegetation structure – related to limitation 2. The demonstrated improvements will often be appropriate for landscapes that can be thematically generalized (e.g., Figure 2.9a). For other thematically more complex landscapes (e.g., Figure 2.9b), however, the demonstrated improvements are not appropriate as such landscapes require improvements of both limitations. The next two sections (section 2.3.4 and 2.3.5) will discuss the shortcomings of the demonstrated improvements.

2.3.4 Improving spatial homogeneity assumption

Current improvements to model vegetation composition are, for instance, hybrid approaches of fields and objects, and contextual classifiers. These improvements acknowledge that thematic representations of spatially heterogeneous vegetation can not be limited to spatial homogeneity.

The hybrid representation approach (Droesen, 1999) constructs fields within nested spatial objects, and uses fuzzy set theory to handle spatial heterogeneity in these fields. This improvement deals with vegetation composition, because it focuses on how a landscape thematically should be represented: if homogeneous then spatial objects, if heterogeneous then fields. It does not address, however, which spatial scales are functional to geometrically represent such a spatially heterogeneous environment. Although Droesen (1999) seemed to acknowledge vegetation structure, he used a classification hierarchy to ‘aggregate’ spatial objects in a dune area prior to a spatio-temporal analysis of vegetation structural dynamics. Such an aggregation is in fact a *thematic generalization* operation (see section 2.3.1). This operation does not allow to move from patches to patch-mosaics.

The hybrid quantification approach (Murwira, 2003) constructs objects within fields, and uses variograms and wavelets to handle spatial heterogeneity within these objects. This improvement deals with vegetation composition, because the maximum variance of a landscape property was used to select the object-scale. Murwira (2003) introduced ‘dominant scale’ to refer to this object scale with maximum variance. Using dominant scale seemed to acknowledge vegetation structure. However, a classification hierarchy was used for the migration from pixel-level to object-level. Consequently, such an operation does not allow to move from patches to patch-mosaics.

Many contextual classifiers consider the landscape as discrete patches. Strictly speaking, such a precondition relies on spatial homogeneity. Therefore, contextual classifiers cannot improve dependency on spatial homogeneity (i.e., limitation 1), because spatial homogeneity is a precondition and not a limitation. Regarding the position of contextual classifiers in remote sensing, this reliance can be considered a special case of limitation 1. Consequently, contextual classifiers treat spatial heterogeneity as a technical problem of autocorrelation and spectral overlap. Techniques to overcome autocorrelation are segmentation algorithms (Hill, 1999; Stuckens et al., 2000, Jong et al., 2001; Lira & Maletti, 2002), filtering (Kenk et al., 1988; Palubinskas et al., 1995; Hill, 1999), and Markov random fields (Cortijo & Perez de la Blanca, 1998). Techniques to overcome spectral overlap are co-occurrencies (Peddle & Franklin, 1991; Kushwada et al., 1994), fractals (Jong & Burrough, 1995), and semi-variograms (Oliver & Webster, 1986; Woodcock & Strahler, 1987; Woodcock et al., 1988; Addink, 2001). Such contextual classifiers generally improve classification accuracies by about 5% compared to spectral per-pixel classifiers. Such a low classification improvement is not a surprising result regarding the underlying reason for their application. Specifically the on-going increase in data resolution of remote sensing imagery 'introduced' the problem of spatial heterogeneity into remote sensing (i.e., regarding it as a problem of autocorrelation and spectral overlap). Spatial heterogeneity is treated only as a technical problem because of advances in remote sensing ('producer thinking'), rather than explicitly regarding spatial heterogeneity as a conceptual generalization issue. Conceptual generalization not only requires *that* a landscape can be quantitatively or qualitatively described (i.e., field approach versus object approach), it also demands to specify *for what* a landscape is described (i.e., purpose and objective versus spatial aggregation levels). The latter requirement can be denoted as 'consumer thinking'. The divergence in thinking, 'producer' versus 'consumer', might explain the low classification improvement when applying contextual classifiers to handle spatial heterogeneity.

2.3.5 Improving single-scaled approaches

Current improvements to model vegetation structure are, for instance, cover frequencies of classified classes, multi-scale segmentation and wavelet transformation. These improvements acknowledge that geometric representation of spatially heterogeneous vegetation cannot be limited to single-scaled information. Cover frequencies, multi-scale segmentation and wavelet transformation, implicitly or explicitly, address image texture.

Cover frequencies of spectrally similar classified classes are used to post-classify those similar classes into final dissimilar classes (Wharton, 1982; Zhang et al., 1988; Gong & Howard, 1992a and 1992b; Bandibas et al., 1995). Such a post-classification implicitly addresses vegetation structure, because it uses moving windows (of different spatial sizes) to calculate the cover frequencies (in this respect, majority filtering can be regarded a specific cover frequency calculation, namely a cover frequency being the majority class only). These cover frequencies of spectrally similar classes are used to construct a new feature space to classify the final dissimilar classes. This two-stage classification approach measures the landscape at two spatial scales, at pixel-level (with spectral classes), and at window-level (with cover-frequency classes). This approach can be considered a *spatial generalization* operation (see section 2.3.1) because both vegetation structure and vegetation composition are acknowledged. Therefore, cover-frequencies could be a viable solution for digital analysis of thematically complex landscapes (Figure 2.9b). Moreover, when compared to pure spectral classifications, the overall accuracy improved up to 12% even in a tropical environment (Bandibas et al., 1995). Unfortunately, cover frequencies face two major limitations: the size of moving windows and distinguishing spatial objects. The size of moving windows is limited to small window sizes because increasing the window size leads to increased blurring of final classification results (Bandibas et al., 1995). This blurring might be a result of a too general generalization of vegetation structure, because all final classes are treated similarly. Distinguishing spatial objects is limited to land cover classes of dissimilar mixture; land cover classes of similar mixture but different structure can not be distinguished (Bandibas et al., 1995). The latter distinction is necessary to model spatial heterogeneity, specifically in tropical rainforest areas, because many mixtures (constituting different change processes) consist of mainly three structural components: trees, shrubs and grasses. Consequently, to overcome both shortcomings when using cover frequencies, explicit geometric information is required to functionally (and not generally) generalize vegetation structure.

Multi-scale segmentation creates spatial objects at different spatial aggregation levels for thematic classes of interest. Such classifications are explicitly addressing vegetation structure, because lower-level objects and higher-level objects are interrelated (see section 2.3.6). Multi-scale segmentation is currently applied for landscapes that can be thematically generalized (e.g., Burnett & Blaschke, 2003; Dorren, 2003; Laliberte et al., 2004; Figure 2.9a). Dorren (2003) used a classification hierarchy to create higher and lower-level objects, whereas Burnett & Blaschke (2003) and Laliberte et al. (2004) assumed that the extents of spatial objects at both object levels were discrete. In all three examples, a top-down analysis is applied for which information on the extent of spatial objects should be available. Such information is not available for thematically more complex landscapes (Figure 2.9b). Defining spatial extent in such landscapes depends on the intuitive decision of the image-specialist. Obviously, such a decision is subjective and limits the application of such a top-down multi-scale segmentation to model spatial heterogeneity.

Wavelet transformation also creates spatial objects at different spatial aggregation levels for thematic classes of interest. Similarly to multi-scale segmentation, using wavelet transformation explicitly addresses vegetation structure, because lower-level objects and higher-level objects are interrelated (see section 2.3.7). Wavelet transformation is currently applied for various applications in remote sensing. Examples are image fusion for removing haze or clouds in imagery (Du et al., 2002; Le Moigne et al., 2002), and for improving spatial resolution (Ma et al., 2002). Other examples are improving image misregistration in digital change detection (Carvalho, 2001), and reducing speckle in SAR imagery (Wikantika et al., 1999; Nyoungui et al., 2002). A few studies use wavelet transformation for calculating texture measures at different scale levels (Simard et al., 2000; Myint et al., 2002; Ruiz et al., 2002; Arivazhagan & Ganesan, 2003). These texture-based applications used the so-called 'detail' images, up to three scale-levels, followed by per-pixel classifications. Although such texture-based classifications produced very high overall accuracy rates (>85-95%), Ruiz et al. (2002) concluded that their main limitation is the so-called border effect that introduces significant errors in the transition areas between texture units. This border effect drastically decreased the overall accuracy to 47%. They argued for further work to reduce this border effect. Regarding spatial heterogeneity, the main cause of this border effect might be the classification part, which assumes spatial homogeneity (i.e., limitation 1, section 2.3.3). Therefore, addressing vegetation structure through decomposing images at different scale levels does not automatically lead to a classification that addresses relevant vegetation composition at pixel level. Consequently, improving a geometric representation (i.e., limitation 2) does not necessarily improve a thematic representation (i.e., limitation 1). Both key components of vegetation, composition and structure, should be addressed at different spatial aggregation levels to model spatially heterogeneous environments like tropical rainforest areas (Chapter 1). In addition, in stead of using only 'detail' images, also the use of 'smooth' images could be studied, because these images also address vegetation structure at different spatial aggregation levels. This thesis used 'smooth' images, up to seven scale-levels, to guide multi-scale segmentation in the spatially heterogeneous Pelangkaraya study area (Chapter 6).

2.3.6 Multi-scale segmentation

Segmentation is one of the most important operations in image analysis (Rosenfeld & Kak, 1982; Haralick & Shapiro, 1992,1993; Muñoz et al., 2003). It is the process of partitioning an image into some non-overlapping regions or categories. As a result, pixels in the same category have similar grayscale or multivariate values and form a connected region. Neighboring pixels that are in different categories have dissimilar values (Glasbey & Horgan, 1995). Formally, segmentation can be defined as follows (Horowitz & Pavlidis, 1974; Pal & Pal, 1993): if *F* is the set of all pixels and $P(S_i)$ is a uniformity (homogeneity) predicate defined on groups of connected pixels, then segmentation is a partitioning of the set *F* into a set of connected subsets or regions $(S_1, S_2, \ldots, S_n)$ such that

$$\bigcup_{i=1}^{n} S_i = F \text{ with } S_i \bigcap S_j = \varnothing, \; i \neq j \qquad (2.1)$$

The uniformity predicate $P(S_i)$ = true for all regions (S_i) and $P(S_i \cup S_j)$ = false, when S_i is adjacent to S_j. In remote sensing applications, the regions (S_i) or categories correspond to objects or parts of objects in the landscape (Nevatia, 1986). Segmentation was already used in the 1970's, but it was for long not popular in remote sensing because of some associated problems. According to Acton (1996) these problems were related to undesirable merging of objects, fragmentation of objects, poor localization and ambiguity of object boundaries, sensitivity to noise, and requirement of large memory and long processing time. Remote sensing has given renewed interest to digital segmentation techniques because of the improvement of spatial resolution of satellite imagery, as well as the increasing hardware capabilities and the newly developed segmentation software packages. Forestry applications use segmentation to reduce local spectral variation of forest classes being a major bottleneck for per-pixel classifiers (Woodcock et al., 1994; Hill, 1999; Abkar et al., 2000; Almeida-Filho & Shimabukuro, 2002; and Dorren et al., 2003). Hundreds of segmentation algorithms have been published. For a review see Zucker, 1977; Fu & Mui, 1981; Haralick & Shapiro, 1985; Nevatia, 1986; Pal & Pal, 1993; Cheng et al., 2001; and Muñoz et al., 2003. The algorithms may either be applied to the images as originally recorded, or after image processing. The decision rules used for segmenting the image depend on the applied segmentation technique. Three general approaches to image segmentation are (Glasbey & Horgan, 1995):

- Thresholding
- Edge-based techniques
- Region-based techniques

Thresholding is the simplest and most commonly used method of image segmentation. Thresholding allocates a pixel to a category according to the range of values in which that pixel fits (Ridler & Calvard, 1978; Trussel, 1979; Kittler & Illingworth, 1986; Glasbey, 1993). Thresholding is most successful when there is little overlap in distributions of pixel values between different categories. For spatial objects with large spectral variance, like vegetation types in tropical rainforest areas, thresholding is not useful to model spatially heterogeneity. It only addresses vegetation composition, not vegetation structure, because it does not consider spatiality. Incorporating contextual information in the thresholding algorithm like using a majority filter (Mardia & Hainsworth, 1988) and prior information on neighboring classes (Besag, 1986) can add information on vegetation structure. The problem of blurring at class boundaries, however, limits the size of the window and thus limits the use of these techniques to address vegetation structure at different spatial aggregation levels.

Edge-based segmentation improves simple thresholding, because zero-crossings always form closed boundaries (Glasbey & Horgan, 1995). Edge-based segmentation applies edge filters (i.e, high spatial frequency filters) to classify pixels as edge or non-edge depending on the filter output. It also allocates pixels that are not separated by an edge to the same category. Well-known edge filters are Laplacian filters, although these filters are very sensitive to noise (Fisher et al., 2003). Generally, the most common problems of edge-based segmentation are the presence of edges in locations where there is no border, and the absence of edges where a real border exists (Sonka et al., 1998). Distinct edges are rare in spatially heterogeneous vegetation, because there are many transitions between different categories. This limits the use of pure edge-based segmentation techniques.

Region-based segmentation is the most advanced method of image segmentation. Region-based segmentation may be regarded as spatial clustering (Glasbey & Horgan, 1995). It is more immune to noise than edge detection methods (Cheng et al., 2001). Region-based segmentation merges pixels that are neighbors and have similar values and split groups of pixels that are dissimilar in values. Merging and splitting are both iterative processes. Therefore, region-based segmentation can be based on merge algorithms (also called region-growing algorithms; e.g., Adams & Bischof, 1994; Baatz & Schäpe, 2000), split algorithms like quadtrees (e.g., Samet, 1984; Burrough & McDonnell, 1998; Molenaar, 1998), and iteratively split and merge algorithms (e.g., Tailor et al., 1986; Laprade, 1988; Ton et al., 1991). The latter algorithms take advantage of the complementary nature of split and merge algorithms (Muñoz et al., 2003). Such advanced region-based methods require 'high-level' knowledge, which falls into the domain of artificial intelligence (Glasbey & Horgan, 1995). Generally, region-growing algorithms are used in forestry applications, especially tropical forestry applications, because of their true bottom-up approach. They can be applied in two ways:

- A single segmentation
- Multi-scale segmentation

A single segmentation does not make explicit assumptions on the spatial extent of the thematic classes, except by defining the threshold of the homogeneity/heterogeneity parameter. Often, such a segmentation does not solve the problem of spatial heterogeneity. It would be naïve to expect that an image segmentation algorithm solely based on spectral and textural pattern recognition (i.e., boundary detection or region growing) will enable to delineate image objects that correspond, one-to-one, to land cover classes that are of interest (Abeyta & Franklin, 1998). The results are either small spatial objects that are thematically straightforward to classify (but spatially fragmented), or large spatial objects at the desired spatial aggregation level (but thematically difficult to classify). In fact, a single segmentation aimed at reducing local spectral variation deals with vegetation composition (i.e., patches), not vegetation structure (i.e., patch-mosaics).

Multi-scale segmentation makes explicit assumptions on the spatial extent of thematic classes (Schiewe, 2001; Burnett & Blaschke, 2003; Chen et al., 2003). This technique is also described as multi-resolution segmentation (Blaschke & Strobl, 2001; Benz et al., 2004), or hierarchical segmentation (Tilton, 2000a,b). These segmentation techniques are implemented in object-oriented image analysis (for principles see Hay et al., 2003; Benz et al., 2004; for examples see Burnett & Blaschke, 2003; Dorren et al., 2003; Laliberte et al., 2004). Although multi-scale segmentation and multi-resolution segmentation are often used interchangeably, there is an important difference between the two.

- **Multi-scale segmentation** should refer to spatial objects that are created at different spatial aggregation levels (i.e., lower level objects, focal level objects, and higher level objects; see section 2.2.2). These spatial scales are interrelated, that is objects on the lower level are 'part-of' objects on a higher level. Such a relation resembles a true multi-scaled system in the sense of landscape ecology (see section 2.2.4).

- **Multi-resolution segmentation** should refer to spatial objects that are created at different resolution levels, but not specifically interrelated. The previous examples of object-oriented image analysis (e.g., Burnett & Blaschke, 2003; Dorren et al., 2003; and Laliberte et al., 2004) are of the multi-resolution type. In fact, multi-resolution segmentation can only deal with vegetation structure if a top-down analysis approach can be applied. For such an analysis, information on the extent of spatial objects at different resolution levels should be available. This is only the case when dealing with landscapes that can be thematically generalized (e.g., Figure 2.9a; see also section 2.3.5).

2.3.7 Wavelet transformation

Wavelet transformation is the process of using a localized function of mean zero in space or time, the wavelet, to study local features of a data set with a level of detail that matches their scale, i.e. broad features on a large scale and fine features on a small scale (Mallat, 1989,1998; Chui, 1992; Daubechies, 1992; Foufoula Georgiou & Kumar, 1994; Kumar & Foufoula-Georgiou, 1997). In other words, by using a wavelet transformation in image analysis one cannot only reveal the trees but also the forest (Pelgrum, 2000). Formally, wavelets decompose a (one-dimensional) signal *f(t)* into a (two-dimensional) joint time-scale representation $\Psi_{s,\tau}(t)$ by scaling and translation: $\Psi_{s,\tau}(t)$ are the wavelet coefficients of the function f(t), $\Psi(t)$ is the analyzing wavelet, *s* is the scaling factor, and τ is the translation factor. In formula (Valens, 2004; Starck et al., 1998):

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \int f(t) \Psi^{*}\left(\frac{t-\tau}{s}\right) dt \tag{2.2}$$

For image data, not time but position is of main importance. Therefore, the signal *f(t)* is described as the signal *f(x)*, and τ becomes the position parameter and is described as *u*. Applying wavelets originated in geophysics in the early 1980s for the analysis of seismic signals (Kumar & Foufoula-Georgiou, 1997). Significant mathematical advances in wavelet theory have enabled a suite of applications in various fields (e.g., astronomy, medicine, handwriting, speech recognition, hydrologic fluxes, atmosphere turbulence, and ocean windwaves). Recently, the use of wavelet transformation entered the field of remote sensing (for applications, see section 2.3.5). The decomposition of image data into different localized scale levels is only limited by the resolution and extent of the original image data (Wiens, 1989). If the localized scales represent distinct degrees of heterogeneity, they can address functional heterogeneity and thus vegetation structure (Reynolds et al., 1997).

There is abundant literature on the theoretical underpinning of wavelet transformation. In addition to previously presented literature references, a friendly guide is provided by Valens (2004). A practical textbook on wavelet transformation in image analysis is provided by Starck et al. (1998). For a comprehensive understanding of the use of wavelet transformation with respect to landscape ecological applications, the remainder of this section elucidates four issues:

- Theoretical background
- Discrete wavelets
- Mexican hat wavelet
- The 'à-trous' algorithm

The ***theoretical background*** for the introduction of wavelet transformation was to overcome shortcomings of the Fourier transform. From Fourier's theory it is known that a signal can be expressed as the sum of a series of sines and cosines (Valens, 2004). This is called a Fourier expansion. A big disadvantage of this expansion is that it only produces a frequency resolution (i.e., what is present), no time resolution (i.e., when this is present). Simultaneously analyzing a signal in both the time and frequency domain (i.e., time-frequency joint representation) would provide more information about the 'when and where' of different frequency components. This approach, however, requires knowledge of how to cut the signal into several parts (and then analyze the parts separately). The problem is that in the Fourier domain a signal can not be simply represented as a point in the time-frequency space. Either frequency or time can be addressed, but never both. Wavelet transformation solved this signal-cutting problem by using a fully scalable modulated window that is shifted along the signal. Wavelet transformation calculates for every position of that window the frequency spectrum. Repeating this process many times with a slightly shorter (or longer) window for every new cycle results is a collection of desired time-frequency representations of the signal, all with different resolutions. The collection of time-frequency representations are called time-scale representations, because the term 'frequency' is exclusively reserved for the Fourier transform. Applying a wavelet transformation is called a multi-scale analysis, not a multi-resolution analysis, because of the collection of interrelated representations (as discussed in section 2.3.6).

Discrete wavelets have been introduced to make wavelet transformation more practical by solving three major problems of the continuous wavelet transformation: removing redundancy of wavelet coefficients, reducing the infinite number of wavelets, and allowing fast algorithms (Valens, 2004). Removing redundancy of wavelet coefficients is obtained through dyadic sampling[5]. Regarding equation 2.1, dyadic sampling is obtained when using the value 2 for the scale factor s and the value 1 for the translation factor τ (Lemire, 2004). Reducing the infinite number of wavelets is obtained through making wavelets orthogonal. Orthogonal wavelets make use of a combination of low-pass and high-pass filters. Scaling functions are low-pass filters, and wavelets are high-pass filters. The combination of a low-pass filter and a high-pass filter is also called a digital filter bank. Recursive implementation of such filter banks allows for fast algorithms, because there is no need to specify the wavelets explicitly. Digital filter banks decompose original image data into broad features called the 'smooths', and fine features called the 'details' (Figure 2.17).

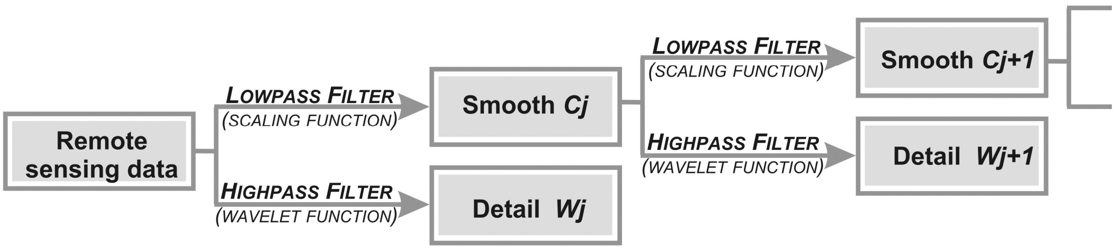


Figure 2.17: Schematic representation of a recursive implementation of a digital filter bank.

The smooth images C_j are based on a scaling function $\Phi(x)$ that correspond to a low-pass filter with filter coefficients $h(l)$. In formula (Starck et al., 1998):

$$\Phi(x) = \sum_{l} h(l)\Phi(2x - l) \tag{2.3}$$

The detail images W_j are based on a discrete wavelet function $\Psi(x)$ and correspond to a high-pass filter with filter coefficients $g(l)$. In formula (Starck et al., 1998):

$$\Psi(x) = \sum_{l} g(l)\Phi(2x - l) \tag{2.4}$$

[5] Dyadic sampling is a natural solution; for instance, human ear and music are also based on dyadic sampling of the frequency.

The two functions are orthogonal, that their product equals zero. The smooths show the image data at a resolution twice as coarse (dyadic analysis). They detect the most dominant features of the image. The details show the amount of detail lost in the process of smoothing between different scale levels. They show how much variability is present at each scale level *j*. The more the wavelet resembles the function to which it is to approximate, the fewer scales *j* are required for this purpose (Zeiss, 2004).

This thesis used a discrete wavelet to guide the segmentation of the geometric extents of spatial objects at composite level (Chapter 6, section 6.2.4). The Mexican hat wavelet (Murenzi, 1988) was selected because of its linear scaling function. It was implemented in the so-called 'à trous' algorithm to maintain the image size of all the transformed images (Holschneider et al., 1989; Shena, 1992). Details and rationale of using the Mexican hat and the 'à trous' algorithm are described hereafter.

The discrete ***Mexican hat wavelet*** consists of a *linear* scaling function, also known as the triangle function, with filter coefficients $h(-1)=1/4$, $h(0)=1/2$, $h(1)=1/4$ (Murenzi, 1988). Applying this triangle function leads to a piecewise linear convolution of the input data. Hootsmans (1996) found that linear functions are most suitable for applications to spatial data, as it is the least suggestive in describing transition zones. Although this conclusion was drawn in a totally different context (i.e., selecting most suitable fuzzy membership functions) the application field is comparable, i.e., spatial data consisting of transition zones. In formula:

$$\Phi(x) = 1 - |x| \quad \text{if } x \in [-1,1]$$
$$\Phi(x) = 0 \quad \text{if } x \notin [-1,1] \tag{2.5}$$

The Mexican hat is a well-known wavelet among Morlet's wavelet (Goupillaud et al., 1985) and Haar wavelet (Daubechies, 1992).

The 'à trous' algorithm (Holschneider et al., 1989; Shena, 1992) is a stationary or redundant transformation because decimation is not carried out. This is very useful in digital image analysis, because throughout all scale levels the transformed images have the same number of pixels (rows and columns) as the original image data. This is called a wavelet plane (Starck et al., 1998). The 'à trous' algorithm is a basic and popular algorithm, because implementation is normally achieved via a simple discrete convolution based on filters and filter banks (Daubechies, 1989; Starck et al., 1998; Carvalho et al., 2001). In stead of reducing the input images, the filter itself is enlarged with a factor two at each scale level. This is achieved by inserting zeros between the samples of the operator when moving from j to $j+1$. Those zeros are the reason why the algorithm bears its name; 'à trous', which is French for ‘with holes’. Figure 2.18 presents a schematic representation of the 'a trous' algorithm using filter coefficients of the triangle function to obtain the discretized Mexican hat wavelet.

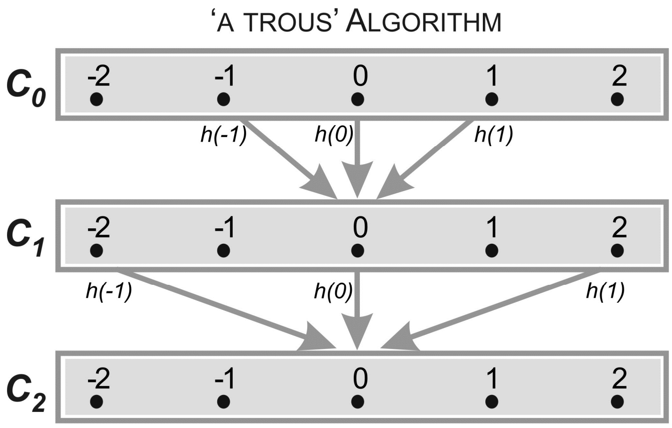


Figure 2.18: Schematic representation of the 'a trous' algorithm; passage form c_o to c_1, and from c_1 to c_2 (after Starck et al., 1998).

Applying the 'a trous' algorithm using the filter coefficients of the triangle function, the first convoluted image c_1 (the smooths) is obtained from:

$$c_1(k) = \frac{1}{4}c_0(k-1) + \frac{1}{2}c_0(k) + \frac{1}{4}c_0(k+1) \tag{2.6}$$

and c_{j+1} is obtained from c_j by:

$$c_{j+1}(k) = \frac{1}{4}c_j(k-2^j) + \frac{1}{2}c_j(k) + \frac{1}{4}c_j(k+2^j) \tag{2.7}$$

The wavelet coefficients (the details) at scale level j are:

$$w_{j+1}(k) = -\frac{1}{4}c_j(k-2^j) + \frac{1}{2}c_j(k) - \frac{1}{4}c_j(k+2^j) \qquad (2.8)$$

Generally, the details are obtained by subtracting two successive convolutions. In formula:

$$w_j(k) = c_{j-1}(k) - c_j(k) \qquad (2.8)$$

The original image c_0 can be reconstructed following:

$$c_0(k) = c_J(k) + \sum_{j=1}^{J} w_j(k) \qquad (2.9)$$

The 2D extension of the 'à trous' algorithm is easily obtained as the Kronecker product of the 1D filter coefficients (using filter coefficients of the triangle function):

$$\begin{pmatrix} 1/4 & 1/2 & 1/4 \end{pmatrix} \otimes \begin{pmatrix} 1/4 \\ 1/2 \\ 1/4 \end{pmatrix} = \begin{pmatrix} 1/16 & 1/8 & 1/16 \\ 1/8 & 1/4 & 1/8 \\ 1/16 & 1/8 & 1/16 \end{pmatrix}$$

The value of *J* defines the scaling of the objects. For example, the original image *j=0* is a Landsat TM image with pixel resolution of 30m, after passing the first low-pass and high-pass filter the spatial objects of the transformed image *j=1* are at a scale of 60 meter, successively, for *j=2 at* 120 meter, for *j=3* at 240 meter, etc. Moving from *j=0* to *j=1* the filter consists of 3 rows and 3 columns. Moving from j=1 to j=2, the filter consists of 5 rows and 5 columns, because zeros (holes) are inserted between the coefficients. Moving from j=2 to j=3 the filter consists of 9 rows and 9 columns, because zeros are again inserted (i.e., putting zeros between zeros and coefficients). Figure 2.19 presents a graphic example of a 2D decomposition using the discrete Mexican hat wavelet implemented in the 'à trous' algorithm for Landsat TM band 4 of the p1990 image of the Pelangkaraya study area. Applying the filter banks, the values of the image boundaries were obtained by continuity.

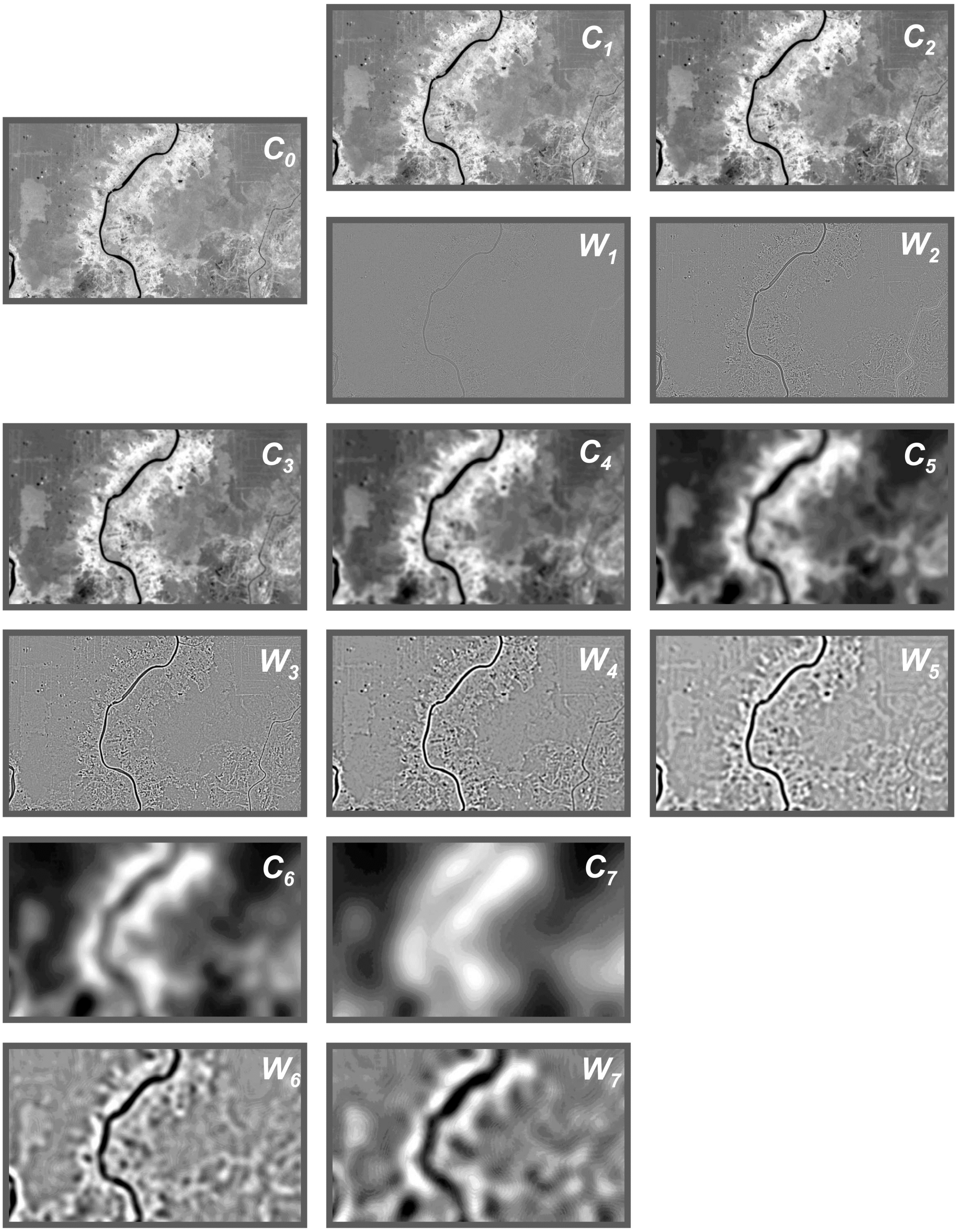


Figure 2.19: Example of a 2D decomposition using the discrete Mexican hat wavelet implemented in the 'à trous' algorithm for Landsat TM band 4 of the p1990 image of the Pelangkaraya study area.

2.4 Patch-Mosaics in categorical image analysis

Classifying ecosystems like tropical rainforest areas at different spatial aggregation levels is a complicated task. Such areas exhibit pattern heterogeneity and border transition at different spatial aggregation levels. Classification by digitally analyzing remote sensing imagery requires an approach that addresses both vegetation composition and vegetation structure (i.e., pattern).

It was concluded in section 2.2.2 that the use of Patch-Mosaic EFTs (Ecosystem Functional Types) could be a valuable analysis strategy to handle spatial heterogeneity, because it is part of a functional hierarchical approach (i.e., the Hierarchical Patch Dynamics Paradigm or HPDP). In this approach, levels correspond to structural and functional units at distinct spatial and temporal scales. As such, landscapes are considered as ordered and interrelated multi-scale composites of local patches and patch-mosaics. According to hierarchy theory, these patch-mosaics can be considered as the focal level, the patches as the lower level, and the landscapes as the upper level in a multi-scaled system. Such a functional hierarchy enables the analysis of both vegetation composition and vegetation structure at different spatial aggregation levels.

Remote sensing data can conceptually represent spatial heterogeneity because it contains both thematic and geometric (spatial) information. Current digital analysis techniques, however, face two major limitations because spatial homogeneity is emphasized and related approaches are single-scaled. Both limitations constrain the implementation of patch-mosaic EFTs as a digitally analysis strategy in remote sensing. They neglect that spatial entities either are often *spatially* not discrete, or their organization has a *functional* hierarchical structure. This distinction between spatiality (structure) and functionality (organization) is of prime importance to handle spatial heterogeneity in remote sensing. Current improvements of both limitations, however, deal with either vegetation composition or vegetation structure. Such improvements can be appropriate for landscapes that can be thematically generalized (e.g., Figure 2.9a), because in this case a classification hierarchy can still be used to identify the geometric extent of spatial entities prior to thematic labeling. This extent-label sequence typically follows a top-down approach. Spatially heterogeneous environments, however, require solutions for both limitations simultaneously, because classification hierarchies cannot address geometric extents of spatial entities. When thematic content is spatially not homogeneous and extent is not discrete, both occurring in many natural environments, an aggregation hierarchy is required. Such hierarchies hierarchically link spatial entities (function) based on both vegetation composition and vegetation structure (i.e., pattern). With aggregation hierarchies, spatial entities can be thematically labeled prior to geometric identification. This label-extent sequence typically follows a bottom-up approach, where basic structural landscape entities (i.e., patches) are identified and aggregated into functional landscape entities (i.e., patch-mosaics). Functional generalization is a spatial generalization strategy following such a bottom-up approach. It merges elementary objects into composite objects based on functional relationships. These relationships can address both vegetation composition and vegetation structure, because this conceptual generalization strategy uses both thematic and geometric aspects of spatial objects. Therefore, functional generalization is instrumental to conceptually represent spatially heterogeneous environments like tropical rainforest areas at different spatial aggregation levels.

A major problem of implementing functional generalization in digital image analysis, however, is the lack of a remote sensing theory and methods that support such an implementation. In other words, it is unknown how to quantitatively move from patches to patch-mosaics with regard to remote sensing imagery. Therefore, a new theory (Chapter 3) and related methods (Chapter 4, 5 and 6) are developed in this thesis to digitally analyze spatial heterogeneous environments based on functional relationships that consider both thematic ánd geometric aspects of their spatial entities.

References

Abeyta, A. & Franklin, J. (1998). The accuracy of vegetation stand boundaries derived from image segmentation in a desert environment. *Photogrammetric Engineering and Remote* Sensing 64(1):59-66.

Abkar, A.A., Sharifi, M.A. & Mulder, N.J. (2000). Likelihood-based image segmentation and classification: A framework for the integration of expert knowledge in image classification procedures. *International Journal of Applied Geo-information and Earth Observation (JAG)* 2(2):104-119.

Acton, S.T. (1996). On unsupervised segmentation of remotely sensed imagery using non-linear regression. *International Journal of Remote Sensing* 17(7):1407-1415.

Adams, R. & Bischof, L. (1994). Seeded region growing. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 16:641-646.

Addink, E. (2001). Change detection with remote sensing: Relating NOAA-AVHRR to environmental impact of agriculture in Europe. PhD Thesis, Wageningen University, Ponsen & Looijen, Wageningen.

Ahl, V. & Allen, T.F.H. (1996). Hierarchy theory: A vision, vocabulary, and epistemology. Columbia University Press, New York.

Allen, T.F.H. & Starr, T.B. (1982). Hierarchy: Perspectives for ecological complexity. University of Chicago Press, Chicago.

Allen, T.F.H. & Hoekstra, T.W. (1991). Role of heterogeneity in scaling of ecological systems under analysis. In: Kolasa, J. & Pickett, S.T.A. (eds), Ecological Heterogeneity, Ecological Studies 86, Springer-Verlag, New York, 47-68.

Almeida-Filho, R. & Shimabukuro, Y.E. (2002). Digital processing of a Landsat-TM time series for mapping and monitoring degraded areas caused by independent gold miners, Roraima State, Brazilian Amazon. *Remote Sensing of Environment* 79(1):42-50.

Arivazhagan, S. & Ganesan, L. (2003). Texture segmentation using wavelet transform. *Pattern Recognition Letters* 24(16):3197-3203.

Baatz, M. & Schäpe, A. (2000). Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation. In: Strobl, J. & Blaschke, T. (eds), Angewandte geographische informationsverarbeitung, Vol. XII, AGIT-Symposium, Salzburg, Herbert Wichmann Verlag, Karlsruhe, 12–23.

Baker, W.L. (1989). A review of models of landscape change. *Landscape Ecology* 2:111-133.

Bandibas, J.C., Bruce, R.C. & Daels, L. (1995). Using frequency based classifier for remote sensing of spatially heterogeneous land-use/land-cover systems in the tropics. *Asian-Pacific Remote Sensing Journal* 7(2):65-70.

Benson, B.J. & MacKenzie, M.D. (1995). Effects of sensor spatial resolution on landscape structure parameters. *Landscape Ecology* 10:113–120.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing* 58:239-258.

Besag, J. (1986). On the statistical analysis of dirty pictures (with discussion). *Journal of the Royal Statistical Society (Series B)* 48:259-302.

Beurden, A.U.C.J. van & Douven, W.J.A.M. (1999). Aggregation issues of spatial information in environmental research. *International Journal of Geographical Information Science* 13(5):513-527.

Blaschke, T. & Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *Geoinformation Systems* 6:12-17.

Bregt, A. & Bulens, J. (1996). Application-oriented generalization of area objects. In: Molenaar, M. (ed), Methods for the generalization of geo-databases, Delft: Netherlands Geodetic Commission, New Series 43:57-64.

Burke, I.C., Kittel, T.G.F., Lauenroth, W.K., Snook, P., Yonker, C.M. & Parton, W.J. (1991). Regional analysis of the Great Plains. *BioScience* 25:685-692.

Burnett, C. & Blaschke, T. (2003). A multi-scale segmentation/object relationship modelling methodology for landscape analysis. *Ecological Modelling* 168(3):233-249.

Burrough, P.A. & McDonnell, R.A. (1998). Principles of geographical information systems. Oxford University Press, Oxford.

Caldwell, C.K. (1995). Graph Theory Glossary. At http://www.utm.edu/departments/math/graph/glossary.html, accessed September 29, 2004.

Cantwell, M.D. & Forman, R.T.T. (1993). Landscape graphs: Ecological modeling with graph theory to detect configurations common to diverse landscapes. *Landscape Ecology* 8(4):239-255.

Carvalho, L.M.T. de, Fonseca, L.M.G., Murtagh, F. & Clevers, J.G.P.W. (2001). Digital change detection with the aid of multiresolution wavelet analysis. *International Journal of Remote Sensing* 22(18):3871-3876.

Chen, Q.-X., Luo, J.-C., Zhou, C.-H. & Pei, T. (2003). A hybrid multi-scale segmentation approach for remotely sensed imagery. International Geoscience and Remote Sensing Symposium (IGARSS) 6:3416-3419.

Cheng, H.D., Jiang, X.H., Sun, Y. & Wang, J. (2001). Color image segmentation: Advances and prospects. *Pattern Recognition* 34:2259-2281.

Chui, C. K. (1992). Wavelets: A tutorial in theory and applications. Wavelet analysis and its applications, Vol. 2. Academic Press, San Diego, CA.

Cortijo, F.J. & Perez de la Blanca, N. (1998). Improving classical contextual classifications. *International Journal of Remote Sensing* 19(8):1591-1613.

Daubechies, I. (1989). Orthonormal bases of wavelets with finite support: Connection with discrete filters. In: Combes, J.M., Grossman, A. & Tchamitchian, P. (eds.), Wavelets: Time-frequency methods and phase space, Springer-Verlag, Berlin, 38-65.

Daubechies, I. (1992). Ten lectures on wavelets. Cbms-Nsf Regional Conference Series in Applied Mathematics, No 61. Society for Industrial and Applied Mathematics (SIAM), Philadelphia.

Dorren, L.K.A., Maier, B. & Seijmonsbergen, A.C. (2003). Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. *Forest Ecology and Management* 183:31-46.

Droesen, W.J. (1999). Spatial modelling and monitoring of natural landscapes with cases in the Amsterdam Waterworks Dunes. PhD Thesis, Wageningen Agricultural University, Ponsen & Looijen, Wageningen.

Du, Y., Guindon, B., & Cihlar, J. (2002). Haze detection and removal in high resolution satellite image with wavelet analysis. *IEEE Transactions on Geoscience and Remote Sensing* 40(1):210-216.

Eng, M. (1997). Spatial Patterns in forested landscapes: Implicationa for biology and forestry. In: Voller, J. & Harrison, S. (eds), Conservation biology principles for forested landscapes, B.C. Ministry of Forests, UBC Press, Vancouver, 42-75.

Farina, A. (1998). Principles and methods in landscape ecology. Chapman & Hall, London.

Fisher, R., Perkins, S., Walker, A. & Wolfart, E. (2003). Image processing learning resources HIPR2. At http:// homepages. inf.ed.ac.uk/rbf/HIPR2/log.htm#2, accessed September 13, 2004.

Forman, R.T.T. (1995). Land mosaics: The ecology of landscapes and regions. Cambridge University Press, Cambridge.

Forman, R.T.T. & Godron, M. (1981). Patches and structural components for a landscape ecology. *Bioscience* 31:733-740.

Forman, R.T.T. & Godron, M. (1986). Landscape ecology. John Wiley & Sons, New York.

Foufoula-Georgiou, E. & Kumar, P. (eds) (1994). Wavelets in geophysics. Wavelet analysis and its applications, Vol 4. Academic Press, San Diego, CA.

Fu, K.S. & Mui, J.K. (1981). A survey on image segmentation. *Pattern Recognition* 13(1):3-16.

Gilbert & Plowes (2004). Field problem: Quantifying heterogeneity of vegetation at Brackenridge field laboratory from a deer's point of view. Biology 373L, February 18, 2004. At http://www.sbs.utexas.edu/bio373l/docs/Habitatassessment/woodland%20Sp04.doc, accessed September 17, 2004.

Gitay H. & Noble, I.R. (1997). What are functional types and how should we seek them? In: Smith, T.M., Shugart, H.H. & F.I. Woodward (eds), Plant functional types, their relevance to ecosystem properties and global change, International Geosphere-Biosphere Programme Book Series, Cambridge University Press, 3-19.

Glasbey, C.A. (1993). An analysis of histogram-based thresholding algorithms. *CVGIP: Graphical Models and Image Processing* 55:532-537.

Glasbey, C.A. & Horgan, G.W. (1995). Image analysis for the biological sciences. John Wiley & Sons, Chichester.

Gong, P. & Howarth, P.J. (1992a). Frequency based contextual classification and gray-level vector reduction for land-use identification. *Photogrammetric Engineering & Remote Sensing* 58(4):423-437.

Gong, P. & Howarth, P.J. (1992b). Land-use classification of SPOT HRV data using a cover-frequency method. *International Journal of Remote Sensing* 13(8):1459-1471.

Goodchild M.F. & Quatrochi, D.A. (1997). Introduction: Scale, multiscaling, remote sensing, and GIS. In: Quatrocchi D.A. & Goodchild, M.F. (eds), Scale in remote sensing and GIS, Lewis Publishers, Boca Raton, 1–12.

Goupillaud, P., Grossman, A. & Morlet, J. (1985). Cycle-octave and related transforms in seismic signal analysis. *Geoexploration* 23:85-102.

Gustafson, E.J. (1998). Quantifying landscape spatial pattern: What is the state of the art? *Ecosystems* 1:143-156.

Hall, F.G., Townshend, J.R., & Engman, E.T. (1995). Status of remote sensing algorithms for estimation of land surface state parameters. *Remote Sensing of Environment* 51(1):138-156.

Haralick, R.M. & Shapiro, L.G. (1985). Image segmentation techniques. *Computer Vision, Graphics and Image Processing* 29:100-132.

Haralick, R.M. & Shapiro, L.G. (1992/1993). Computer and robot vision,Vol. 1/2. Addison-Wesley, Reading, Massachussets.

Hay, G.J., Marceau, D.J., Dub, P., & Bouchard, A. (2001). A multiscale framework for landscape analysis: Object-specific analysis and upscaling. *Landscape Ecology* 16:471–490.

Hay, G., Blaschke, T., Marceau, D. & Bouchard, A. (2003). A comparison of three image-object methods for the multiscale analysis of landscape structure. *ISPRS Journal of Photogrammetry & Remote Sensing* 57:327-345.

He, H.S., Ventura, S.J. & Mladenoff, D.J. (2002). Effects of spatial aggregation approaches on classified satellite imagery. *International Journal of Geographical Information Science* 16(1):93-109.

Hill, R.A. (1999). Image segmentation for humid tropical forest classification in Landsat TM data. *International Journal of Remote Sensing* 20(5):1039-1044.

Holschneider, M., Kronland-Martinet, R., Morlet, J. & Tchamitchian, P. (1989). A real-time algorithm for signal analysis with the help of the wavelet transform. In: Combes, J.M., Grossman, A. & Tchamitchian, P. (eds), Wavelets: Time-frequency methods and phase space, Springer-Verlag, Berlin, 286-297.

Hootsmans, R.M. (1996). Fuzzy sets and series analysis for visual decision support in spatial data exploration. PhD Thesis, University of Utrecht, Utrecht.

Horowitz, S.L., & Pavlidis, T. (1974). Picture segmentation by directed split and merge procedure. Proceedings, 2nd International Joint Conference on Pattern Recognition, 424-433.

Huising, J. (1993). Land use zones and land use patterns in the Atlantic zone of Costa Rica. A pattern recognition approach to land use inventory at the sub-regional scale, using remote sensing and GIS, applying an object-oriented and data-driven strategy. PhD Thesis, Wageningen University, Ponsen & Looijen, Wageningen.

Ingegnoli, V. (2002). Landscape ecology: A widening foundation. Springer-Verlag, Berlin Heidelberg.

Iverson, L.R., Cook, E.A., & Graham, R.L. (1994). Regional forest cover estimation via remote sensing: The calibration center concept. *Landscape Ecology* 9(3):159-174.

Janssen, L.L.F. (1994). Methodology for updating terrain object data from remote sensing data: The application of Landsat TM data with respect to agricultural fields. PhD Thesis, Wageningen University, CIP-data Koninklijke Bibliotheek, Den Haag.

Jelinski, D.E. & Wu, J. (1996). The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology* 11(3):129-140.

Jong, S.M. de & Burrough, P.A. (1995). A fractal approach to the classification of Mediterranean vegetation types in remotely sensed images. *Photogrammetric Engineering & Remote Sensing* 61(8):1041-1053.

Jong, S.M. de, Hornstra, T. & Maas, H.G. (2001). An integrated spatial and spectral approach to the classification of Mediterranean land cover types: The SSC method. *International Journal of Applied Geo-information and Earth Observation (JAG)* 3(2):176-183.

Kenk, E., Sondheim, M. & Yee, B. (1988). Methods for improving accuracy of thematic mapper ground cover classifications. *Canedian Journal of Remote Sensing* 14(1):17-31.

Kilpelaïnen, T. (1992). Multiple representations and knowledge-based generalization of topographical data. XVII Congress of ISPRS, Aug 2-14, Washington DC, USA. International Archives of Photogrammetry and Remote Sensing, Vol. XXIX, Part B7, 954-964.

Kilpelaïnen, T. (ed) (1999). Map Generalisation in the Nordic Countries. Reports of the Finnish Geodetic Institute, 99:6, Kirkkonummi. See also At http://www.fgi.fi/osastot/karto/julkaisut/nordic_abstract_99.htm, accessed November 11, 2004.

Kittler, J. & Illingworth, J. (1986). Minimum error thresholding. *Pattern Recognition* 19:41-47.

Kolasa, J. & Pickett, S.T.A. (eds) (1991). Ecological Heterogeneity. Ecological Studies 86, Springer-Verlag, New York.

Kolasa, J. & Rollo, C.D. (1991). The heterogeneity of heterogeneity: A glossary. In: Kolasa, J. & Pickett, S.T.A. (eds), Ecological heterogeneity, Ecological Studies 86, Springer-Verlag, New York, 1-23.

Kotliar, N. & Wiens J.A. (1990). Multiple scales of patchiness and patch structure: A hierarchical framework for the study of heterogeneity. *Oikos* 59:253-260.

Kumar, P. & Foufoula-Georgiou, E. (1997). Wavelet analysis for geophysical applications. *Reviews of Geophysics* 35(4):385-412.

Kushwada S.P.S., Kuntz, S. & Oesten, G. (1994). Applications of image texture in forest classification. *International Journal of Remote Sensing* 15(11):2273-2284.

Laliberte, A.S., Rango, A., Havstadk, K.M., Paris, J.F., Beck, R.F., Reldon F., McNeely, R. & Gonzalez, A.L. (2004). Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment* 93(1-2):198-210.

Laprade, R.H. (1988). Split-and-merge segmentation of aerial photographs. *Computer Vision Graphics and Image Processing* 48:77-96.

Lemire, D. (2004). 20 years of wavelets: Tales from industry and academia. At http://www.ondelette.com/NRC/UNBMath3113/wavelet.pdf, accessed November 9, 2004.

Le Moigne, J., Laporte, N. & Netanyahu, N.S. (2002). Enhancement of tropical land cover mapping with wavelet-based fusion and unsupervised clustering of SAR and Landsat image data. Proceedings of SPIE - The International Society for Optical Engineering 4541:190-198.

Li, H., & Reynolds, J. F. (1995). On definition and quantification of heterogeneity. *Oikos* 73:280–284.

Lira, J. & Maletti, G. (2002). A supervised contextual classifier based on a region-growth algorithm. *Computers & Geosciences* 28:951-959.

Ma, J., Hasibagan, Ma, C., Han, X., Liu, Z. Ma, J., Hasibagan, Ma, C., Han, X. & Liu, Z. (2002). The use of wavelet fusion method to improve multi-spectral imagery for land cover change monitoring. IEEE International Geoscience and Remote Sensing Symposium, IGARSS '02, 24-28 June, Toronto, Canada, Vol. 2, 1198-1200.

Mallat, S. (1989). A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 11:674-693.

Mallat, S. (1998). A wavelet tour on signal processing. Academic Press, San Diego, CA.

Marceau, D.J. (1999). The scale issue in the social and natural sciences. *Canadian Journal of Remote Sensing* 25:347–356.

Marceau D.J., Howarth, J. & Gratton, D.J. (1994a). Remote sensing and the measurement of geographical entities in a forested environment: 1. The scale and spatial aggregation problem. *Remote Sensing of Environment* 49:93-104.

Marceau D.J., Gratton, D.J., Fournier, R.A. & Fortin, J.P. (1994b). Remote sensing and the measurement of geographical entities in a forested environment: 2. The optimal spatial resolution. *Remote Sensing of Environment* 49:105-117.

Mardia, K.V. & Hainsworth, T.J. (1988). A spatial thresholding method for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 10:919-927.

Martinez Casasnovas, J.A. (1994). Hydrographic information abstraction for erosion modelling at a regional level. MSc Theisis, Wageningen University, Wageningen.

McIntosh, R.P. (1991). Concept and terminology of homogeneity and heterogeneity in ecology. In: Kolasa, J. & Pickett, S.T.A. (eds), Ecological Heterogeneity, Ecological Studies 86, Springer-Verlag, New York, 24-46.

Meentemeyer, V. (1989). Geographical perspectives of space, time, and scale. *Landscape Ecology* 3:163-173.

Molenaar, M. (1996). The role of topologic and hierarchical spatial object models in database generalizationl In: Molenaar, M. (ed), Methods for the generalization of geo-databases, Delft: Netherlands Geodetic Commission, New Series 43:13-36.

Molenaar, M. (1998). An introduction to the theory of spatial object modelling for GIS. Taylor & Francis, London.

Moody, A. & Woodcock, C.E. (1995). The influence of scale and the spatial characteristics of landscapes on land-cover mapping using remote sensing. *Landscape Ecology* 6:363–379.

Müller, J.C., Lagrange, J.P. & Weibel, R. (1995). GIS and generalization: Methodology and practice. Taylor & Francis, London.

Muñoz, X., Freixenet, J., Cufí, X. & Martí, J. (2003). Strategies for image segmentation combining region and boundary information. *Pattern Recognition Letters* 24(1-3):375-392.

Murenzi, R. (1988). Wavelet transforms associated with the n-dimensional Euclidean group with dilations: Signal in more than one dimension. In: Combes, J.M., Grossman, A. & Tchamitchian, P. (eds), Wavelets: Time-frequency methods and phase space, Springer-Verlag, Berlin, 239-246.

Murwira, A. (2003). Scale matters! A new approach to quantify spatial heterogeneity for predicting the distribution of wildlife. PhD Thesis, Wageningen University, ITC Dissertation number 106.

Myint, S.W., Tyler, J. & Lam, N. (2002). An evaluation of four different wavelet decomposition procedures for spatial feature discrimination in urban areas. *Transactions in GIS* 6(4):403-429.

Naveh, Z. & Lieberman, A.S. (1984). Landscape ecology, theory and application. Springer-Verlag, New York.

Naveh, Z., & Lieberman, A.S. (1994). Landscape ecology, theory and application (2nd edition). Springer-Verlag, New York.

Nevatia, R. (1986). Image segmentation. In: Young, T.Y. & Fu, K.S. (eds), Handbook of pattern recognition and image processing, Academic Press, New York, 215-231.

Nyerges, T.L. (1991). Representing geographical meaning. In: Buttenfield, B.P. & McMaster, R.B. (eds), Map generalization: Making rules for knowledge representation, Longman Scientific & Technical, Essex, 59-85.

Nyoungui, A.N., Tonye, E. & Akono, A. (2002). Evaluation of speckle filtering and texture analysis methods for land cover classification from SAR images. *International Journal of Remote Sensing* 23(9):1895-1925.

Oliver, M.A. & Webster, R. (1986). Semi-variograms for modelling the spatial pattern of landform and soil properties. *Earth Surface Processes and Landforms* 11:491-504.

O'Neill, R.V. (1996). Recent developments in ecological theory: Hierarchy and scale. In: Scott, J.M, Tear, T.H. & Davis, F.W. (eds), GAP Analysis: A landscape approach to biodiversity planning, American Society of Photographic Remote Sensing, 5-13.

O'Neill, R.V., DeAngelis, D.L., Waide, J.B. & Allen, T.F. (1986). A hierarchical concept of ecosystems. Princeton University Press, Princeton.

Openshaw, S. (1984). The modifiable areal unit problem. CAT-MOG 38, GeoBooks, Norwich, England.

Pal, N.R. & Pal, S.K. (1993). A review on image segmentation techniques. *Pattern Recognition* 26(9):1277-1294.

Palubinskas, G., Lucas, R.M., Foody, G.M. & Curran, P.J. (1995). An evaluation of fuzzy and texture-based classification approaches for mapping regenerating tropical forest classes from Landsat-TM data. *International Journal of Remote Sensing* 16(4):747-759.

Panopoulos, G., Stamatopoulos, A. & Kavouras, M. (2003). Spatio-temporal generalization: The chronograph application. Proceedings of the 21st International Cartographic Conference, Durban, 10-16 August, South Africa.

Peddle, D.R. & Franklin, S.E. (1991). Image texture processing and data integration for surface pattern discrimination. *Photogrammetric Engineering & Remote Sensing* 57(4):413-420.

Pelgrum, H. (2000). Spatial aggregation of land surface characteristics: Impact of resolution of remote sensing data on land surface modelling. PhD Thesis, Wageningen University, CIP-data Koninklijke Bibiotheek, Den Haag.

Picket S.T.A. & Cadenasso M.L. (1995). Landscape ecology: Spatial heterogeneity in ecological systems. *Science* 269:331–334.

Reynolds, J.F, Virginia, R.A. & Schlesinger, W.H. (1997). Defining functional types for models of desertification. In: Smith, T.M., Shugart, H.H. & F.I. Woodward (eds), Plant functional types, their relevance to ecosystem properties and global change, International Geosphere-Biosphere Programme Book Series, Cambridge University Press, Cambridge, 195-216.

Reynolds, J.R. & Wu, J. (1999). "Do landscape structural and functional units exist?" In: Tenhunen, J.D. & Kabat, P. (eds), Integrating hydrology, ecosystem dynamics, and biogeochemistry in comples landscapes, John Wiley, 273-296.

Richardson, D.E. (1993). Automated spatial and thematic generalization using a context transformation model. R & B Publications, Ottawa.

Ridler, T. & Calvard, S. (1978). Picture thresholding using an iterative selection method. *IEEE Transactions on Systems, Man and Cybernetics* 8:630-632.

Rigaux, P. & Scholl, M. (1995). Multi-scale partitions: Applications to spatial and statistical databases. In: Egenhofer, M.J. & Herring, J.R. (eds), Advances in spatial databases, Springer-Verlag, Berlin, 170-183.

Robinson, G.J. (1995). A hierarchical top-down bottom-up approach to topographic map generalization. In: Müller, J.C., Lagrange, J.P. & Weibel, R. (eds), GIS and generalization: Methodology and practice, Taylor & Francis, London, 235-245.

Rosenfeld, A. & Kak, A.C. (eds) (1982). Digital picture processing,Vol. 2 (2nd edition). Academic Press, Orlando, Florida.

Rowe, J.S. (1961). The level-of-integration concept and ecology. *Ecology* 42:420-427.

Ruiz, L.A, Fdez-Sarría, A. & Recio, J.A. (2002). Texture feature extraction for classification of remote sensing data using wavelet decomposition: A comparative study. XX Congress of the ISPRS, Istanbul, July 2004. International Archives of Photogrammetry and Remote Sensing. Vol. XXXV, part B, 1109-1115.

Samet, H. (1984). The quadtree and related hierarchical data structures. *ACM Computing Surveys* 16:187-260.

Schiewe, J., Tufte, L., & Ehlers, M. (2001). Potential and problems of multi-scale segmentation methods in remote sensing. Geo-Informations-Systeme 14(6):34-39.

Shena, M.J. (1992). The discrete wavelet transform: Wedding the à trous and Mallat algorithms. *IEEE Transactions on Signal Processing* 40:2464-2482.

Shugart, H.H. (1997). Plant and ecosystem fucntional types. In: Smith, T.M., Shugart, H.H. & F.I. Woodward (eds), Plant functional types, their relevance to ecosystem properties and global change, International Geosphere-Biosphere Programme Book Series, Cambridge University Press, 21-43.

Simard, M., Saatchi, S.S. & De Grandi, G. (2000). Use of decision tree and multiscale texture for classification of JERS-1 SAR data over tropical forest. *IEEE Transactions on Geoscience and Remote Sensing* 38(5 I):2310-2321.

Simon, H.A. (1962). The architecture of complexity. Proceedings of the American Philosophical Society 106:467-482.

Simon, H.A. (1969). The Sciences of the Artificial. MIT Press, Cambridge.

Smaalen, J.W.N. (2003). Automated aggregation of geographic objects: A new approach to the conceptual generalisation of geographic databases. PhD Thesis, Wageningen University, Wageningen. See also http://library.wur.nl/wda/dissertations/dis3483.pdf

Smith, T.M., Shugart, H.H. & F.I. Woodward (eds) (1997). Plant functional types, their relevance to ecosystem properties and global change. International Geosphere-Biosphere Programme Book Series, Cambridge University Press.

Sonka, M., Hlavac, V. & Boyle, R. (1998). Image processing, analysis, and machine vision (2nd edition). Brooks Cole Publishing. See also:

At http://www.icaen.uiowa.edu/~dip/LECTURE/Segmentation.html, accessed September 13, 2004.

Starck, J.-L., Murtagh, F. & Bijaoui, A. (1998). Image processing and data analysis: The multiscale approach. Cambridge University Press, Cambridge.

Steffen, W.L., Walker, B.H., Ingram, J.S.I. & Koch, G.W. (eds) (1992). Global change and terrestrial ecosystems: The operational plan. IGBP and ICSU, Stockholm.

Steffen F., Bartholome, E., Belward, A., Hartley, A., Stibig, H.-J., Eva, H., Mayaux, P., Bartalev, S., Latifovic, R., Aggarwal, S., Kolmert, S., Bingfang, W., Ledwith, M., Pekel, J.-F., Giri, C., Mücher, S., Badts, E. de, Tateishi, R. & Champeaux, J.-L. (2003). Harmonisation, mosaicing and production of the Global Land Cover 2000 database. EUR 20489. European Commission, Directorate-General, Joint Research Centre (JRC), Ispra.

Stuckens, J, Coppin P.R. & Bauer, M.E. (2000). Integrating contextual information with per-pixel classification for improved land cover classification. *Remote Sensing of Environment* 71(3):282-296.

Tailor, A., Cross, A., Hogg, D.C. & Mason, D.C. (1986). Knowledge-based interpretation of remotely sensed images. *Image and Vision Computing* 4:67-83.

Tilton, J.C. (2000a). A Region Labeling Tool for use with Hierarchical Segmentation. Disclosures of Invention and New Technology (Including Software): NASA Case No. GSC 14,331-1.
At http://backserv.gsfc.nasa.gov/code935/tilton/region_label_old/index.html, accessed May 23, 2002.

Tilton, J.C. (2000b). Method for Recursive Hierarchical Segmentation by Region Growing and Spectral Clustering with a Natural Convergence Criterion", Disclosures of Invention and New Technology (Including Software): NASA Case No. GSC 14,328-1. At http://backserv.gsfc.nasa.gov/code935/tilton/, accessed May 23, 2002.

Ton, J., Sticklen, J. & Jain, A.K. (1991). Knowledge-based segmentation of Landsat images. IEEE Transactions on Geoscience and Remote Sensing 29:222-231.

Townshend, J.R.G. & Justice, C.O. (1990). The spatial variation of vegetation changes at very coarse scales. *International Journal of Remote Sensing* 11:149-157.

Trussel, H.J. (1979). Comments on 'Picture thresholding using an iterative selection method'. *IEEE Transactions on Systems, Man and Cybernetics* 9:311.

Turner, M.G. (1989). Landscape ecology: The effect of pattern on process. *Annual Review of Ecology and Systematics* 20:171-197.

Turner, M.G., O'Neill, R.V., Gardner, R.H. & Milne, B.T. (1989). Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology* 3:153–162.

Turner, M.G. & R. H. Gardner (eds) (1991). Quantitative methods in landscape ecology: The analysis and interpretation of landscape heterogeneity. Ecological Studies 82, Springer-Verlag, New York.

Turner, M.G., Gardner, R.H. & O'Neill, R.V. (2001). Landscape ecology in theory and practice: Pattern and process. Springer-Verlag, New York.

Uitermark, H.T.J.A (2001). Ontology-based geographic data set integration. PhD Thesis, Twente University, CIP-data Koninklijke Bibliotheek, Den Haag.

Valens, C. (2004). A really friendly guide to wavelets. At http://perso.wanadoo.fr/polyvalens/clemens/wavelets/wavelets.html, accessed September 7, 2004.

Wharton, S.W. (1982). A contextual classification method for recognizing land use patterns in high resolution remotely sensed data. *Pattern recognition* 15(4):317-324.

Wiens, J.A. (1976). Population responses to patchy environments. *Annual Review of Ecology and Systematics* 7:81-120.

Wiens, J.A. (1989). Spatial scaling in eclogy. *Functional Ecology* 3:385-397.

Wiens, J.A. (1995). Landscape mosaics and ecological theory. In: Hansson, L., Fahrig, L. & Merriam, G. (eds), Mosaic landscapes and ecological processes, Chapman & Hall, London, 1-26.

Wikantika, Ketut, Tetuko, J., Wihartini, S.S., Tateishi, Ryutaro, Park, Jong-Hyun, B.H. & Agung (1999). Method for land use/land cover identification in a tropical area using multi-sensor optical and radar imageries. Proceedings of SPIE - The International Society for Optical Engineering 3750:186-194.

Wilson, R.J. (1979). Introduction to graph theory. Academic Press, New York.

Withers, M. & Meentemeyer, V. (1999). Concepts of scale in landscape ecology. In: Klopatek, J.M. & Gardner, R.H. (eds), Landscape ecological analysis: Issues and applications, Springer, New York, 205–252.

Woodcock, C.E. & Strahler, A.H. (1987). The factor of scale in remote sensing. *Remote Sensing of Environment* 21:311-332.

Woodcock, C.E., Strahler, A.H. & Jupp, D.L.B. (1988). The use of variograms in remote sensing: II. Real digital images. *Remote Sensing of Environment* 25:349-379.

Woodcock, C.E., Collins, J.B., Gopal, S., Jakabhazy, V.D., Li, X., Macomber, S., Ryherd, S., Harward, V.J., Levitan, J., Wu, Y. & Warbington, R. (1994). Mapping forest vegetation using Landsat TM imagery and a canopy reflectance model. *Remote Sensing of Environment* 50(3):240-254.

Wu, J. (1999). Hierarchy and scaling: Extrapolating information along a scaling ladder. *Canadian Journal of Remote Sensing* 25:367–380.

Wu, J. & Levin, S.A. (1994). A spatial patch dynamic modeling approach to pattern and process in an annual grassland. *Ecological Monographs* 64: 447-467.

Wu, J. & Loucks, O.L. (1995). From balance-of-nature to hierarchical path dynamics: A paradigm shift in ecology. *Quarterly Review of Biology* 70:439–466..

Wu, J. & Levin, S.A. (1997). A patch-based spatial modeling approach: Conceptual framework and simulation scheme. *Ecological Modeling* 101:325-346.

Wu, J., Jelinski, D.E., Luck, M. & Tueller, P.T. (2000). Multi-scale analysis of landscape heterogeneity: Scale variance and pattern metrics. *Geographic Information Sciences* 6(1):6-19.

Zeiss (2004). Wavelet analysis. At http://www.zeiss.de/C12567BB00549F37/ContentsWWWIntern/66849F3C0F9B694C41256D97004A0143, accessed October 7, 2004.

Zhang, Z., Shimoda, H., Fukue K. & Sakata, T. (1988). A new spatial classification algorithm for high ground resolution images. IEEE International Geoscience and Remote Sensing Symposium, IGARSS'88, 12-16 September, Edinburgh, Scotland, Vol. 1, 509-512.

Zonneveld, I.S. (1989). Scope and concepts of landscape ecology as an emerging science. In: Zonneveld, I.S. & Forman, R.T.T. (eds), Changing landscapes: An ecological perspective, Springer-Verlag, New York, 3-20.

Zonneveld, I.S. (1995). Land ecology: An introduction to landscape ecology as a base for land evaluation, land management and conservation. SPB Academic Publishing, Amsterdam.

Zucker, S.W. (1977). Algorithms for image segmentation. In: Rosenfeld, A. & Simon, J.C. (eds), Digital Image Processing and Analysis, Nordhoff International Publ., 169-183.

CHAPTER 3

AGGREGATE-MOSAIC THEORY

“Als er licht is in de ziel, zal er schoonheid zijn in de mens
Als er schoonheid is in de mens, zal er harmonie zijn in het huis
Als er harmonie is in het huis, zal er rust zijn in het land
Als er rust is in het land, zal er vrede zijn in de wereld”

“If there is light in the soul, there will be beauty in the person
If there is beauty in the person, there will be harmony in the house
If there is harmony in the house, there will be order in the nation
If there is order in the nation, there will be peace in the World“
Lao Tzu (600 b. Chr.)

3.1 Introduction

The Aggregate-Mosaic Theory is a new theory on the functional classification of remote sensing data into land cover mosaics (LCMs). It describes the implementation of patch-mosaics (Chapter 2, section 2.2.2) in digital image analysis. Such an implementation enables a quantitative modeling of spatial heterogeneity at different spatial aggregation levels (i.e., at elementary level and at composite level). Patch-mosaics originates from landscape ecology. This branch of ecology considers landscapes as ordered and interrelated multi-scaled composites of local patches and patch-mosaics. Subsequently, the Aggregate-Mosaic Theory considers remote sensing imagery as ordered and interrelated multi-scaled composites of *homogeneous* land cover classes (i.e., the patches) and *heterogeneous* LCM classes (i.e., the patch-mosaics). Considering remote sensing in its broadest sense of spatial object modeling (Chapter 2, section 2.3.1), patches are represented as elementary objects and patch-mosaics as composite objects (Figure 3.1).

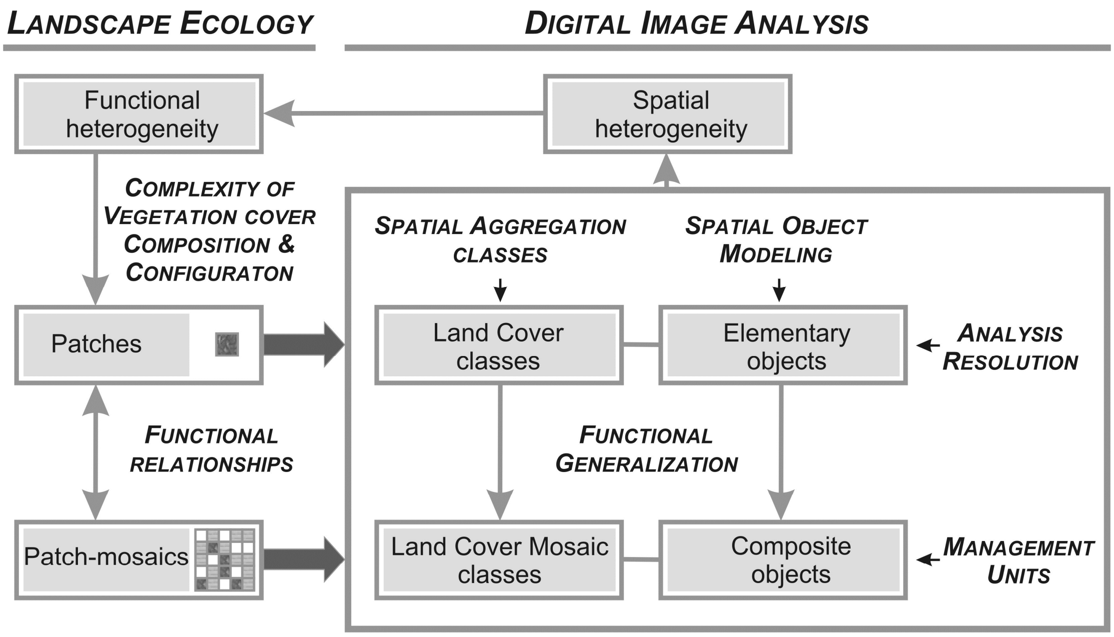


Figure 3.1: Aggregate-Mosaic Theory: implementation of patch-mosaics in digital image analysis.

Functional relationships describe links between patches and patch-mosaics. A conceptual generalization strategy based on functional relationships is functional generalization (Chapter 2, section 2.3.2). The Aggregate-Mosaic Theory uses functional generalization to link elementary objects and composite objects. It uses explicit geometric rules (i.e., *area* of elementary objects) besides topologic rules (i.e., *mixture* of elementary objects) to functionally upscale land cover classes at elementary level into LCM classes at composite level. Classifying remote sensing data into such functional spatial entities is called a LCM classification. Applying a LCM classification fully acknowledges both vegetation composition (spectral characteristics of remote sensing data) and vegetation structure (i.e., pattern configuration; spatial characteristics of remote sensing data) of spatially heterogeneous environments. Using both the spatial and the spectral characteristics in digital image analysis is necessary to functionally classify spatially heterogeneous environments like tropical rainforest areas into management units.

The Aggregate-Mosaic Theory is developed because conventional land cover classifications using remote sensing data assume homogeneity of land cover classes. Such an assumption can not hold for the many heterogeneous vegetation types in for instance tropical rainforest areas because of both their composition and structure (i.e., pattern). The novelty of the Aggregate-Mosaic Theory is to use spatial heterogeneity to functionally characterize vegetation types. LCM classification, therefore, can be regarded as functionally upscaling spatial information from the spatial aggregation level of homogeneous land cover classes to the spatial aggregation level of heterogeneous LCM classes. End-users need geo-information at such different spatial aggregation levels (i.e., the management units) to suit macro and micro policies, to explain the driving forces and mechanisms (actors) behind forest cover changes, and to predict future trends (Chapter 1, section 1.2.3).

Functionally upscaling from land cover classes to land cover mosaic classes requires new concepts and tools, especially for thematically complex landscapes (Chapter 2, Figure 2.9b). Therefore, details of the Aggregate-Mosaic Theory will be explained in the next four sections, where each section discusses an aspect of this new remote sensing digital analysis theory. First, section 3.2 explains LCMs. Then, section 3.3 describes the need for defining *spatial aggregation classes* to tailor spatial aggregation levels to end-users. After that, section 3.4 introduces a new scale component, *analysis resolution*, to analyze the two parameters of LCM classes (i.e., *mixture* and *area*). Finally, section 3.5 describes a *LCM classification* demonstrating its advantage. This is compared to a conventional maximum likelihood-based land cover classification. Each of these sections consists of three parts: definition, functionality, and consequences.

3.2 Land Cover Mosaics

The term *Land Cover Mosaic* (LCM) originates from land mosaics. Land mosaics are defined as spatial units consisting of mixtures of land cover classes that differ from their surroundings by expressing spatial heterogeneity as a discrete pattern (Kotliar & Wiens, 1990; Forman, 1995). This definition, however, does not address how to express spatial heterogeneity as a discrete *spatial* pattern. Therefore, in the Aggregate-Mosaic Theory, the word 'cover' is added, because it inherently addresses the spatial component 'area'.

3.2.1 Definition

A land cover mosaic (LCM) is a spatial entity (i.e., patch-mosaic) consisting of different sub-entities (i.e., patches). Those sub-entities can differ with respect to their type (i.e., quantifying vegetation composition) *and* to their area (i.e., quantifying vegetation configuration). In either case, the spatial entity is called heterogeneous. Only if both type and area of sub-entities within a spatial entity show comparable characteristics, the spatial entity can be called homogeneous. Consequently, spatial homogeneity is a *special case* of spatial heterogeneity. Thus, describing spatial entities into land cover classes (spatially homogeneous) is a *special case* of describing spatial entities into LCM classes (spatially heterogeneous). In other words, a spatially heterogeneous LCM class consists of different spatially homogeneous land cover classes. LCM classes express spatial heterogeneity in two types of variations when regarding their land cover classes:

I

Variations in their *mixture* (i.e., expressing variation in patch-composition).
An example of this mixture variation is given in Figure 3.2 showing five different LCM classes composed of six different land cover classes.

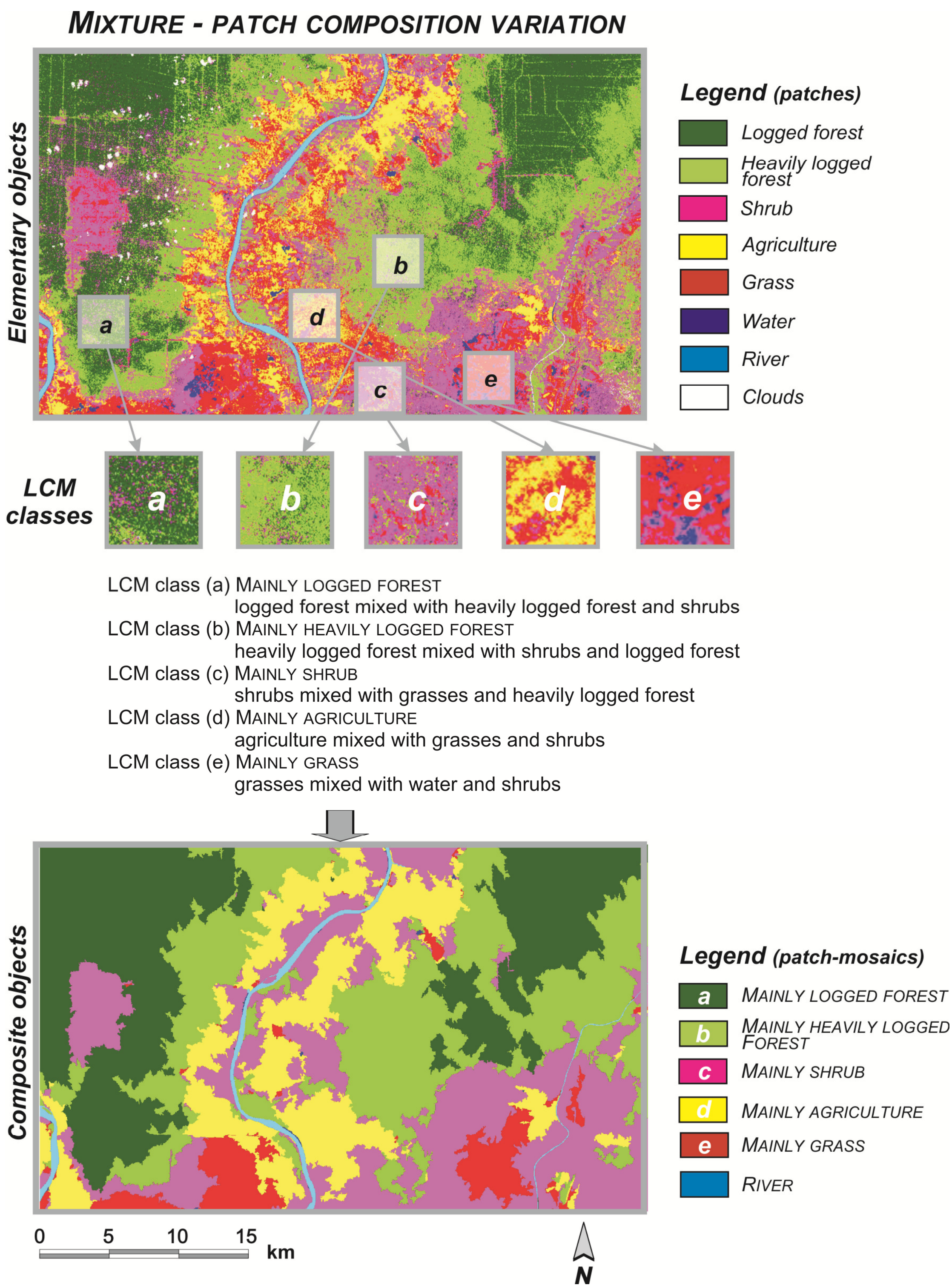


Figure 3.2: Examples of LCM classes: expressing spatial heterogeneity as variations in the mixture of land cover classes (composite objects obtained by lc-driven functional upscaling; see Chapter 6, section 6.2.1).

II

Variations in their *area* (i.e., expressing variation in patch-configuration).

An example of this area variation is given in Figure 3.3 showing two different LCM classes composed of two similar land cover classes with different area.:

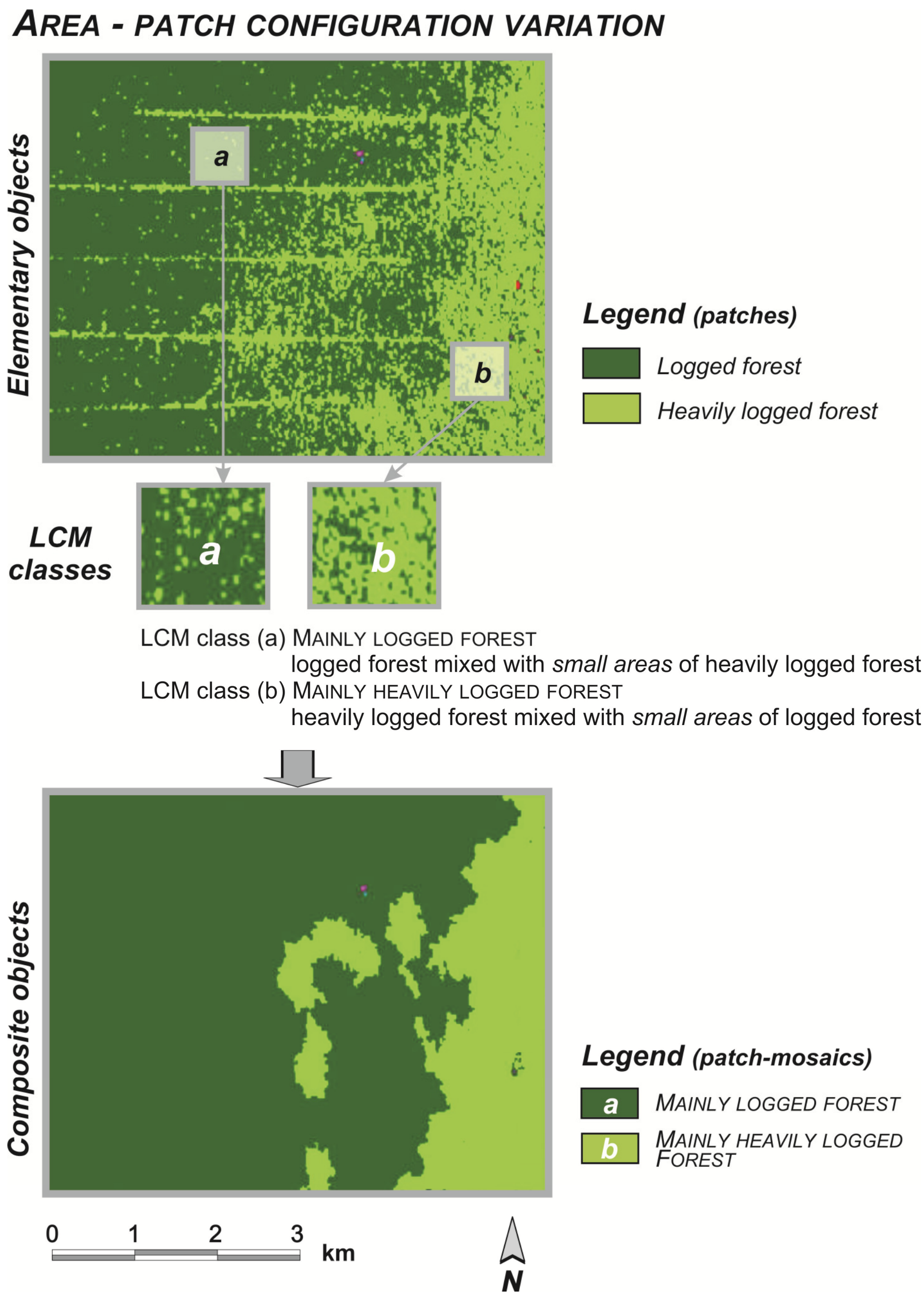


Figure 3.3: Examples of LCM classes: expressing spatial heterogeneity as variations in the area of land cover classes (composite objects obtained by lcm-driven functional upscaling; see Chapter 6, section 6.2.2).

Mathematically, many combinations of mixtures of land cover classes are possible at each spatial aggregation level. In practice, however, combinations are limited, because spatial heterogeneity is the result of interferences of humans and nature. These interferences are not randomly defined; they have a sequential order (action and reaction). Therefore, at each spatial aggregation level, mixtures of land cover classes are described by a limited number of LCM classes. In the examples of Figure 3.2 and Figure 3.3, the number of LCM classes is about the number of land cover classes.

3.2.2 Functionality

LCMs are introduced to model quantitatively spatial heterogeneity as a discrete spatial pattern. Two parameters, *mixture* and *area*, are used to functionally quantify spatial heterogeneity. Mixture addresses the land cover classes occurring in a vegetation composition. Area addresses the coverage of each land cover class in a vegetation composition. Both mixture and area can be described in quantitative terms; mixture in number of components and area in square meters. Such a quantification of spatial heterogeneity supports the management of spatially heterogeneous environments. This advantage for managers will be explained below for the land cover class 'heavily logged forest', and for a large transition zone in a logged forest area (see Figure 3.3).

In the case of a heavily logged forest, management strategies to improve such an area are for instance natural regeneration, enrichment planting and buffer zones. At the spatial aggregation level of land cover classes, however, only one land cover class 'heavily logged forest' can be distinguished. At this aggregation level it is unclear 'which' management strategy would be most suitable 'where' in the area. At the spatial aggregation level of LCMs, for example, three (distinct) LCM classes can be distinguished: 'heavily logged forest mixed with *logged forest*', 'heavily logged forest mixed with *shrubs*', and 'heavily logged forest mixed with *agriculture*'. Having these three *functional* spatial entities, the *'which'* and *'where'* of a management strategy can be selected as follows: *natural regeneration* for 'a mixture of heavily logged forest and logged forest', *enrichment planting* for 'a mixture of heavily logged forest and shrubs', and *buffer zones* for 'a mixture of heavily logged forest and agriculture'. Consequently, digitally analyzing remote sensing data at the spatial aggregation level of LCMs enables a *specific* management strategy, and thus money and time can be explicitly allocated to specific areas.

In the case of a large transition zone (like Figure 3.3), a logged forest area requires less intervention on the progress of natural regeneration than a heavily logged forest. At the aggregation level of land cover classes, however, the large transition zone reduces the practicability of such an intervention plan. It is unclear which intervention is required for this area: an intervention suitable for logged forest or an intervention suitable for heavily logged forest? At the aggregation level of LCMs, the large transition zone is divided into two (distinct) LCM classes: ‘logged forest mixed with small areas of heavily logged forest’, and ‘heavily logged forest mixed with small areas of logged forest’. Consequently, functionally upscaling from land cover classes to LCM classes leads to a clear *spatial* distinction between a forest area that has been logged and a forest area that has been heavily logged. Such a distinction supports effective management, because the ‘which’ and ‘where’ of a required intervention can be selected based on these two functional spatial entities.

3.2.3 Consequences

Each pixel in a remote sensing image can be related to different LCMs depending on the spatial aggregation level at which spatial heterogeneity is quantified. This restriction, however, necessitates to define appropriate *spatial aggregation classes* to describe such a dependency. The next section covers this dilemma (section 3.3).

3.3 Spatial aggregation classes

Conventional land cover class descriptions do not consider different spatial aggregation levels (i.e., elementary objects and composite objects) when digitally analyzing remote sensing data. The Aggregate-Mosaic Theory introduces, therefore, *spatial aggregation classes* to enable such a spatial distinction in class descriptions. These spatial aggregation classes specifically represent the spatial component of remote sensing data. The commonly used thematic generalization levels (i.e., subclasses and superclasses) represent the thematic component of remote sensing data. Both generalizations are concerned in conceptual generalization (Chapter 2, section 2.3.1). Figure 3.4 illustrates the implementation of spatial aggregation classes in conceptual generalization. It shows that the superclass ‘forest’ at elementary level differs from the superclass ‘forest’ at composite level. At the elementary level, forest consists solely of the subclasses ‘logged forest’ and ‘heavily logged forest’. At the composite level, forest also consist of the subclass ‘shrub’ besides the two subclasses ‘logged forest’ and ‘heavily logged forest’.

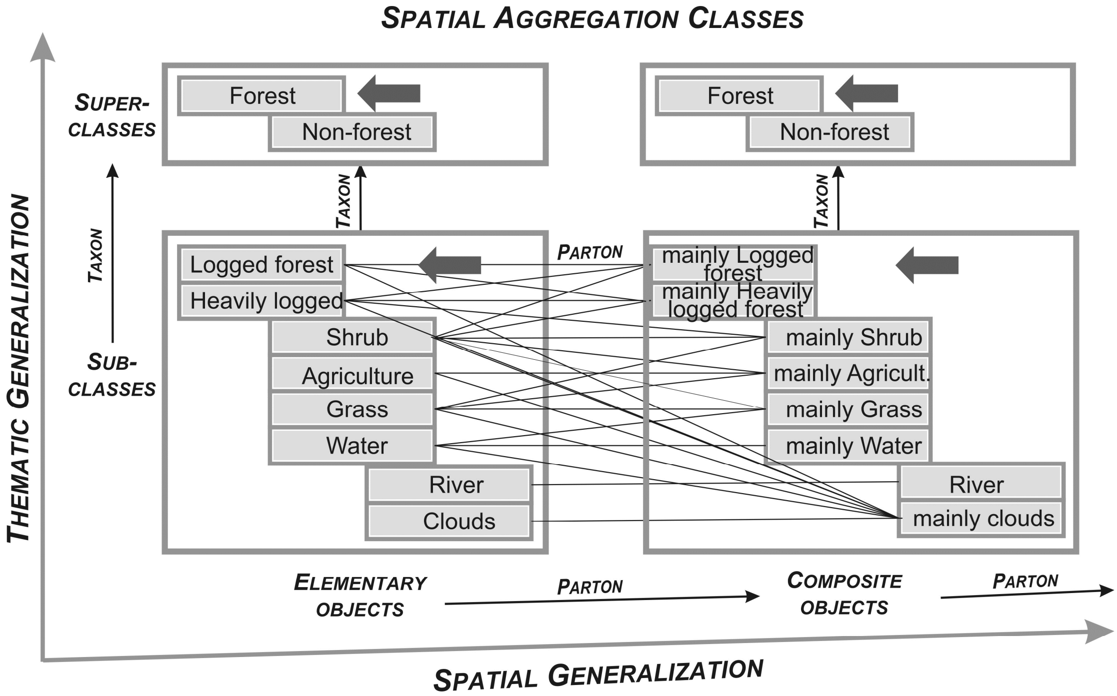


Figure 3.4: Spatial aggregation classes in conceptual generalization (e.g., compare the subclass ‘logged forest’ at elementary level with the subclass ‘mainly logged forest’ at composite level; the latter consists of large areas of logged forest, mixed with small areas of heavily logged forest and shrub). Following thematic generalization, class descriptions are similar at superclass level (‘forest’). Following spatial generalization class descriptions are distinct (‘logged forest’ and ‘mainly logged forest’).

3.3.1 Definition

A spatial aggregation class is a functional spatial unit (i.e., management unit) for an end-user of geo-information. Spatial aggregation classes result from explicit rules regarding both *mixture* (class topology) and *area* (class geometry) of land cover classes. Based on such rules, spatially heterogeneous environments can be quantified into LCM classes at distinct spatial aggregation levels.

3.3.2 Functionality

Spatial aggregation classes are introduced to specify *functional* management units of end-users. This is necessary, because end-users are related to different decision levels and different management issues, ranging from local to global. At each decision level, different spatial aggregation levels of forest cover information is of interest (see Chapter 1, section 1.2.3). As a result, forest cover needs to be described at spatial aggregation levels that range from trees to forest stands to forest types (Figure 3.5). Each level of description will lead to a different *spatial* distribution of forest cover, because forest stands not only consist of trees; they also include small areas of shrubs. Moreover, forest types not only consist of forest stands; they also include larger areas of shrubs or even include other land cover types like grasses.

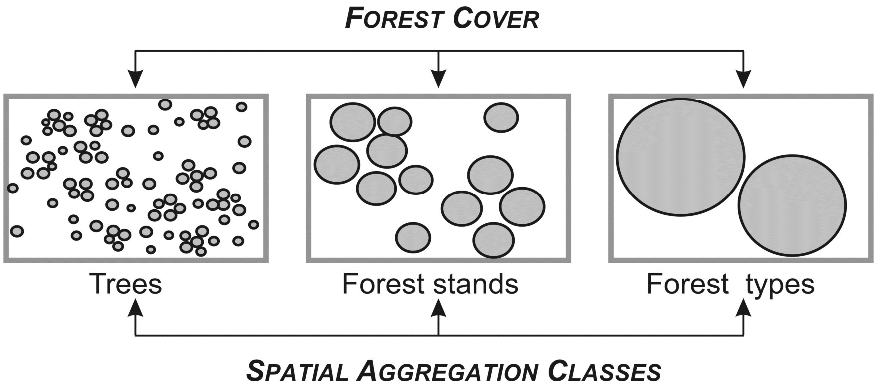


Figure 3.5: Spatial distribution of forest cover for three different spatial aggregation classes (i.e., trees, forest stands and forest types in terms of functional management units).

3.3.3 Consequences

Remote sensing specialists alone can not define such spatial aggregation classes in a way that is appropriate for specific decision-levels of end-users. Defining spatial aggregation classes requires involvement of both remote sensing specialists (*RS*-domain) and end-users (*U*-domain). Conventionally, the information exchange between these two domains has a strong *supply* flow from product (*RS*-domain) to decision (*U*-domain) and a minor *needs* flow to provide remote sensing specialists with end-users' objectives and requirements (Figure 3.6A). Procedural steps in the *U*-domain are decision-making, implementation and evaluation of the decisions. Each procedural step often requires geo-information from the *RS*-domain (Chapter 1, Figure 1.5). Procedural steps in the *RS*-domain are data acquisition, pre-processing like calibration, data analysis, information validation and conversion, and product presentation. Acquisition and analysis are, however, too often based on only *general* objectives of end-users (i.e., general needs flow). The RS-domain dominates such a conventional relation as the technical producers of geo-information. The U-domain are in a 'take it or leave it' position as the dependent consumers of their required geo-information (i.e., general supply flow).

Like in any market-driven environment, supply and demand of geo-information need to be balanced, otherwise the produced geo-information can not result in proper end-user decisions. Therefore, an *interactive* information flow is required between the *U*-domain and the *RS*-domain to address explicitly the spatial aggregation levels of functional management units by means of spatial aggregation classes (Figure 3.6B). Spatial aggregation classes explicitly define the LCM classes at distinct spatial aggregation levels having specified rules on both *mixture* and *area* of land cover classes. The *RS*-domain needs such an interaction to tailor acquisition and analysis of remote sensing data (i.e., resulting in a tailored supply flow). Without explicitly addressing end-users' need, even highly accurate geo-information can be useless (Aronoff, 1989). Emphasizing the end-users' perspective, Smits et al. (1999) extended the concept of information *accuracy* to information *quality*. They created a link between objectives, accuracy, and costs related to wrong decisions to identify the usefulness of per-pixel classification procedures for a specific application. This kind of involvement of end-users, however, generally maintains the dominant direction flow from product (*RS*-domain) to decision (*U*-domain). Moreover, Smiths' concept still addresses the general objectives of end-users only (e.g., forest cover information). It does not address explicitly the spatial aggregation levels exclusively related to the functional management units at which end-users need their geo-information. With the introduction of spatial aggregation classes, a strong interactive information flow can be formalized. This requires expertise of both the *U*-domain (i.e., specific needs flow) and the *RS*-domain (i.e., technical constraints flow). Spatial aggregation classes improve both decision-making by specifying what kind of decisions can be made and user-requirements by specifying the spatial resolutions at which remote sensing data should be analyzed (this will be further discussed in section 3.4). Consequently, spatial aggregation classes can be regarded as a means to connect the expertise of the *U*-domain and that of the *RS*-domain in an interactive fashion.

3.4 Analysis resolution

Explicit rules on *mixture* (class topology) and *area* (class geometry) of land cover classes are specified in spatial aggregation classes to define LCM classes at distinct spatial aggregation levels. Therefore, 'mixture' and 'area' can be regarded as parameters of LCM classes. When using conventional spatial scale components in remote sensing (i.e., data resolution and area of coverage), *mixture* and *area* can be only analyzed with respect to functional generalization at the spatial aggregation level of the data resolution. This level, however, not necessarily is the spatial aggregation level from which a functional generalization should start, because spatial aggregation classes are bound to geometric restrictions (Chapter 2, Table 2.1). Consequently, the spatial size of related land cover classes (i.e., of elementary objects or patch-size) are also bound to geometric restrictions. To include such restrictions, the Aggregate-Mosaic Theory introduces a third component of spatial scale, the so-called *analysis resolution*. The need to introduce a third component of spatial scale was also addressed by Pelgrum (2000) in his study on land surface modeling of hydrological processes. He introduced *integration* besides the two commonly used spatial scale components resolution and extent.

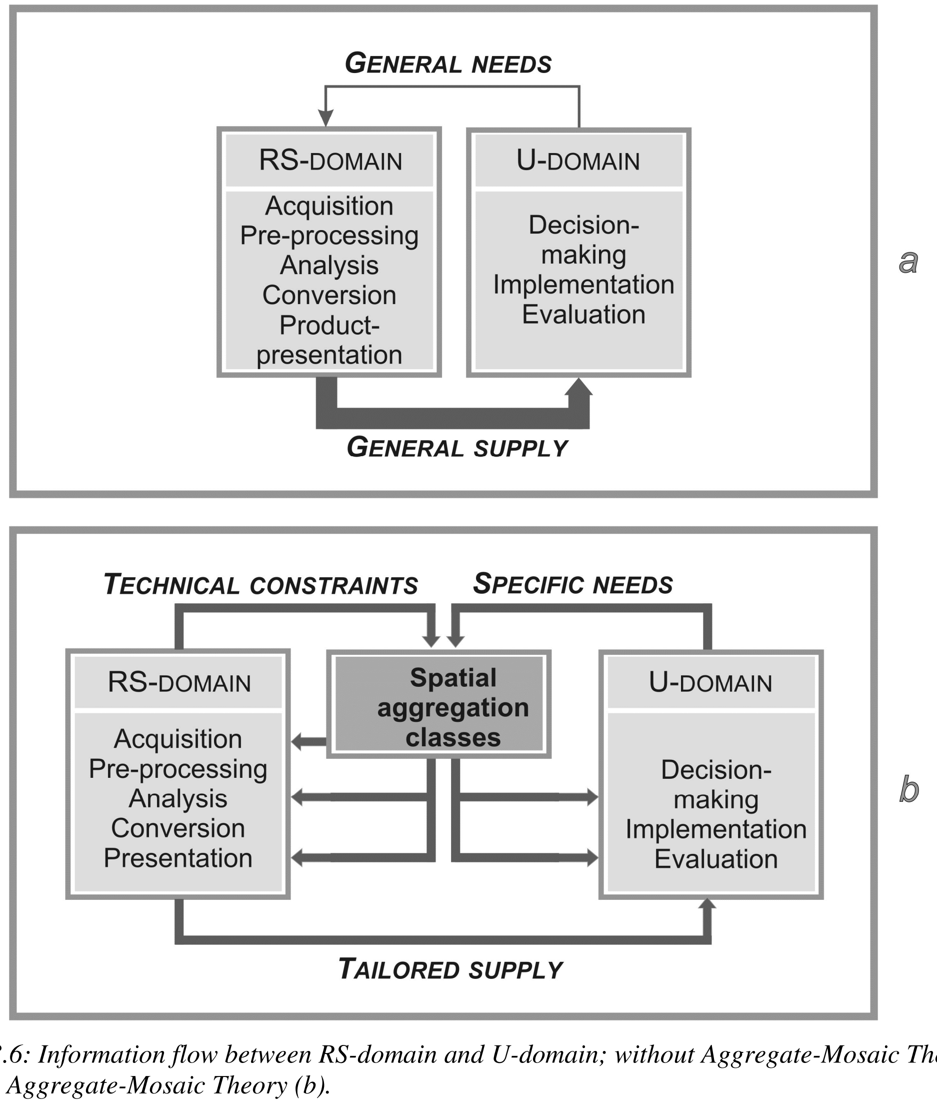


Figure 3.6: Information flow between RS-domain and U-domain; without Aggregate-Mosaic Theory (a), with Aggregate-Mosaic Theory (b).

3.4.1 Definition

The analysis resolution specifies the spatial resolution from which a functional generalization starts (i.e., it provides the required minimum/maximum spatial size of elementary objects). This resolution is a spatial scale component specifically used during data *analysis*. The *analysis resolution* provides a functional spatial aggregation level besides data resolution (spatial, spectral, and temporal) and area of coverage (extent). Whereas both data resolution and area of coverage are two characteristics of data collection (Lillesand & Kiefer, 2000), analysis resolution is a characteristic of data *analysis*. Despite this difference, the analysis resolution is confined by both data resolution and area of coverage. Data resolution provides the lower limit of the analysis resolution, and area of coverage the upper limit. Whenever the analysis resolution exceeds one of these limits, the characteristics of data collection have to be changed. In such cases, the data resolution of the remote sensing imagery is too course, or its area of coverage is too small.

3.4.2 Functionality

One can argue that a functional spatial aggregation level is already incorporated in the two conventional spatial scale components of remote sensing imagery (i.e., data resolution, and area of coverage). Of course, data resolution and area of coverage are two important factors when selecting remote sensing imagery for a certain analysis task. However, the spatial aggregation level(s) of the data resolution(s) of image data does (do) not always correspond one-to-one to the spatial aggregation level(s) of elementary objects that are meaningful to start a functional generalization.

Figure 3.7 shows an example of the relation between data resolution, analysis resolution and the results after a functional generalization (based on *mixture* and *area*, section 3.2). An area consisting of two land cover classes 'trees' and 'grasses' are functionally generalized into two LCM classes 'woodland' and 'grassland' (see also Chapter 2, Figure 2.9). If the analysis resolution is *minute* (close to the data-resolution), the target pixel that shows the characteristics of the land cover class 'trees' is functionally generalized into the LCM class 'woodland'. However, if the analysis resolution is *coarse* (the terms minute and coarse refer to the definition of landscape ecologists; Chapter 2, section 2.2.1), that same target pixel is functionally generalized into the LCM class 'grassland'. Consequently, defining the analysis resolution is necessary to meaningfully classify land cover classes into LCM classes (i.e., upscaling from elementary objects into composite objects).

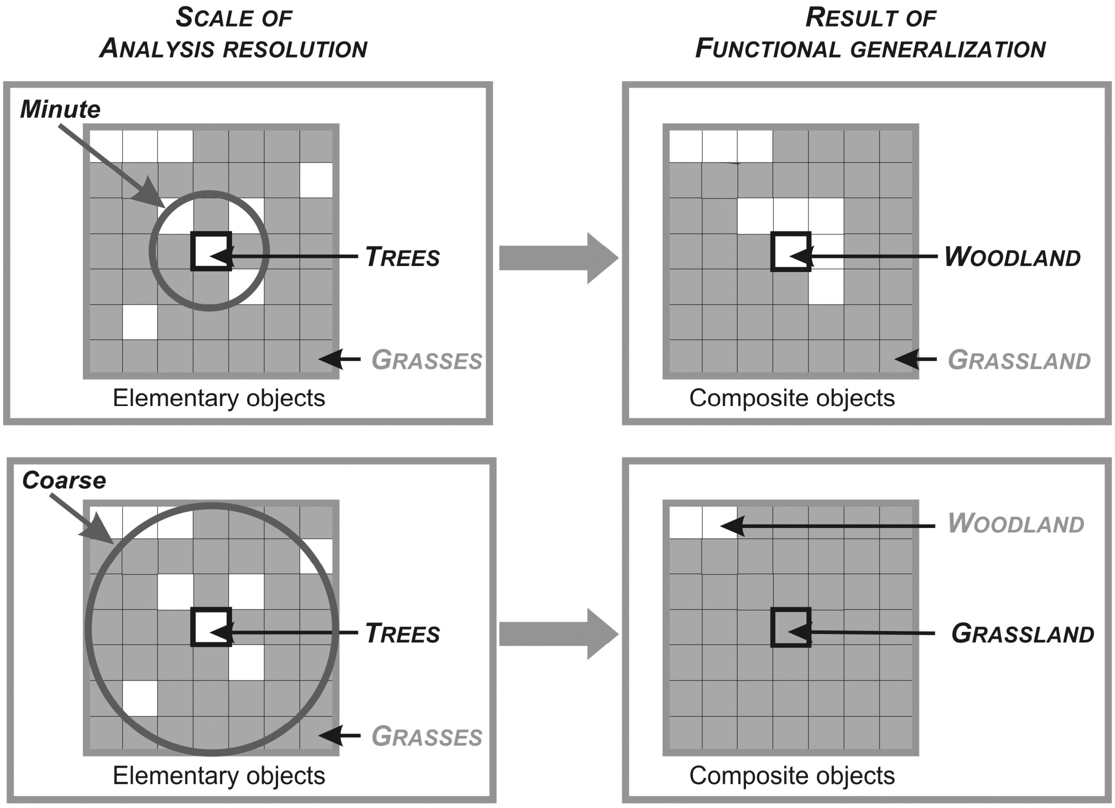


Figure 3.7: Impact of selected analysis resolution on functional generalization results.

3.4.3 Consequences

Indicating the need for an analysis resolution is one thing, defining it is another. What should be the area of elementary objects (i.e., patches) from which to start a functional generalization? This problem of finding a true estimate for the scale of measurement is addressed in landscape ecology (Cullinan & Thomas, 1992; Marceau et al., 1994a,b). For example, Cullinan & Thomas (1992) concluded “no one method provides consistently good estimates of scale […] and no one method is correct because each method addresses a different statistical question and each has a different sensitivity over changes in scale”. The latter was confirmed by Marceau et al. (1994a,b) who stated, “there is no *unique* spatial resolution appropriate for the detection and discrimination of all geographical entities composing a complex natural scene such as a forested environment”. However, with the introduction of a third component of spatial scale (i.e., analysis resolution) the attitude of digital image analysis has been changed from a *data-driven* approach with two spatial scale components to a *decision-driven* approach with three spatial scale components. This means that the problem of finding a true estimate for the scale of measurement has been changed from an *acquisition-driven* problem to an *analysis-driven* problem. Data acquisition belongs solely to the previously described *RS*-domain, whereas data analysis belongs to both the *RS*-domain and *U*-domain, because data analysis concerns the conceptual formalization of the analysis task (i.e., defining spatial aggregation classes; see section 3.3). Consequently, defining spatial aggregation classes enables to determine a *specific* estimate for the scale of measurement (i.e., analysis resolution), and thus overcomes the constraint of an *a priori*, but inappropriate, scale of measurement (i.e., data resolution).

3.5 LCM classification

Conventionally, land cover classifications are based on a ‘one-pixel-one-class’ approach (Wang, 1990a,b; Foody and Trodd, 1994), further referred to as a 'one-to-one' approach. Such an approach is suitable for (homogeneous) land cover classes where neighboring image pixels are mostly part of the same land cover class. After a one-to-one approach, neighboring pixels often obtain the same land cover class. The result is a map with spatially crisp patterns (Chapter 1, Figure 1.11). When classifying remote sensing images into LCM classes such an ‘one-to-one’ approach is not suitable, because LCMs are per definition heterogeneous. Neighboring image pixels can be part of different land cover classes, but together they form one specific LCM class. Consequently, moving from land cover classes to LCM classes an additional 'many-to-one' classification approach is necessary that considers different land cover classes being classified as one LCM. Therefore, the Aggregate-Mosaic Theory introduces *LCM classification* to support both classification approaches, a ‘one-to-one’ and a ‘many-to-one’ (Figure 3.8).

3.5.1 Definition

A LCM classification is a hierarchical upscaling framework to enable a functional classification of remote sensing data into useful management units at decisive level (i.e., from pixels to elementary objects to composite objects).

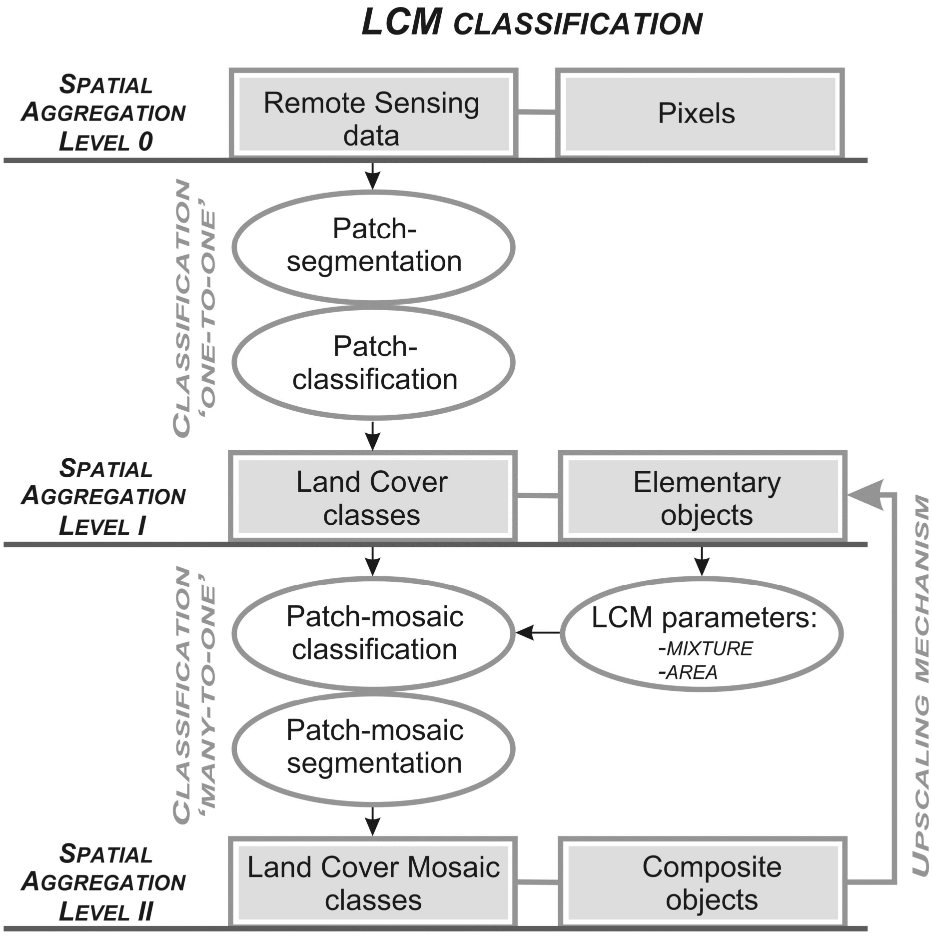


Figure 3.8: LCM classification (explanation of terms see text).

3.5.2 Functionality

LCM classification is introduced to functionally exploit the spatial information of remote sensing data through *spatial* generalization besides exploiting the spectral information of remote sensing data through *thematic* generalization. Therefore, the Aggregate-Mosaic Theory considers LCM classes as being (heterogeneous) composite objects and land cover classes as being (homogeneous) elementary objects. The theory of spatial object modeling (Molenaar, 1998; Chapter 2, section 2.3.1) supports the concept that each composite object can be built from elementary objects, and that each composite object is again an elementary object for composite objects at higher spatial aggregation levels, and so on (Droesen, 1999). Consequently, the first step in LCM classification concerns the creation of elementary objects and their classification into (homogeneous) land cover classes. This creation of elementary objects (i.e., segmenting the image into homogeneous spectral classes) is called *patch-segmentation*, while their classification into land cover classes is called *patch-classification*. The spatial size of an elementary object in patch-segmentation should take the minimum spatial size of a (homogeneous) land cover class as defined in the decision rules of the spatial aggregation classes (section 3.3). Patch-classification requires a 'one-to-one' classification approach, because spatially the 'one-pixel' is read as 'one-patch', whereas thematically the 'one-class' refers to one land cover class. This means that each elementary object (i.e., a patch) is member of only one land cover class (for details see Chapter 4).

The second step in LCM classification concerns the classification of elementary objects into (heterogeneous) LCM classes and the creation of composite objects. This classification into LCM classes is called *patch-mosaic classification*, while the creation of composite objects is called *patch-mosaic segmentation*. For a spatially heterogeneous environment with its many gradual changes it is often impossible to define the extent of composite objects prior to classification, either in the field or in the image (Chapter 2, section 2.2.5). Therefore, the extent of composite objects can be often only obtained after a patch-mosaic classification. This classification functionally upscales land cover classes at elementary level into LCM classes at composite level based on the two LCM parameters *mixture* and *area* (section 3.4). Patch-mosaic classification requires a 'many-to-one' classification approach, because spatially the 'many' refers to neighboring elementary objects with different land cover classes, whereas thematically the 'one' refers to one LCM class. This means that each composite object (i.e., a patch-mosaic) is member of only one LCM class (for details see Chapter 5). Patch-mosaic segmentation groups at composite level the neighboring elementary objects having a similar LCM class (i.e., resulting from the patch-mosaic classification). It can make use of advanced techniques like multi-scale segmentation and wavelet transformation (for details see Chapter 6).

3.5.3 Consequences

With two different classification approaches at two different spatial aggregation levels there is a need for transparency at both levels. The theory of spatial object modeling (Molenaar, 1998) describes how spatial aggregation levels can be structured according to an aggregation hierarchy in spatial generalization, whereas classification levels can be structured according to a classification hierarchy in thematic generalization (Chapter 2, section 2.3.1). Such a *conceptual generalization* is an important tool to study scale-dependent phenomena in geographical information systems (McMaster &

Monmonier, 1989; Müller, 1991). Land cover patterns often only emerge after a generalization (Huising, 1993; João, 1998; Bian & Butler, 1999). Consequently, management units (i.e., spatial aggregation classes) emerge only at specific spatial aggregation levels where they can be analyzed; at other spatial aggregation levels they disappear, or do not exist, and thus can not be analyzed.

Figure 3.9 presents an example of a LCM classification compared to a conventional maximum likelihood-based land cover classification. The figure shows three maps per approach. The first map of the LCM classification shows the classification results at elementary level (i.e., the results after patch-segmentation and patch-classification). The settings used in patch-segmentation can be found in Chapter 4, Table 4.6. A supervised fuzzy classifier of the standard nearest neighbor was used in patch-classification (for details see Chapter 4, section 4.3.1). The details on the eight land cover classes used in patch-classification can be found in Chapter 4, Table 4.1. The second map of the LCM classification shows the classification results at composite level (i.e., the results after patch-mosaic classification and patch-mosaic segmentation). Patch-mosaic classification was developed in this thesis to implement functional generalization in digital image classification based on the two LCM parameters *mixture* and *area*. It uses an aggregation hierarchy besides the commonly used classification hierarchy (for details see Chapter 5, section 5.2). Details on the eight LCM classes used in patch-classification can be found in Chapter 5, Table 5.1. Four patch-mosaic segmentation methods were studied in this thesis (Chapter 6). The second map of the LCM classification used a taxonomy-based segmentation process called lc-driven segmentation (for details see Chapter 6, section 6.2.1). The third map of the LCM classification shows the results after a thematic generalization of the subclasses at composite level (i.e., mainly logged forest, mainly heavily logged forest, mainly shrub, etc.) into the superclasses at composite level (i.e., logged-forest, heavily logged forest, and non-forest). The first map of the conventional classification at pixel level shows the classification results after a supervised maximum likelihood classifier. It used the same land cover classes as in the LCM classification. The second map of the conventional classification shows the post-processing results using a majority filter (window size 5x5 pixels). Such a post-processing can be regarded a spatial generalization operation (for discussion see Chapter 2, section 2.3.5). The third map of the conventional classification also shows the results after a thematic generalization of the subclasses (i.e., logged forest, heavily logged forest, shrub, etc.) into the superclasses (i.e., logged forest, heavily logged forest, and non-forest).

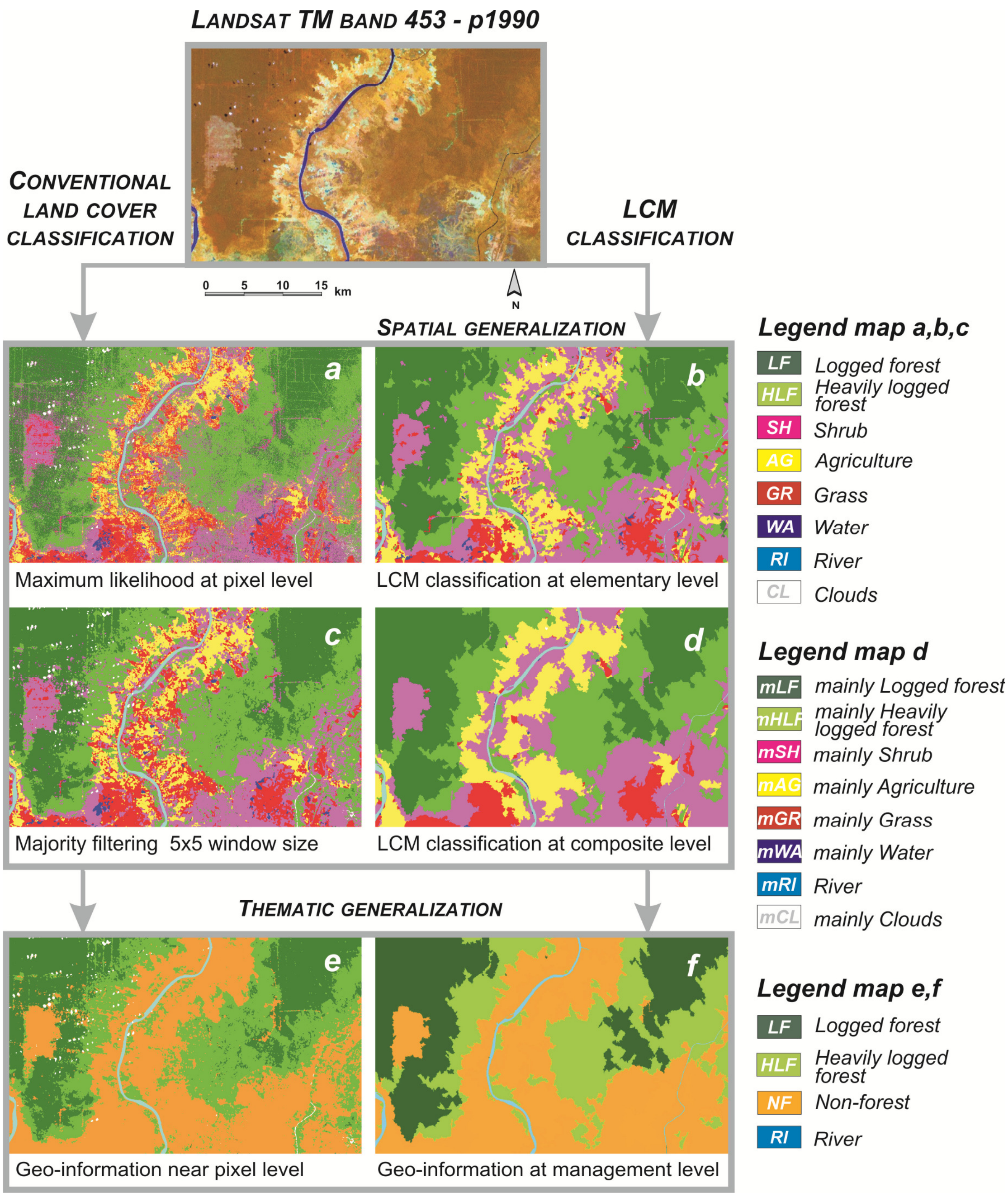


Figure 3.9: LCM classification versus a conventional land cover classification (see text for detailed explanation).

The two resulting forest/non-forest maps show remarkable differences. Whereas the conventional map shows quite a noisy distribution, the map based on the Aggregate-Mosaic Theory shows a very clear distribution (useful for management). In addition, crisp objects (e.g., the large shrub area at the left of the image) and small linear objects (e.g., the tiny river at the right of the image) remain crisp and clear when applying the Aggregate-Mosaic Theory. Moreover, the many small clouds are removed when applying LCM classification. Though the forest/non-forest map based on the Aggregate-Mosaic Theory looks like a map that is manually interpreted, it actually is the result of a digital LCM classification using quantitative parameters. Such a classification is objective and can handle large data sets and therefore favors the use of remote sensing data for monitoring tropical rainforests. Ultimately, quantification of spatial heterogeneity will improve interpretation inaccuracies. Therefore, it is also useful in change assessment studies (Chapter 1, see also Figure 1.14).

References

Aronoff, S. (1989). Geographic information systems: A management perspectives. WDL Publishers, Ottawa.

Bian, L. & Buthler, R. (1999). Comparing effects of aggregation methods on statistical and spatial properties of simulated spatial data. Photogrammetric Engineering & Remote Sensing 65(1):73-84.

Cullinan, V.I. & Thomas, J.M. (1992). A comparison of quantitative methods for examining landscape pattern and scale. Landscape Ecology 7(3):211-227.

Droesen, W.J. (1999). Spatial modelling and monitoring of natural landscapes with cases in the Amsterdam Waterworks Dunes. PhD Thesis Wageningen Agricultural University, Ponsen & Looijen, Wageningen.

Foody, G.M. & Trodd, N.M. (1994). Non-classificatory analysis and representation of heathland vegetation from remotely sensed imagery. GeoJounal 29(4): 343-350.

Forman, R.T.T. (1995). Land mosaics: The ecology of landscapes and regions. Cambridge University Press, Cambridge.

Huising, J. (1993). Land use zones and land use patterns in the Atlantic zone of Costa Rica. A pattern recognition approach to land use inventory at the sub-regional scale, using remote sensing and GIS, applying an object-oriented and data-driven strategy. PhD Thesis Wageningen University, Ponsen & Looijen, Wageningen.

João, E.M. (1998). Causes and consequences of map generalisation. London School of Economics. Taylor & Francis, London.

Kotliar, N. & Wiens J.A. (1990). Multiple scales of patchiness and patch structure: A hierarchical framework for the study of heterogeneity. Oikos 59:253-260.

Lillesand, T.M. & Kiefer, R.W. (2000). Remote sensing and image interpretation (4th edition). John Wiley & Sons, New York.

Marceau D.J., Howarth, J. & Gratton, D.J. (1994a). Remote sensing and the measurement of geographical entities in a forested environment: 1. The scale and spatial aggregation problem. Remote Sensing of Environment 49:93-104.

Marceau D.J., Gratton, D.J., Fournier, R.A. & Fortin, J.P. (1994b). Remote sensing and the measurement of geographical entities in a forested environment: 2. The optimal spatial resolution. Remote Sensing of Environment 49:105-117.

McMaster, R. & Monmonier, M. (1989). A conceptual framework for quantitative and qualitative raster-mode generalisation. Proceedings of GIS/LIS '89, Orlando, Florida, Vol. 2, 390-403.

Molenaar, M. (1998). An introduction to the theory of spatial object modelling for GIS. Taylor & Francis, London.

Müller, J.-C. (1991). Generalization of spatial databases. In: Maguire, D., Goodchild, M. & Rhind, D. (eds), Geographical information systems: Principles and applications, Longman, Harlow, Vol. 1, 457-475.

Pelgrum, H. (2000). Spatial aggregation of land surface characteristics: Impact of resolution of remote sensing data on land surface modelling. PhD Thesis Wageningen University, CIP-data Koninklijke Bibiotheek, Den Haag.

Smits, P.C, Dellepiane, S.G., & Schowengerdt, R.A. (1999). Quality assessment of image classification algorithms for land cover mapping: A review and a proposal for a cost-based approach. International Journal of Remote Sensing 20(8):1461-1486.

Wang, F. (1990a). Fuzzy supervised classification of remote sensing images. IEEE Transactions on Geoscience and Remote Sensing 28(2):194-201.

Wang, F. (1990b). Improving remote sensing image analysis through fuzzy information representation. Photogrammetric Engineering and Remote Sensing 56(8):1163-1169.

CHAPTER 4

PATCH-SEGMENTATION

"We kunnen geen grootse dingen doen, alleen kleine dingen met veel liefde"

"We can not do great things, we can only do little things with great love"

Mother Teresa (1910-1997)

4.1 Introduction

Aggregate-Mosaic Theory (Chapter 3) provided the framework to classify remote sensing images into Land Cover Mosaics (i.e., LCM classification). A major issue in LCM classification is the upscaling from elementary objects (i.e., patches containing the land cover classes) to composite objects (i.e., patch-mosaics containing the land cover mosaic classes) based on functional generalization. This chapter describes the application of the Aggregate-Mosaic Theory for creating elementary objects with specific focus on the effect of parameter settings in patch-segmentation (Figure 4.1). Elementary objects are groups of neighboring image pixels that can contain different radiometric values, but represent together the same single land cover class (i.e., patches). Subsequently, only the combination of the geometric and the thematic information can define the elementary objects. Therefore, creating elementary objects requires two main processes being segmentation and classification. At elementary level, these two main processes are called *patch-segmentation* and *patch-classification*. Patch-segmentation defines the geometric extent of the elementary objects. It groups, at elementary level, the neighboring image pixels having a similar land cover class (i.e., patches). Patch-classification defines the thematic content of the elementary objects. It classifies, at elementary level, radiometric values or digital numbers into a same single land cover class.

The sequence of patch-segmentation and patch-classification, however, can be twofold. Patch-segmentation can be performed prior to patch-classification or posterior to patch-classification. In this thesis, elementary objects are created using patch-segmentation prior to patch-classification because this sequence results in a significant improvement of the signal-to-noise ration (Baatz et al., 2002). The spectral variance of created elementary objects within a spectral class (noise) is reduced while the spectral variance between the different land cover classes (signal) increases. This is especially useful for tropical rainforest areas where spectral classes show a high overlap in the feature space.

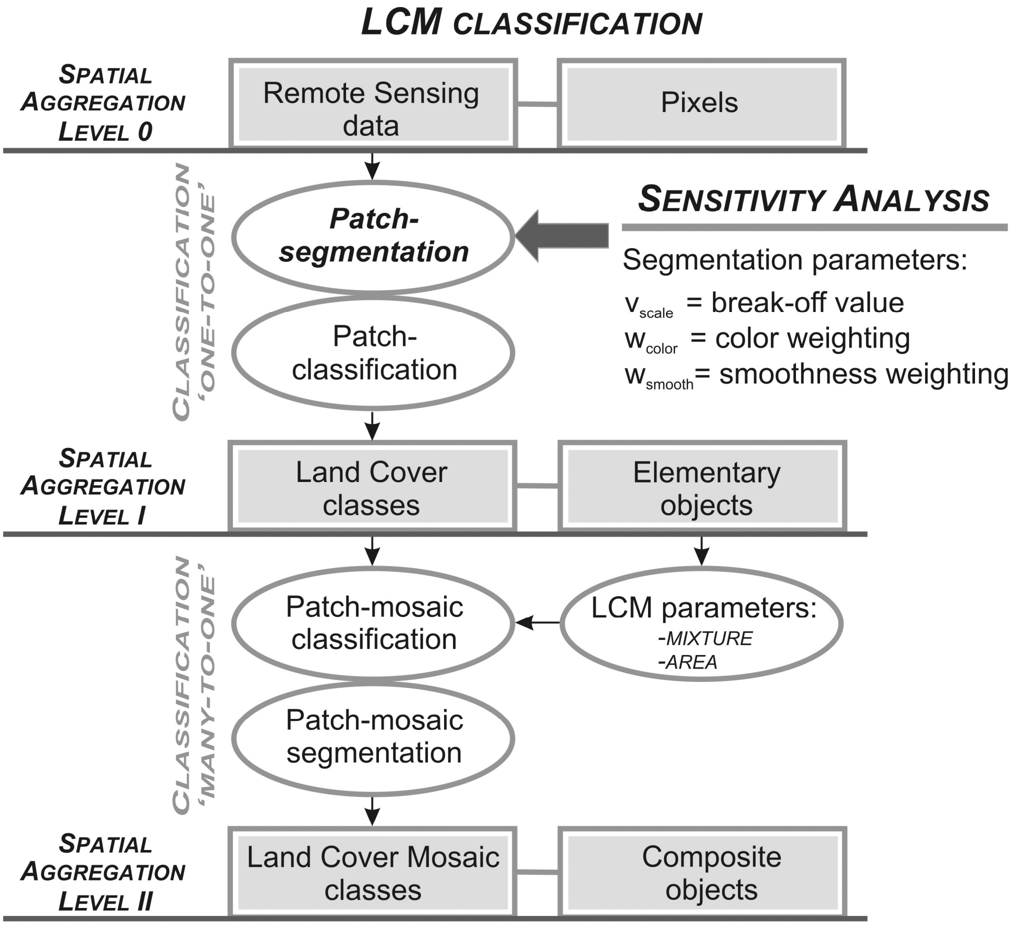


Figure 4.1: A sensitivity analysis on patch-segmentation in LCM classification when creating elementary objects (using the segmentation algorithm embedded in eCognition 3.0 software) .

While patch-classification is widely investigated in remote sensing literature, patch-segmentation is reasonably new, specifically in relation to spatial heterogeneous environments like tropical rainforest areas (see Chapter 2, section 2.3.5). Therefore, this chapter mainly focuses on patch-segmentation by means of a sensitivity analysis. It specifically investigates the effect of three user-defined segmentation parameters on four output aspects of created elementary objects (i.e., extent of under-segmentation, patch-classification accuracy, forest area, and variability and arrangement of forest cover and forest cover pattern). The results of the sensitivity analysis are used to define which elementary objects are used as input to continue the LCM classification at composite level (Chapter 5 and Chapter 6). The details and rationale of selected segmentation algorithm and segmentation parameters are explained in section 4.2. The details of the patch-classification and the land cover classes used at elementary level are given in section 4.3. Next, section 4.4 provides the parameter settings and patch-segmentation scheme that were used in the sensitivity analysis. A total of six evaluation metrics were used to study the effect of parameter settings on the four output aspects mentioned above. Details and rationale of these six evaluation metrics and required reference data are elucidated in section 4.5. The results of the sensitivity analysis are presented and discussed in section 4.6. Finally, in section 4.7 conclusions are drawn related to the four output aspects, the six evaluation metrics, and the input settings of the three segmentation parameters for upscaling elementary objects into composite objects.

4.2 Patch-segmentation method

4.2.1 Segmentation algorithm

In tropical forestry applications, mostly region-growing algorithms are used to segment remote sensing images into homogeneous patches (see discussion in section 2.3.6). Region-growing segmentation generates seed points over the entire image, followed by grouping neighboring pixels into a spatial object under a specific homogeneity criterion (Kettig & Landgrebe, 1976; Wang et al., 2004). Generally, the homogeneity criterion is a measure of local spectral heterogeneity. Local spectral heterogeneity is defined with a certain choice of a 'spectral closeness' metric, like the commonly used Euclidean distance and the Mahalanobis distance (Richards, 1986; Tilton, 1998). The spatial objects keep growing until their spectral closeness metric exceeds a predefined break-off value. The higher the break-off value, the larger the segmented objects will be (Wang et al., 2004).

This research used the segmentation algorithm embedded in eCognition 3.0 software to create the patches at elementary level (i.e., elementary objects). This segmentation algorithm was selected, because it is a region-growing algorithm with an additional local spatial heterogeneity measure (Baatz et al., 2002). In addition, it showed the least under-segmentation comparing six segmentation programs (Neubert & Meinel, 2003). Moreover, it is increasingly used for land cover mapping using optical remote sensing data in other studies (e.g., Benz et al., 2004; Burnett & Blaschke, 2003; Dorren et al., 2003; Sande et al., 2003). The addition of a local spatial heterogeneity measure besides a local spectral heterogeneity measure in the homogeneity criteria is useful for very heterogeneous image data to inhibit frayed segment borders. Under-segmentation is a serious problem in heterogeneous environments (Figure 4.2). It decreases the spectral variance between the different land cover classes causing patch-classification problems. Over-segmentation, however, should not cause a patch-classification problem in heterogeneous environments. In over-segmentation, the spectral variance of created spatial objects within a land cover class is still reduced while remaining the spectral variance between the different land cover classes. In other studies, the segmentation algorithm of eCognition is increasingly used because it allows both segmentation based on spectral and spatial features and – after an initial classification – classification-based segmentation (Benz et al., 2004). In addition, it can build a model of the relationships between the segmented objects (Burnett & Blaschke, 2003). Moreover, it brings together several contextual and object-oriented methods and approaches that are experimental or developed for research experiments only (Sande et al., 2003). For spatial heterogeneous environments like tropical rainforest areas, however, the effect of parameter settings in creating elementary objects is yet unknown. Therefore, studying this effect is a main focus of this chapter.

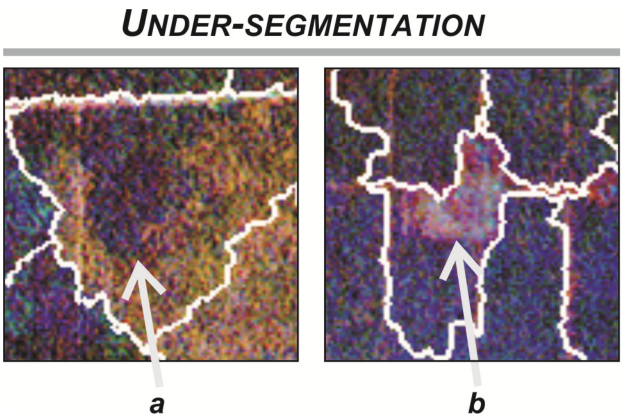


Figure 4.2: Two examples of under-segmentation of elementary objects in vegetation of heavily logged forest (a) and shrub (b) in the Pelangkaraya study area.

4.2.2 Segmentation parameters

Three user-defined segmentation parameters need a setting to run the segmentation algorithm of eCognition. These three segmentation parameters are:

- break-off value v_{scale}
- color weighting w_{color}
- smoothness weighting w_{smooth}

The **break-off value v_{scale}** is related to the average size of segmented objects *(v_{scale} > 0)*. This parameter is used to terminate the region-growing process being a measure for the maximum change in heterogeneity that may occur when merging two spatial objects. This break-off value is denoted as ‘scale’ in the segmentation algorithm of eCognition because a small break-off value will give spatial objects of small sizes on average (small features), while a large break-off value will lead to spatial objects of large sizes on average (large features; note, however, that the used terms small and large are not congruent with the cartographic context related to scale, i.e., small scale and large scale; Chapter 2, section 2.2.1).

The **color weighting w_{color}** defines to which extent local spectral heterogeneity h_{color} is contributing to the segmentation process $(0.1 \le w_{color} \le 1)$. Local spectral heterogeneity h_{color} and local spatial heterogeneity h_{shape} are the two measures of the homogeneity criterion $f(h)$. In the segmentation algorithm of eCognition, optimal local homogeneity is defined as (Baatz et al., 2002):

$$f(h) = w_{color} \cdot h_{color} + (1 - w_{color}) \cdot h_{shape} \tag{4.1}$$

Equation (4.1) shows that an increase in the color weighting w_{color} reduces the contribution of the local spatial heterogeneity measure h_{shape} leading to jagged boundaries of the spatial objects. The local spectral heterogeneity measure h_{color} is defined as the sum of the standard deviations of spectral values in each image layer σ_c weighted with the weights awarded for each layer w_c. The change in spectral heterogeneity caused by merging spatial objects is evaluated by calculating the difference between the situation after and before the merge, whereas the standard deviations themselves are weighted by the object sizes. In formula (Baatz et al., 2002):

$$h_{color} = \sum_c w_c \left(n_{merge} \cdot \sigma_{merge} - \left(n_{obj1} \cdot \sigma_{obj1} + n_{obj2} \cdot \sigma_{obj2}\right)\right)_c \tag{4.2}$$

where c is the number of bands with $c \ge 1$; w_c is the weight for band c with $0 \le w_c \le 1$; n_{merge}, n_{obj1} and n_{obj2} are respectively the number of pixels within the merged object, initial object 1 and initial object 2; and σ_{merge}, σ_{obj1} and σ_{obj2} are the standard deviations of merged object, initial object 1, and initial object 2. Equation (4.2) shows that even with a stable standard deviation of merged object σ_{merge}, local spectral heterogeneity

h_{color} increases when spatial objects keep growing (increasing n_{merge}). A stable σ_{merge} can be found in spatial homogeneous regions (e.g., grasslands).

The **smoothness weighting w_{smooth}** defines to which extent the smoothness criterion h_{smooth} is contributing to the segmentation process ($0.1 \le w_{smooth} \le 1$). The smoothness criterion h_{smooth} and the compactness criterion h_{cmpct} are the two criteria of the local spatial heterogeneity measure h_{shape} to describe ideal shapes. In the segmentation algorithm of eCognition, the local spatial heterogeneity measure h_{shape} is defined as (Baatz et al., 2002):

$$h_{shape} = w_{smooth} \cdot h_{smooth} + (1 - w_{smooth}) \cdot h_{cmpct} \tag{4.3}$$

Equation (4.3) shows that an increase in the smoothness weighting w_{smooth} reduces the contribution of the compactness criterion h_{cmpct}. The smoothness criterion h_{smooth} optimizes smooth borders of spatial objects. This is useful for very heterogeneous image data to inhibit frayed segment borders. The compactness criterion h_{cmpct} optimizes compactness of spatial objects. This is useful for images with very contrasting compactness of spatial objects, such as for urban data. The smoothness criterion h_{smooth} is described as the ratio of the de facto border-length l and the shortest possible border-length b given by the bounding box of an image object parallel to the raster. The compactness criterion is described as the ratio of the de facto border-length l and the square root of the number of pixels n forming the spatial objects. The change in spatial heterogeneity caused by merging spatial objects is evaluated by calculating the difference between the situation after and before the merge, whereas the measures are weighted by the object sizes. In formula (Baatz et al., 2002):

$$h_{smooth} = n_{merge} \cdot \frac{l_{merge}}{b_{merge}} - \left(n_{obj1} \cdot \frac{l_{obj1}}{b_{obj1}} + n_{obj2} \frac{l_{obj2}}{b_{obj2}} \right) \tag{4.4}$$

$$h_{cmpct} = n_{merge} \cdot \frac{l_{merge}}{\sqrt{n_{merge}}} - \left(n_{obj1} \cdot \frac{l_{obj1}}{\sqrt{n_{obj1}}} + n_{obj2} \frac{l_{obj2}}{\sqrt{n_{obj2}}} \right) \tag{4.5}$$

where n_{merge}, n_{obj1}, n_{obj2} are respectively the number of pixels within the merged object, initial object 1 and initial object 2; $l_{merge,}$ l_{obj1}, l_{obj2} are the de facto border-length l of merged object, initial object 1, and initial object 2; and $b_{merge,}$ b_{obj1}, b_{obj2} are the shortest possible border-length b of merged object, initial object 1, and initial object 2. Equations (4.4) and (4.5) show that even for spatial objects having ideal shapes after merging objects, local spatial heterogeneity h_{shape} increases when spatial objects keep growing (increasing n_{merge}). Ideal shapes can be found in cultivated or urban areas. Finally, an overview of the composition of the homogeneity criterion is given in Figure 4.3.

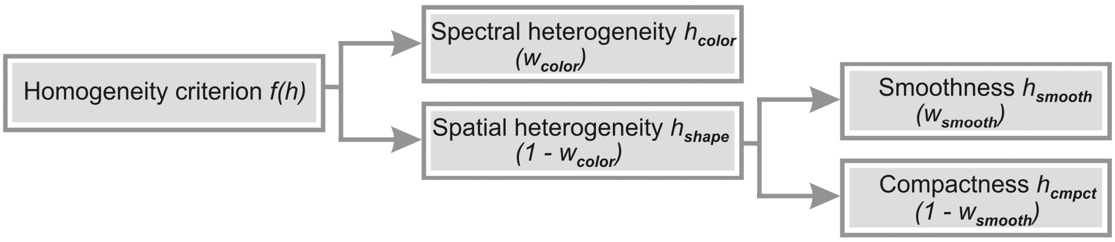


Figure 4.3: Composition of the homogeneity criterion related to the two weighting parameters (w_{color}, w_{smooth}) using the segmentation algorithm imbedded in eCognition.

4.3 Patch-classification method

4.3.1 FNEA method

Patch-classification quantitatively estimates the land cover class according to the radiometric information of the pixels of each elementary object. This thesis used a supervised fuzzy classifier of the standard nearest neighbor. This object-based classifier was chosen in patch-classification because it is in combination with the previously described segmentation algorithm of eCognition known as the *Fractal Net Evolution Approach* or shortly *FNEA (*Baatz & Schäpe, 2000; Hay et al., 2003). FNEA was found very useful for ecological applications where crisp boundaries between land cover classes are often absent (Blaschke & Strobl, 2001; Burnett & Blaschke, 2003).

A fuzzy classifier uses so-called *possibilities* to indicate the extent to which an individual (elementary object) is a member of a set (land cover class). Possibilities describe the degree of *membership* μ *(*$0 \leq \mu \leq 1$*)* of an individual to a set. The degree of membership has values on a continuous range between [0,1], where 0 indicates that the object definitely does not belong to a set, and 1 that it definitely belongs to a set. Possibilities are not probabilities, as the latter describe the degree of likelihood *P(x)* that an individual is a member of a set. Being not probabilistic, possibilities do not have to add up to 1. Zadeh (1965) first proposed fuzzy classification in his paper on fuzzy set theory. It lasted until the nineties before fuzzy classification was applied in remote sensing (see for instance Key at al., 1989; Fisher and Pathirana, 1990; Wang, 1990a & 1990b; Foody, 1994 & 1996; Palubinskas et al., 1995; Droesen, 1999; Molenaar & Cheng, 2000). The standard nearest neighbor classifies the elementary objects into predefined land cover classes based on a distance *d* between the mean spectral value of the pixels of each elementary object and the mean spectral value of the elementary training objects in the n-dimensional feature space. The Mahalanobis distance was used in order to include the covariance matrix of each land cover class gathered in the training stage. The fuzzy classifier of the standard nearest neighbor classifies the elementary objects as belonging to that land cover class with the highest possibility. However, a possibility interpretation requires a membership function. FNEA computes such a membership function *z(d)* based on the Mahalanobis distance *d*. This 'fuzzy' distance *z(d)* is defined as (Baatz et al., 2002):

$$z(d) = e^{-k \cdot d^2} \tag{4.6}$$

were parameter *k* determines the decrease of *z(d)* as a variable of a user-defined function-slope according to (Baatz et al., 2002):

$$k = \ln\left(\frac{1}{functionslope}\right) \tag{4.7}$$

This function-slope equals *z(d)* for *d=1* and can have a value on a continuous range between [0,1]. This means that the function-slope is the membership value of an elementary object belonging to a land cover class that has a distance of 1 times the standard deviation from the closest training object. The smaller the value for the function slope, the larger the range of possibilities that an elementary object belongs to a land cover class. The default value for the function slope was set at 0.2 (Figure 4.4).

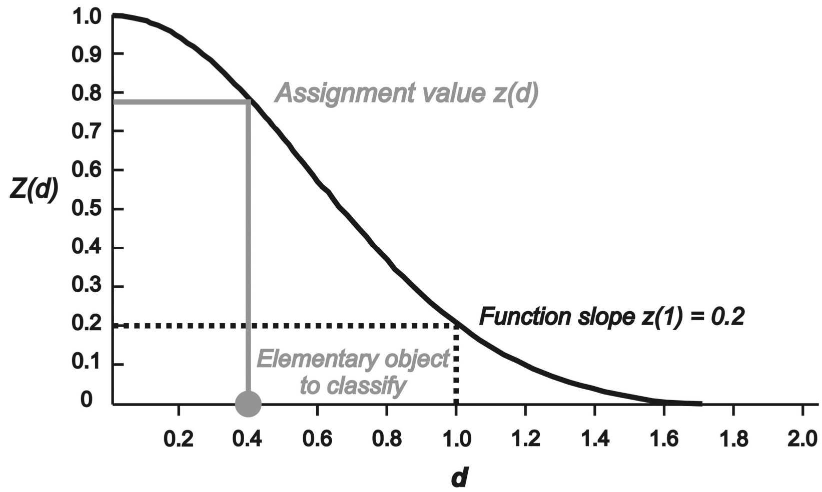


Figure 4.4: Membership value z(d) for an elementary object using function slope 0.2 based on Mahalanobis distance d in the fuzzy standard nearest neighbor classifier (from Baatz et al., 2002).

4.3.2 Land cover classes

This research classified the elementary objects into eight land cover classes typically occurring in a tropical peatswamp forest (Obbink, 1992 & 1993). The eight land cover classes are *logged forest*, *heavily logged forest*, *shrub*, *grass*, *agriculture*, *waterbody*, *river*, and *clouds*. Details are given in Table 4.1. During patch-classification, it was necessary to distinguish a total of eleven spectral classes. The land cover class *shrub* needed two spectral classes (wet and dry), the land cover class *agriculture* needed two spectral classes (crops and trees), and the class *clouds* needed two spectral classes (cloud and cloud-shadow). The other land cover classes needed only one spectral class.

4.4 Sensitivity analysis

A sensitivity analysis was executed to get more insight in the significance and the effect of the settings of the three segmentation parameters v_{scale}, w_{color}, and w_{smooth} on created elementary objects.

Table 4.1: Description of land cover classes at elementary level (Indonesian terms are put in brackets).

Land cover class	*Code*	*Description*
Logged forest	*LF*	*Areas covered with logged-over peatswamp forest due to logging of commercial species (hutan sekundair).*
Heavily logged forest	*HLF*	*Areas covered with logged-over peatswamp forest due to logging of commercial and non-commercial species (hutan bekas).*
Shrub	*SH*	*Areas covered with shrub vegetation lower than 10-12 meters in height (belukar).*
Agriculture	*AG*	*Areas covered with crops or trees for agricultural purposes or rubber plantations (kebun transmigrasi)*
Grass	*GR*	*Areas covered with grass vegetation, alang-alang or woody vegetation lower than 3-5 meters in height (semak)*
Waterbody	*WA*	*Areas where water level is higher than existing vegetation (daerah basah).*
River	*RI*	*River streams (sungai).*
Clouds	*CL*	*Image data covered with cloud or cloud-shadow (tertutup awan).*

A sensitivity analysis is the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation (JRC, 2005). As such, a sensitivity analysis allows a quantitative analysis of the contribution of each input factor to the output variance (Crosetto et al., 2000). This chapter deals with three input factors and four output variances. The three input factors are the settings of the three segmentation parameters v_{scale}, w_{color}, and w_{smooth} in patch-segmentation. The four output variances are under-segmentation of the elementary objects, patch-classification accuracy (elementary objects), forest area at elementary level, and variability and arrangement of forest cover and forest cover pattern at elementary level. The reason to study these four output variances are:

- Under-segmentation causes patch-classification problems specifically in heterogeneous environments.
- Patch-classification accuracy indicates the patch-segmentation performance at elementary level. The classified elementary objects are used as input to study patch-mosaic classification (Chapter 5) and patch-mosaic segmentation (Chapter 6).
- Forest area is an easily understood baseline parameter that provides the first indication of the relative importance of forests in a country or region (FAO, 2001).

- Variability (composition) and arrangement (configuration) of forest cover and forest cover pattern are essential indicators of change processes in tropical rainforest areas.

A total of 11 patch-segmentation runs were carried out on two Landsat TM images of the Pelangkaraya study area. Section 4.4.1 provides the details and reasoning of the used parameter settings, whereas section 4.4.2 explains the patch-segmentation scheme of the sensitivity analysis.

4.4.1 Parameter settings

The values and weightings selected for the three segmentation parameters v_{scale}, w_{color}, and w_{smooth} are presented in Table 4.2. Note that a sensitivity analysis does not deal with the choice of the distributions followed by the model inputs. These distributions need to be derived from available sources of information, such as expert opinions or literature (JRC, 2005).

Table 4.2: Selected settings for the three segmentation parameters in the sensitivity analysis.

Segmentation parameter	*Symbol*	*Values*
Break-off value	v_{scale}	*10, 15, 20, 25*
Color weighting	w_{color}	*0.5, 0.6, 0.7, 0.8, 0.9*
Smoothness weighting	w_{smooth}	*0.5, 0.7, 0.9, 1.0*

Four break-off values (v_{scale}) were selected. The selection was based on the spectral variability of the two Landsat TM images related to the objective of patch-segmentation, i.e. creating elementary objects in a peatswamp forest. After some preliminary investigations, v_{scale} values smaller than 10 resulted in unnecessary small elementary objects that represented only tiny parts of a single land cover class. Therefore, v_{scale} was not investigated below a value of 10. Values larger than 25 were also not investigated, because they resulted in too large elementary objects in terms of patch-classification perspective. These too large elementary objects represented several land cover classes instead of one land cover class.

Five color weightings (w_{color}) were selected. The selection was based on reducing spectral overlap between the different land cover classes. Spectral overlap is a major problem in heterogeneous environments. A relatively high color weighting is necessary to achieve high spectral homogeneity within spatial objects (Baatz et al., 2002). Therefore, w_{color} was not investigated below 0.5. A weighting of 1.0 resulted in spatial objects that were extremely jagged, causing the elementary objects to appear strangely shaped and hard to differentiate. Therefore, w_{color} equal 1.0 was not included in the investigation.

Four smoothness weightings (w_{smooth}) were selected. The selection was based on the absence of urbanization in the study area. In heterogeneous rural areas, the smoothness of spatial objects is more important than their compactness. In addition, the two Landsat TM images of the study area did not show very contrasting compactness. As a result, w_{smooth} was not investigated below 0.5.

4.4.2 Patch-segmentation scheme

All three segmentation parameters need a setting to start the patch-segmentation process. Analyzing all combinations as given in Table 4.2 would result in 80 segmentation runs per image. In case of a large number of inputs, a screening exercise is performed to select the subset of the best explanatory factors (JRC, 2005). Performing such a screening exercise revealed that some values and weightings affected the segmentation process more than others. Therefore, not all combinations were analyzed, but a scheme was constructed starting with investigating the parameter mostly affecting the segmentation. First, v_{scale} was studied with w_{color} at 0.9 to achieve high spectral homogeneity within the elementary objects and w_{smooth} at 0.7 because the two images of the Pelangkaraya study area showed little contrasting compactness. After that, w_{color} was studied with v_{scale} at 15 to reduce the number of patches while maintaining a low under-segmentation and w_{smooth} at 0.5. Similarly, w_{smooth} was studied with v_{scale} at 15 and w_{color} at 0.9. This segmentation scheme is presented in Table 4.3.

Table 4.3: Patch-segmentation scheme of the sensitivity analysis.

Sensitivity analysis for	*Parameter settings*			*Number of patch-segmentation runs*
	v_{scale}	w_{color}	w_{smooth}	
v_{scale}	v_{scale}	*0.9*	*0.7*	*4*
w_{color}	*15*	w_{color}	*0.5*	*5*
w_{smooth}	*15*	*0.9*	w_{smooth}	*2**
Total				*11*

**To test all four settings of w_{smooth} only two additional runs are needed, because w_{smooth} values 0.5 and 0.7 are already included in the sensitivity analysis when testing the parameters v_{scale} and w_{color}.*

4.5 Evaluation metrics

Two discrepancy metrics and four landscape pattern metrics were used to study the effect of parameter settings on the previous discussed four output aspects. The two discrepancy metrics were the Relative Ultimate Measurement Accuracy *RUMA* and the Chance-corrected measure of agreement *KHAT*. The *RUMA* was used to study the extent of under-segmentation after each patch-segmentation run. This empirical discrepancy metric was selected because for quality evaluation in real applications, empirical metrics are more useful than analytical metrics, and the need to have a reference makes discrepancy metrics more powerful than goodness metrics (Zhang, 1996). In addition, discrepancy metrics are capable to detect very small variations in segmented images, and therefore are of more interest in practice (Zhang & Gerbrands, 1994). The Chance-corrected measure of agreement *KHAT* was used to study the patch-classification accuracy of each patch-segmentation run. This discrepancy metric is the most commonly used accuracy assessment test in remote sensing and has a long history (e.g., Cohen, 1960; Bishop et al., 1975; Aronoff, 1982a, 1982b; Congalton & Mead, 1983; Story & Congalton, 1986; Hudson & Ramm, 1987; Foody, 1992). Forest area at elementary level was compared to forest area at pixel level as derived from the reference data set (i.e., *mlk* and *mlk5x5,* see section 4.5.2). The four landscape pattern metrics were the Percentage of Landscape *PLAND*, the Number of Patches *NP*, the Simpson's Diversity Index *SIDI*, and the Landscape Shape Index *LSI*. The first two class-level metrics describe variability and arrangement of forest cover, whereas the other two landscape-level metrics describe variability and arrangement of forest cover pattern. These four landscape pattern metrics were selected because they provide a quantitative description on both composition ('how different things are') and configuration ('how things are distributed'). Composition and configuration are two important ecological components in landscape ecology (Forman, 1995; McGarigal & Marks, 1995; Gustafson, 1998; see also Chapter 2, section 2.2). In addition, these metrics have been developed exclusively for categorical map patterns (Urban et al., 1987; McGarigal et al., 2002) and they have been used recently in the field of remote sensing to describe spatially image complexity (e.g., Chuvievo, 1999; Luque et al., 2002; Stein & Beurs, 2004). Details of the *RUMA* metric and reference used are described in section 4.5.1. Next, details of the *KHAT* metric and reference used are described in section 4.5.2. Finally, details of the four landscape pattern metrics *PLAND*, *NP*, *SIDI* and *LSI* are described in section 4.5.3.

4.5.1 Discrepancy metric RUMA

The *RUMA* is defined as (Zhang & Gerbrands, 1994):

$$RUMA = \frac{|R_f - S_f|}{R_f} \times 100\% \tag{4.8}$$

were R_f is the total number of segment boundaries in the reference, and S_f is the total number of correctly segmented boundaries. This means that a lower *RUMA* represents less under-segmentation. This study used the *RUMA* to count the number of correctly segmented boundaries. S_f was counted as the total number of segment boundaries minus 'incorrect' segment boundaries. Segment boundaries were identified as being incorrect when they under-segment a land cover class (causing patch-classification problems specifically in spatially heterogeneous environments, see section 4.2.1). An image is under-segmented when neighboring image pixels do not represent the same (single) land cover class. Over-segmentation, however, was not counted as being incorrect because of the definition of the elementary objects (i.e., groups of neighboring image pixels representing the same land cover type). R_f was obtained by manually counting the total number of segment boundaries. In literature, many studies using real imagery are manually segmented to obtain the reference data set (Lee et al., 1990).

4.5.2 Discrepancy metric KHAT

The *KHAT* is a discrete multivariate analysis technique to test the agreement between similarity matrices (Cohen, 1960; Congalton & Mead, 1983). The first computer program implementing such a test to analyze similarity matrices was called *KAPPA*, and therefore, a calculation of this test is also called a KAPPA analysis (Congalton &

Mead, 1983). A KAPPA analysis calculates *KHAT* coefficients, *KHAT* variances, the test statistics Z for each pair of similarity matrices, and the results of the test.

KHAT coefficients

The *KHAT coefficient* $\hat{\kappa}$ is a measure of how well a classification agrees with a reference data set (Aronoff, 1982a, 1982b; Story & Congalton, 1986). It is the maximum likelihood estimate from a multinomial distribution and is a measure of the actual agreement minus the chance agreement. The actual agreement is the cell value itself in a similarity matrix while the chance agreement is defined as the product of the marginals (row and column totals) for that cell. As such, the *KHAT* coefficient is defined as (Bishop et al., 1975):

$$\hat{\kappa} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} \cdot x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+} \cdot x_{+i}\right)} \tag{4.9}$$

where r is the number of rows in a similarity matrix, x_{ii} is the number of observations in row i and column i (i.e., the i^{th} diagonal element), x_{i+} and x_{+i} are the marginal totals of row i and column i, respectively, and N is the total number of observations. The *KHAT* coefficient lies typically on a scale between 0 and 1 where the latter indicates complete agreement. This coefficient is often multiplied by 100 to obtain a percentage measure of classification accuracy (Foody, 1992).

KHAT variance

The *KHAT variance* $\hat{\sigma}^2$ is used to construct a hypothesis test for significant difference between similarity matrices (Cohen, 1960). As presented by Bishop *et al.* (1975), the approximate large sample variance of Kappa is defined as (Hudson & Ramm, 1987):

$$\hat{\sigma}^2(\hat{\kappa}) = \frac{1}{N}\left[\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2\left(\theta_4 - 4\theta_2{}^2\right)}{(1-\theta_2)^4}\right] \tag{4.10}$$

where

$$\theta_1 = \sum_{i=1}^{r} x_{ii} / N \,, \tag{4.11}$$

$$\theta_2 = \sum_{i=1}^{r} x_{i+} x_{+i} / N^2 \,, \tag{4.12}$$

$$\theta_3 = \sum_{i=1}^{r} x_{ii} \left(x_{i+} + x_{+i} \right) / N^2 \text{ , and} \tag{4.13}$$

$$\theta_4 = \sum_{i=1, j=1}^{r} x_{ij} \left(x_{j+} + x_{+i} \right)^2 / N^3 \tag{4.14}$$

Z-statistic

For large samples, the test statistics for significant difference between two similarity matrices is defined as (Congalton & Mead, 1983):

$$Z \approx \frac{\hat{\kappa}_1 - \hat{\kappa}_2}{\sqrt{\hat{\sigma}_1^2 + \hat{\sigma}_2^2}} \tag{4.15}$$

where K_1 and K_2 are the estimated *KHAT* coefficients for two classifications and σ_1^2 and σ_2^2 are the large sample variances of the respective *KHAT*'s. This so-called *Z-statistic* is a pair-wise test of significance (Cohen, 1960). It compares a pair of independent *KHAT*'s using the normal distribution curve deviate to determine whether they are significantly different. The null hypothesis (H_0) states that there is no significant difference between two patch-segmentation runs after patch-classification, and consequently the alternative hypothesis (H_1) states that there is a significant difference between two patch-segmentation runs after patch-classification. For a 95% confidence level the conditions are H_0: $Z \leq 1.96$ and H_1: $Z > 1.96$.

Random sampling

Similarity matrices should be representative for the actual classification results. This means that an appropriate sampling scheme and an adequate number of samples need to be chosen when generating the similarity matrices. This research used a random sample of 10000 points per image (i.e., n=10000, N=$1.27 * 10^6$) to create the contingency tables. This sample size was determined by using a statistic for calculating the sample size for multinomial tests, as is *KAPPA*. Tortura (1978) developed a criterion for large populations. The required sample size n_i to obtain an absolute precision of b_i for class i = [1 … k] for a probability of Type I error α is computed from the expected proportion $\hat{p}_i$ as (Tortura, 1978):

$$n_i = \frac{B}{b_i^2} \cdot \hat{p}_i (1 - \hat{p}_i) \tag{4.16}$$

Where B is the upper *(α/k) x 100* percentile of the cumulative Chi-square distribution with one degree of freedom such that Pr{χ^2} > α/k. The $\hat{p}_i$ is estimated from the proportions of each land cover class in the classified images. The total number of samples to estimate all land cover classes with the required precision is calculated as the maximum of individual estimates (Tortura, 1978):

$$n = \max_i \{n_i\} \tag{4.17}$$

With eight defined land cover classes (k = 8), the probability of a Type I error set to 0.05, a class proportion of 0.5 (max. samples) and an absolute precision of 1.5% for each class, the number of samples required should be 8307. A sample size of 10000 was used to ensure to meet these settings.

Reference data set

A reference data set is needed to compute similarity matrices. This study used a per-pixel based reference with and without majority filtering (window size 5x5) as the reference data set (Figure 4.5). A per-pixel based reference is a standard approach to compare classification results of segmented images (Ryherd & Woodcock, 1996; Abeyta & Franklin, 1998; Stein & Beurs, 2004). They are suitable to analyze the often small classification variations of segmented images, because such references are spatially more detailed (and thus very useful in a sensitivity analysis). However, per-pixel based references do not provide any information on which classification result of segmented images is the most accurate because of a difference in spatial aggregation level. Choosing a spatial aggregation level is related to the problem of defining functional management units appropriate for a specific task or objective (Chapter 3, section 3.3). Using aerial photographs or secondary data sources as reference data, spatial aggregation levels are incorporated when they are manually interpreted. Like in many tropical areas, no aerial photographs covering the same time span, or accurate secondary data sources were available for the Pelangkaraya study area. Note that a same time span is important for areas with many vegetation changes in a short time frame. In addition, the collected ground truth data was not sufficient to evaluate the many small output variations as a result of the different settings of the segmentation parameters. The spatial aggregation level of per-pixel based classifications, however, can be increased by post-processing (Chapter 2, section 2.3.5). Post-processing quantitatively modifies land cover classes according to neighboring classified image pixels using spatial filters. It reduces the speckle appearance of the classified image, and enlarges classification units to adhere more to the human perception of land cover (Stuckens et al., 2000). The decision rules used for post-processing depend on the method applied. Generally, post-processing involves filtering with a majority filter, whereby each pixel is recoded to the majority class of a neighborhood (Gurney & Townshend, 1983).

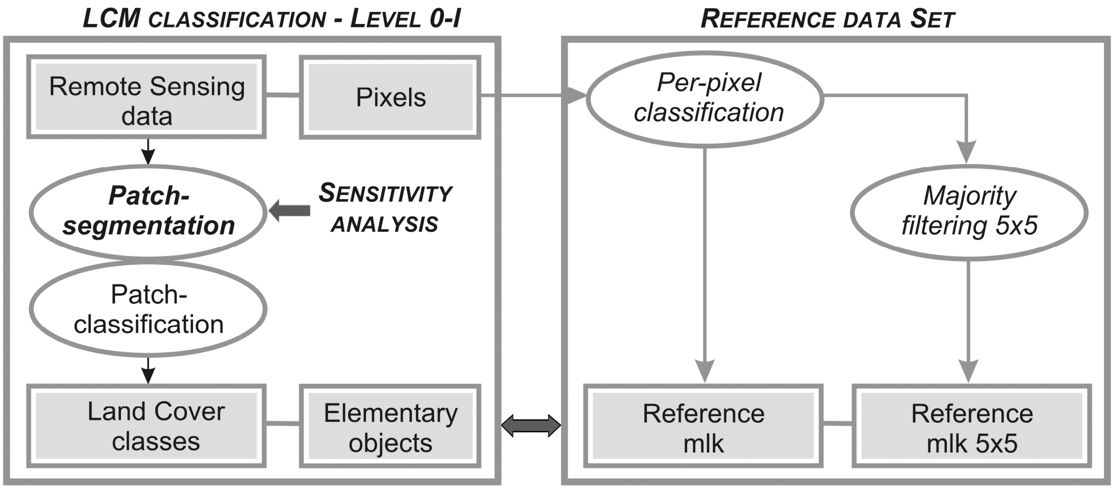


Figure 4.5: Reference data set for evaluating patch-segmentation settings in LCM classification (assessed at elementary level).

The reference data set used the Gaussian Maximum Likelihood classifier (MLC). This classifier was selected, because it is the most common classifier in literature (Jensen et al., 1997) and it is mainly used in operational applications when digitally analyzed. A common classifier (and thus a well-know reference) is a prerequisite to understand and explain the often many small LCM classification variations assessed at elementary level due to patch-segmentation. A majority filter of size 5x5 was used to post-process the per-pixel based reference (Gurney and Townshend, 1983; Kenk et al., 1988). A larger filter size could not be used, because of blurring the patch-classification results.

4.5.3 Landscape pattern metrics PLAND, NP, SIDI, LSI

A rich array of landscape pattern metrics is available to quantify both composition and configuration (Forman & Godron, 1986; O'Neill et al., 1988; Turner, 1990; Musick & Grover, 1991; Turner & Gardner, 1991; Gustafson & Parker, 1992; Li & Reynolds, 1993, McGarigal & Marks, 1995; Jaeger, 2000). Commonly, they are defined at three spatial aggregation levels (McGarigal et al., 2002):

- Patch-level metrics are defined for individual patches; they characterize the spatial character and context of patches. These metrics serve primarily as the computational basis for class-level metrics and landscape-level metrics.
- Class-level metrics are integrated over all patches of a given type; they quantify the amount and spatial distribution of each patch type in the landscape. These metrics are often interpreted as *fragmentation indices* as they measure the extent and spatial configuration of land cover classes.
- Landscape-level metrics are integrated over all patch types over the full extent of the landscape mosaic. These metrics are often interpreted as *landscape heterogeneity indices* as they measure the overall landscape pattern.

No single comprehensive landscape pattern metric exists that fully considers both composition and configuration at each spatial aggregation level. Usually, two or three carefully selected metrics are sufficient to address a specific question in order to minimize the probability of misinterpretation based on a single metric (Forman, 1995; McGarigal & McComb, 1995; Riitters et al., 1995; Tischendorf, 2001). This study selected four landscape pattern metrics, two composition metrics and two configuration metrics (Table 4.4). The Spearman Rank Correlation Coefficient test was used to select these four metrics, because most high-level metrics are correlated (Appendix 4.1). They are derived from similar patch-level attributes (i.e., type, area, edge, and neighbor type). The Spearman Rank Correlation Coefficient was selected, because the data tested was not normally distributed. Spearman's *rho* is a measure for the linear relation between two variables. It is a nonparametric version of the Pearson's correlation coefficient, based on the ranks of the data rather than the actual values (Easton & McColl, 1997).

The ***Percentage of Landscape* (*PLAND*)** quantifies *class-composition*. It measures the proportional abundance of each patch type in the landscape. *PLAND* is defined as the sum of the areas (m^2) of all patches of the corresponding patch type (land cover class), divided by total landscape area (m^2), multiplied by 100 (to convert to a percentage). In formula (McGarigal et al., 2002):

$$PLAND = p_i \times 100 = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100 \quad (4.18)$$

where p_i is the proportion of the landscape occupied by patch type i, a_{ij} is the area (m^2) of patch *ij*, and *A* is the total landscape area (m^2). *PLAND* approaches 0 when the corresponding patch type becomes increasingly rare in the landscape. *PLAND* reaches 100 when the entire landscape consists of a single patch type.

Table 4.4: Description of selected landscape pattern metrics to quantify vegetation heterogeneity.

	Metric	*Description*	*Category*	*Spatial aggregation level*	*Unit*	*Limit*
Forest cover	*PLAND*	*Percentage of Landscape*	*Composition*	*Class*	*%*	*0<PLAND≤100*
	NP	*Number of Patches*	*Configuration*	*Class*	*none*	*NP≥1*
Forest cover pattern	*SIDI*	*Simpson's Diversity Index*	*Composition*	*Landscape*	*none*	*0 ≤ SIDI < 1*
	LSI	*Landscape Shape Index*	*Configuration*	*Landscape*	*none*	*LSI≥1*

The ***Number of Patches* (*NP*)** quantifies *class-configuration*. It measures the extent of subdivision or fragmentation of the patch type. *NP* is considered as one of the most basic aspects of landscape pattern that can affect myriad processes. A landscape with a greater number of patches has a finer grain; that is, the spatial heterogeneity occurs at a finer resolution. *NP* is defined as the number of patches of corresponding patch type (land cover class). In formula (McGarigal et al., 2002):

$$NP = n_i \quad (4.19)$$

where n_i is the number of patches in the landscape of patch type *i*. *NP* equals 1 when the landscape contains only one patch of the corresponding patch type; that is, when the class consists of a single patch.

The ***Simpson's Diversity Index (SIDI)*** quantifies *landscape-composition*. It measures the relative numbers of patch types present in landscape mosaics (Simpson, 1949; Forman, 1995). This diversity index combines two ecological components (richness and evenness) into a single measure. Richness refers to the number of patch types present, whereas evenness refers to the distribution of area among patch types. Being more sensitive to evenness than richness, the *SIDI* places more weight on the common patch types and thus is less sensitive to the presence of rare types. The index is a probability that any two pixels selected at random would belong to different patch types (McGarigal et al., 2002). The higher the value the greater the likelihood that two randomly selected pixels will be of different patch types. *SIDI* is defined as 1 minus the sum, across all patch types, of the proportional abundance of each patch type squared. In formula (McGarigal et al., 2002):

$$SIDI = 1 - \sum_{i=1}^{m} p_i^{\,2} \qquad (4.20)$$

where p_i is the proportion of the landscape occupied by patch type i, with m patch types. *SIDI* is 0 when the landscape contains only one patch (i.e., no diversity). It approaches 1 as the number of different patch types (i.e., patch richness) increases, and the proportional distribution of area among patch types becomes more equitable (i.e. patch evenness).

Landscape Shape Index (LSI) quantifies *landscape-configuration*. It measures the perimeter-to-area ratio for the landscape as a whole. *LSI* provides a standardized measure of total edge or edge density that adjusts for the size of the landscape. Consequently, it has a direct interpretation as a measure of patch aggregation. The total amount of edge in a landscape is directly related to the degree of spatial heterogeneity in that landscape, and therefore a critical piece of information in the study of fragmentation (McGarigal & Marks, 1995). *LSI* is defined as the total length of the edges in the landscape, given in number of cell surfaces, divided by the minimum total length of edge possible, also given in number of cell surfaces. In formula (McGarigal et al., 2002):

$$LSI = \frac{E}{\min E} \qquad (4.21)$$

where E is the total length of edges (or perimeter) in terms of number of cell surfaces including landscape boundary; and *minE* is the minimum total length of edges (or perimeter) in terms of number of cell surfaces (for detailed explanation see McGarigal et al., 2002). *LSI* is 1 when the landscape consists of a single square (or almost square) patch. *LSI* increases without limit as landscape shape becomes more irregular and/or as the length of the edges within the landscape increases; that is when the patches become increasingly desaggregated.

4.6 Results & discussion

4.6.1 Under-segmentation

Figure 4.6 shows two examples of patch-segmentation for two different break-off values (v_{scale} 10 and v_{scale} 25). It clearly shows that the number of elementary objects was drastically reduced using the larger break-off value. Generally, increasing the break-off value parameter v_{scale} steadily increased *RUMA* and thus increased under-segmentation (Figure 4.7). Under-segmentation increased also when lowering the color weighting parameter w_{color} for both images. Apparently, patch-segmentation based on local spectral heterogeneity provided less under-segmentation than patch-segmentation based on local spatial heterogeneity in heterogeneous environments. The smoothness weighting parameter w_{smooth}, however, did not affect under-segmentation in both the images. Throughout all patch-segmentation runs, the more heterogeneous p1996 image showed less under-segmentation than the p1990 image. It is most likely that the higher standard deviations of the more heterogeneous p1996 image reduced the growing of the elementary objects. The larger the elementary objects grow, the higher the possibility of under-segmentation. The sensitivity of both Landsat TM images towards the three segmentation parameters were similar. While the *RUMA* indicates patch-classification difficulties, the analysis resolution (Chapter 3, section 3.4) defines the require minimum spatial size of elementary objects (i.e., patch-size). The *RUMA* can provide, therefore, information on technical constraints when using a specific remote sensing data source.

4.6.2 Patch-classification accuracy

Figure 4.8 (p1990 image) and Figure 4.9 (p1996 image) show each six classification results at elementary level for different settings of the three segmentation parameters in patch-segmentation. Both figures clearly show that the tropical land cover classes were less fragmented for a higher break-off value v_{scale}, were less compacted for a higher color weighting w_{color}, and had many subtle differences when changing the smoothness weighting parameter w_{smooth}. Surprisingly, the KHAT metric did not show these differences in fragmentation and compactness for the p1990 image, neither using the per-pixel reference nor using the majority filtered reference (see Figure 4.10). The *RUMA* results (section 4.6.1) indicated that both images showed about similar sensitivity towards the three segmentation parameters. Therefore, it could be expected that the *KHAT* results should also indicate that both images showed similar sensitivity towards the three segmentation parameters. However, the KHAT results did not indicate this. One reason could be that per-pixel classifiers face classification difficulties in spatially heterogeneous environments like the p1996 image because spatial context is not considered during per-pixel classification.

The above means that the difference in KHAT results of the two images were not a result of differences in the settings of the segmentation parameters. Instead, they might be a result of differences in the conceptual description of the Pelangkaraya study area. Actually, two different spatial models were used to describe the spatially heterogeneous study area. One was a patch model at elementary level: patch-segmentation and patch-classification. The other was a per-pixel model at per-pixel level: per-pixel classification (the latter being the reference data set). For homogeneous land cover classes, the spatial models did not show much differences (i.e., a stable *KHAT*). However, for heterogeneous land cover classes, the spatial models showed distinctive differences (i.e., a descending KHAT specifically for larger elementary objects). Consequently, the *KHAT* metric in this study seemed to address differences in spatial aggregation levels. Such a difference can also be noticed comparing the two references used. A higher *KHAT* value was obtained using the majority filtered reference (see also findings in the next section on *PLAND* figures that underline the above presented explanation). Therefore, spatially heterogeneous environments require reconsideration of applying the standard approach that uses per-pixel classified images to assess classification accuracy of segmented images (see

Ryherd & Woodcock, 1996; Abeyta & Franklin, 1998; Stein & Beurs, 2004). The results of the Z-statistics are presented in Appendix 4.2. They show that the more heterogeneous an image is (spatially), the larger the range in significance level of the difference between the two spatial models (i.e., per-pixel level versus elementary level).

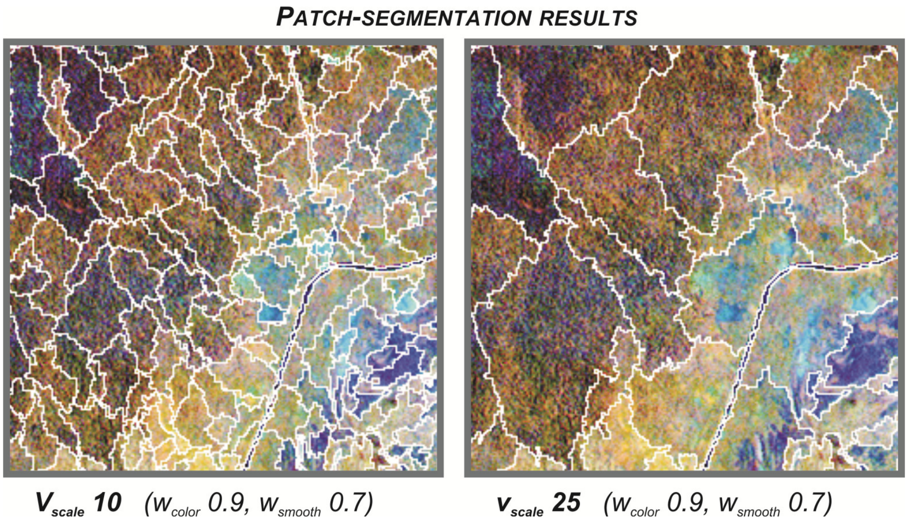


Figure 4.6: Patch-segmentation results (elementary objects) for two different break-off values v_{scale} 10 and v_{scale} 25; detail of p1990 image.

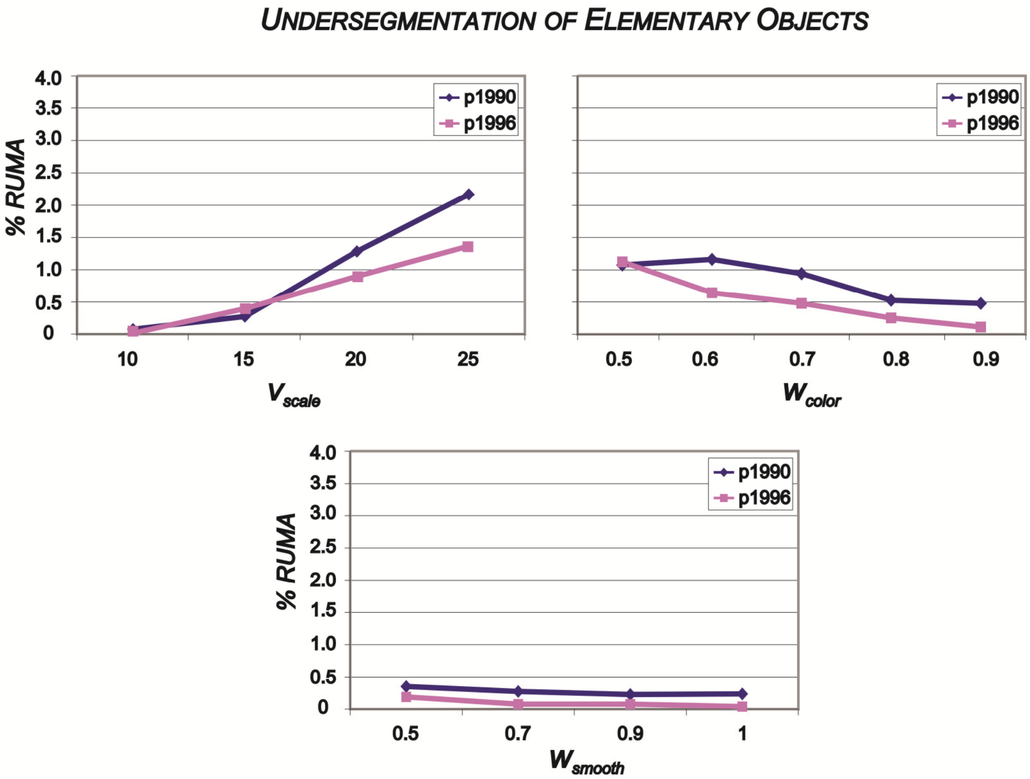


Figure 4.7: Under-segmentation of elementary objects expressed in RUMA values for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color} and smoothness weighting w_{smooth} in patch-segmentation.

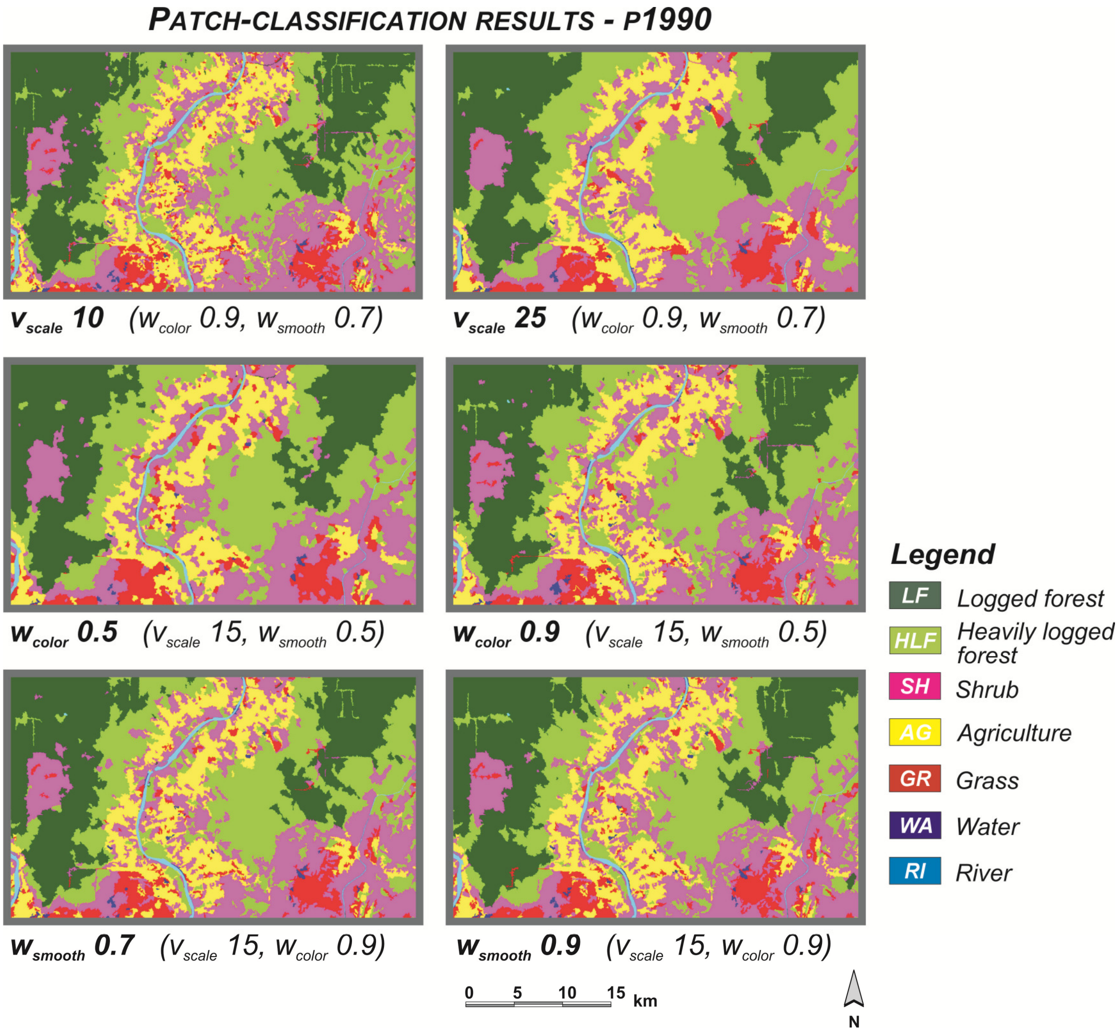


Figure 4.8: Patch-classification results (elementary objects) for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color}, smoothness weighting w_{smooth} in patch-segmentation; p1990 image.

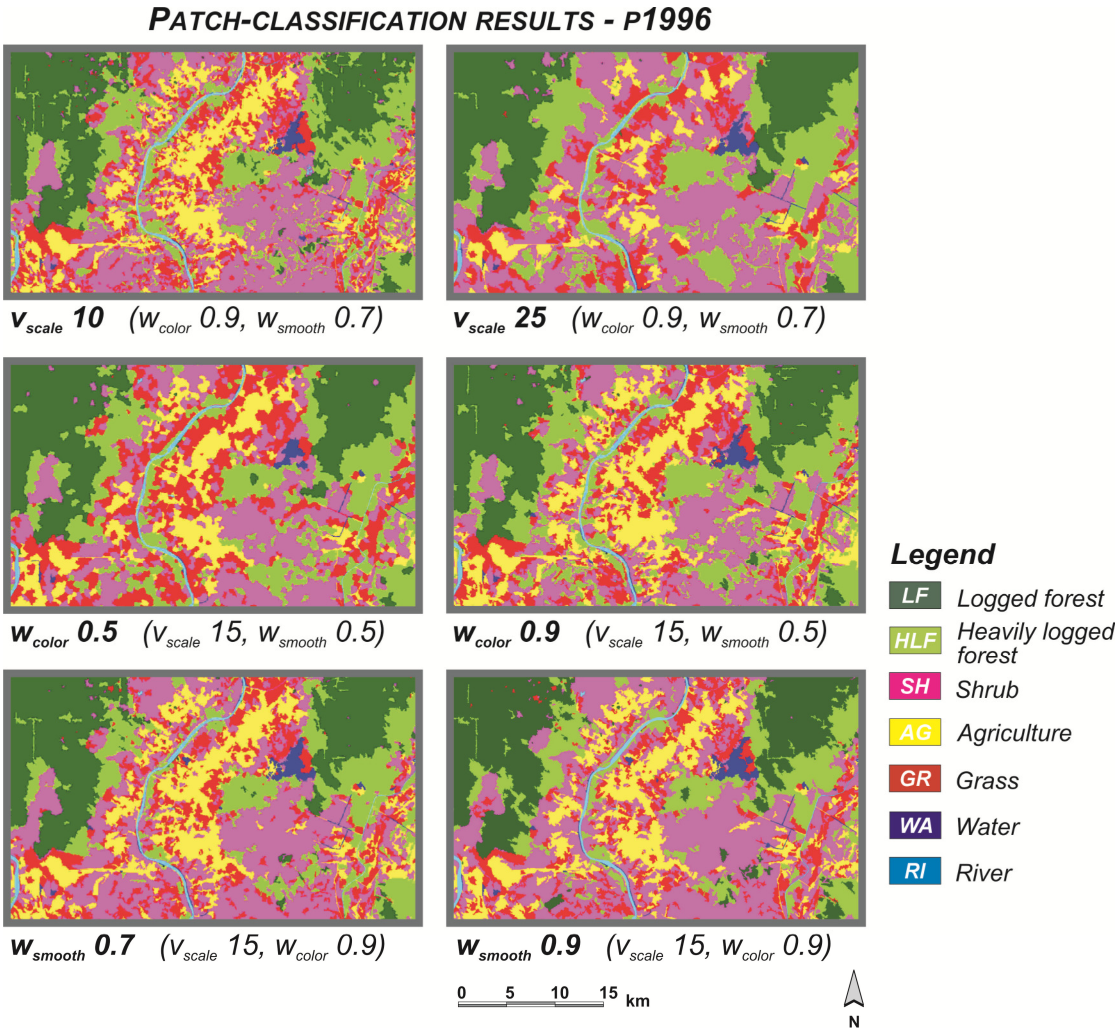


Figure 4.9: Patch-classification results (elementary objects) for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color}, smoothness weighting w_{smooth} in patch-segmentation; p1996 image.

4.6.3 Forest area

Table 4.5 provides an overview of the cover percentages of the eight tropical land cover classes after patch-classification (i.e., PLAND mean including all 11 patch-segmentation runs per image). It provides also the cover percentages obtained from a conventional per-pixel classification (i.e., used as reference data set). As such, forest area and change scenario can be examined at two different spatial aggregation levels (i.e., at elementary level and at per-pixel level). At elementary level, the standard deviations of the p1990 image were much smaller than the standard deviations of the spatially more heterogeneous p1996 image.

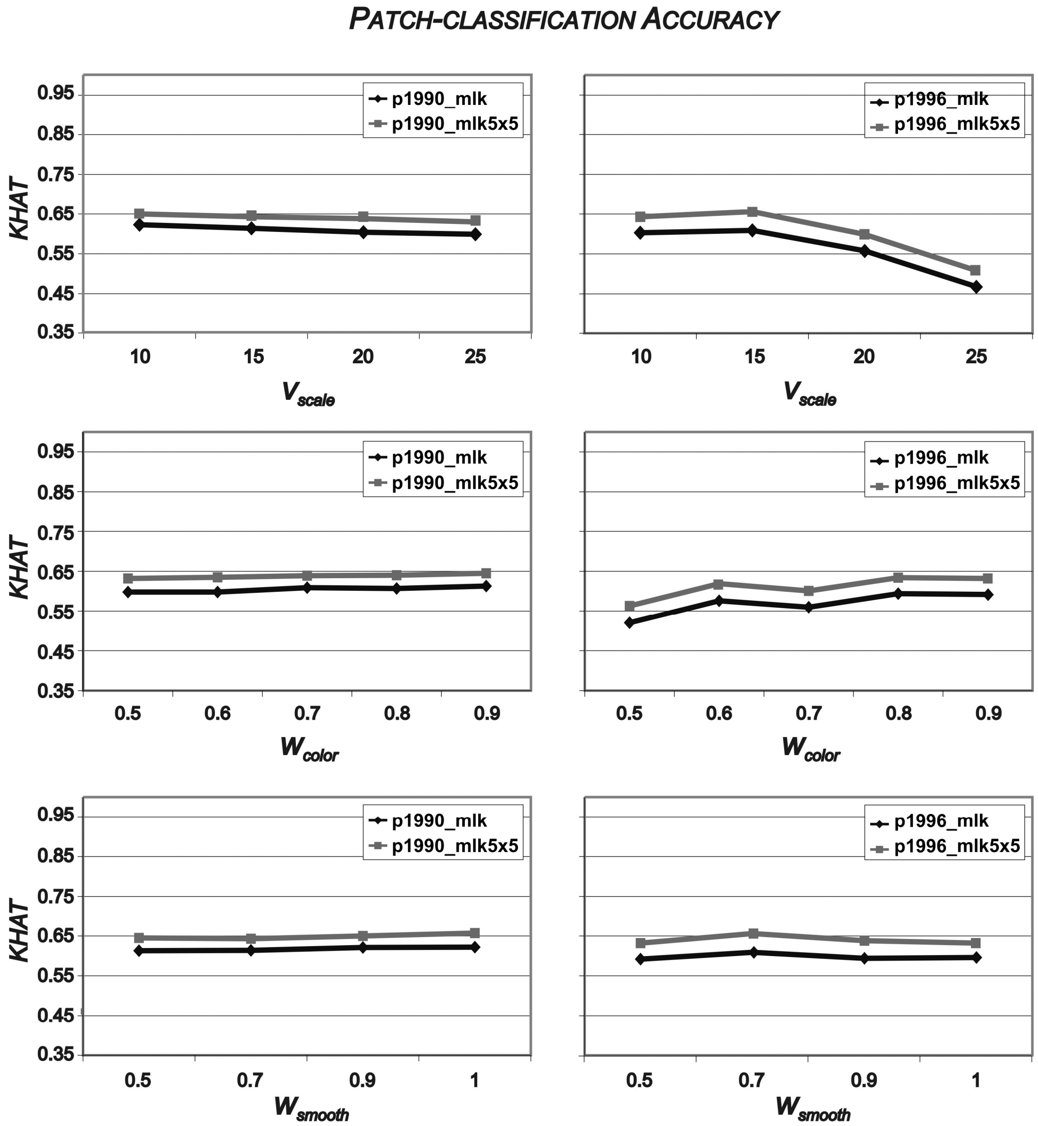


Figure 4.10: Patch-classification accuracy (elementary objects) expressed in KHAT values for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color} and smoothness weighting w_{smooth} in patch-segmentation.

This means that the latter was more sensitive to the chosen settings of the three segmentation parameters than the spatially homogeneous p1990 image. Concerning forest area, logged forest (LF) was less sensitive for the chosen settings of the three segmentation parameters than heavily logged forest (HLF) specifically for the p1996 image. This means that fragmented land cover classes like HLF were more sensitive for the chosen settings of the three segmentation parameters than less-fragmented land cover classes like LF. At per-pixel level with majority filtering, the total cover percentages of the two forest classes (LF and HLF), and thus forest area, slightly increased for both images. Nevertheless, there were no striking *PLAND* differences between the two references regarding all eight tropical land cover classes. As such, majority filtering did not broaden the spatial aggregation level from per-pixel towards elementary.

Table 4.5: Classification results at elementary level versus per-pixel classification results without (mlk) and with majority filtering (mlk5x5) expressed in proportional abundance (i.e., PLAND mean and standard deviation).

Land cover class	p1990 image				p1996 image			
	per-pixel		elementary level		per-pixel		elementary level	
	PLAND mlk	PLAND mlk5x5	PLAND Mean 11 runs	PLAND Sd 11 runs	PLAND mlk	PLAND mlk5x5	PLAND mean 11 runs	PLAND sd 11 runs
LF	23.06	24.39	24.81	0.48	17.92	19.49	20.21	0.88
HLF	28.17	29.78	27.95	0.60	19.99	19.76	21.96	2.67
SH	22.74	20.40	24.91	0.34	23.25	22.71	28.65	3.32
AG	10.92	10.58	14.41	0.25	20.30	21.14	13.64	2.16
GR	11.86	12.21	6.22	0.29	12.52	11.68	13.19	2.31
WA	0.89	0.61	0.39	0.06	2.38	2.09	1.06	0.21
RI	1.14	1.28	1.32	0.04	1.16	1.33	1.22	0.10
CL	1.05	0.57	0.01	0.01	2.30	1.61	0.07	0.04

Comparing elementary level with per-pixel level, thus comparing the two spatial aggregation levels, two interesting findings need to be mentioned. First, both spatial aggregation levels show a decrease in forest cover between 1990 and 1996. However, at elementary level less deforestation occurred (about 10.5%) than at per-pixel level (about 14%). Second, at elementary level, agriculture (AG) faced a subtle decrease between 1990 and 1996 along with a doubling of grass (GR), and a substantial increase of shrub (SH). These results are in sharp contrast with the results at per-pixel level, where agriculture doubled along with almost no change in grass, and only a slight increase of shrub. The latter could be interpreted that forest was almost successfully converted into agriculture. At elementary level, however, forest was not only converted into agriculture, but also into grass. In addition, agricultural areas were abandoned leading to an increase of shrub. Regarding the difficulties of practicing agriculture in peatswamp forests (see Chapter 1, section 1.6), interpreting *PLAND* figures at elementary level results in a change scenario that is more likely than interpreting *PLAND* figures at the per-pixel level.

4.6.4 Variability and arrangement of forest cover

Figure 4.11 shows the Percentage of Landscape *PLAND* of the three land cover classes logged forest (LF), heavily logged forest (HLF), and shrub (SH) for different settings of the three segmentation parameters. The land cover class shrub is added in the figure, because it depicts the problem of practicing agriculture in tropical peatswamp forests. The figure clearly shows that the three segmentation parameters only affected class-composition in the more heterogeneous p1996 image. Specifically, they slightly affected the proportional abundance of heavily logged forest (HLF) and more substantially the proportional abundance of shrub (SH). The proportional abundance of shrub increased for larger break-off values; it showed a peak at a color weighting of w_{color} 0.7 and a peak at a smoothness weighting of w_{smooth} 0.9. These results indicate that certain parameter settings specifically affect land cover classes that are abundant but highly spatially fragmented (i.e., numerous small elementary objects). For the land cover class shrub, the proportional abundance could vary up to 10% when changing segmentation parameters. It is most likely that spectral overlap changed its class-composition (e.g., between shrub and heavily logged forest).

Figure 4.12 shows the Number of Patches *NP* of the three land cover classes logged forest (LF), heavily logged forest (HLF), and shrub (SH) for different settings of the three segmentation parameters. The figure clearly shows that all three segmentation parameters affected class-configuration in both images. Generally, the three land cover classes were less fragmented when increasing the break-off value parameter v_{scale}. A striking exception was the fragmentation of heavily logged forest (HLF) in the p1996 image that stops at a break-off value of v_{scale} 15. Apparently, the standard deviation of heavily logged forest hampered the growing of its elementary objects. As such, heavily logged forest is an extremely heterogeneous land cover class. The three land cover classes were also more fragmented when increasing the color weighting parameter specifically from w_{color} 0.8 to w_{color} 0.9, and when increasing the smoothness weighting parameter w_{smooth}. In some cases, however, a smoothing weighting of w_{smooth} 0.5 and of w_{smooth} 1.0 deviated from this trend in both images.

It seems that the local spatial heterogeneity measure requires fine-tuning of its two criteria (smoothness h_{smooth} and compactness h_{cmpct}). Finally, considering the fact that the break-off value parameter v_{scale} was investigated with a color weighting of w_{color} 0.9 and a smoothness weighting of w_{smooth} 0.7, the results showed that the number of patches was highest in images that were segmented with a small break-off value, a high color weighting and a high smoothness weighting. This means that the larger the number of patches, and thus the number of elementary objects, the lower the possibility of under-segmentation (see 4.6.1).

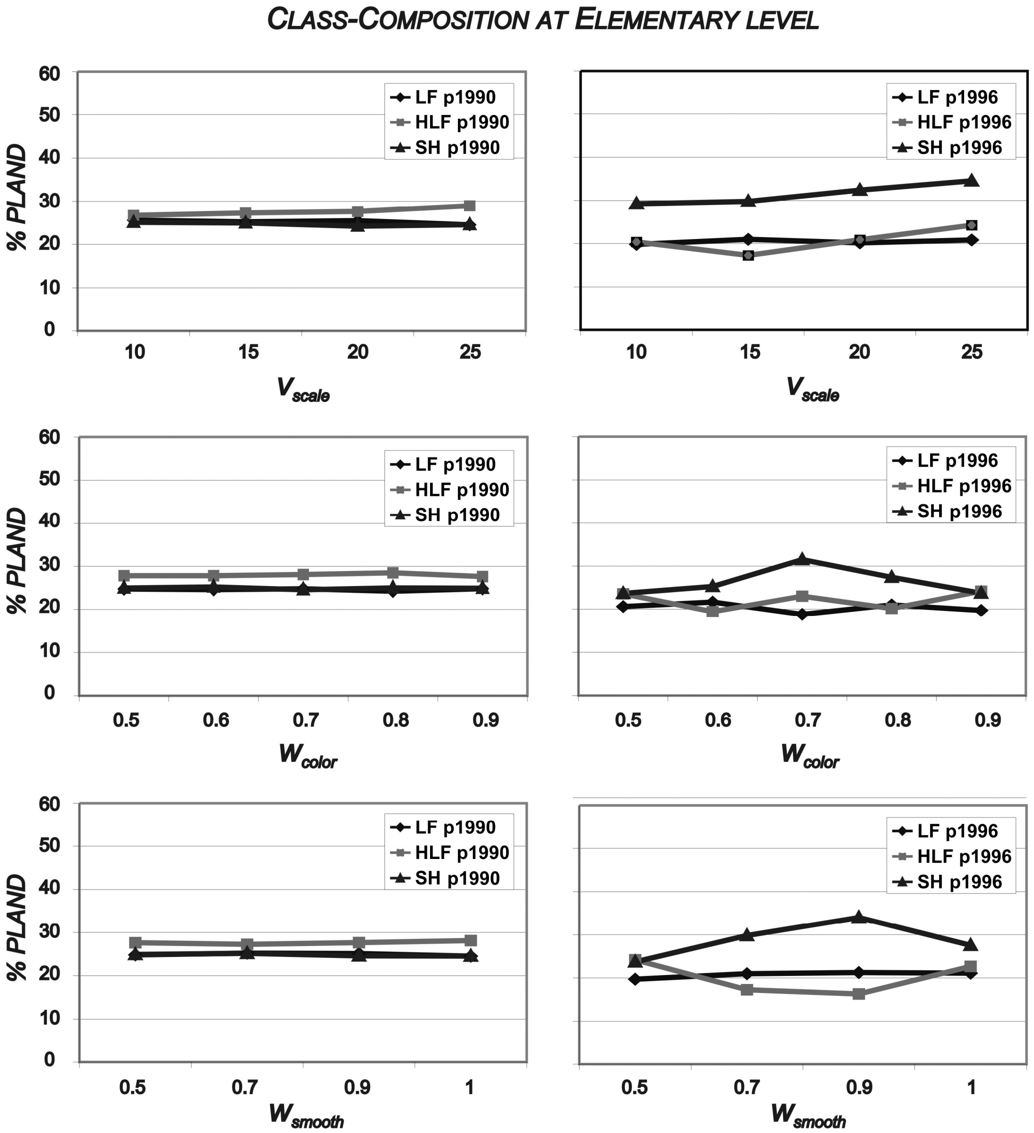


Figure 4.11: Class-composition at elementary level of the land cover classes logged forest (LF), heavily logged forest (HLF), and shrub (SH) expressed in Percentage of Landscape (PLAND) for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color} and smoothness weighting w_{smooth} in patch-segmentation.

4.6.5 Variability and arrangement of forest cover pattern

Figure 4.13 shows the Simpson's Diversity Index *SIDI* and the Landscape Shape Index *LSI* for different settings of the three segmentation parameters including all eight land cover classes (see Table 4.1). The figure clearly shows that the three segmentation parameters did not affect the relative proportions of the eight land cover classes in the p1990 image. For the more heterogeneous p1996 image, however, SIDI decreased at larger break-off values, at a color weighting of w_{color} 0.7, and at a smoothness weighting of w_{smooth} 0.9. Such a decrease means that dominance of one or a few land cover classes increased. Combining SIDI and PLAND, this increasing dominance can be explained. At larger break-off values, the two land cover classes heavily logged forest and shrub showed a PLAND increase, whereas at a color weighting of w_{color} 0.7 and a smoothness weighting of w_{smooth} 0.9, the land cover class shrub increased. This means that the land cover classes have their own specific composition in the landscape having a constant SIDI and a constant PLAND. Nevertheless, for parameter settings having effect on certain classes, like the land cover class shrub, SIDI quantified this compositional change

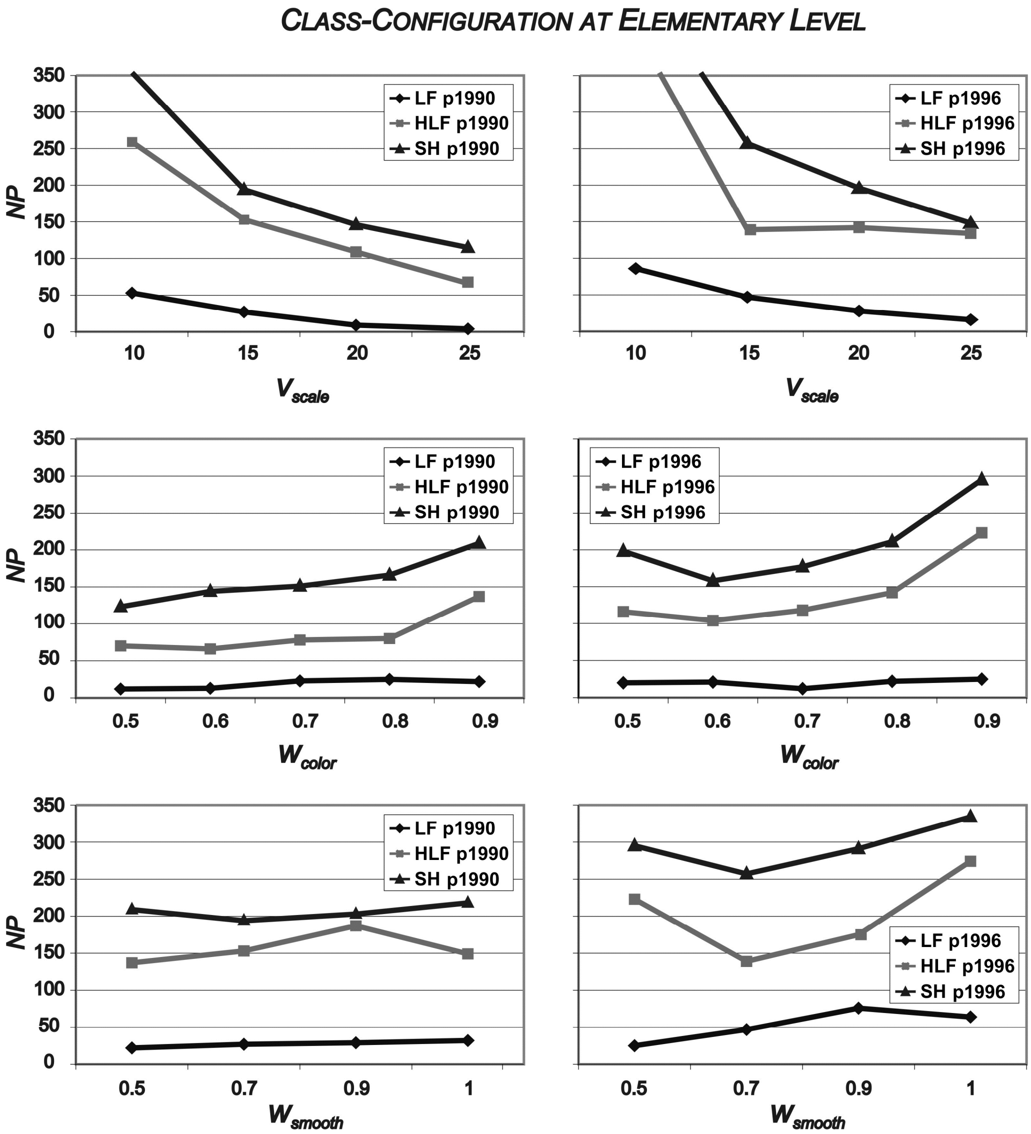


Figure 4.12: Class-configuration at elementary level of the land cover classes logged forest (LF), heavily logged forest (HLF), and shrub (SH) expressed in Number of Patches (NP) for different settings of the three segmentation parameters break-off value v_{scale}, color weighting w_{color} and smoothness weighting w_{smooth} in patch-segmentation.

Finally, figure 4.13 also clearly shows that the three segmentation parameters affected the perimeter-to-area ratio for both images. The *LSI* decreased at larger break-off values, at lower color weightings, and at lower smoothness weightings. At these settings the elementary objects (i.e., the patches) became larger, which resulted in decreased spatial heterogeneity. Obviously, the *LSI* of the more heterogeneous p1996 image was higher than of the p1990 image, but both images showed similar trends when changing the three segmentation parameters.

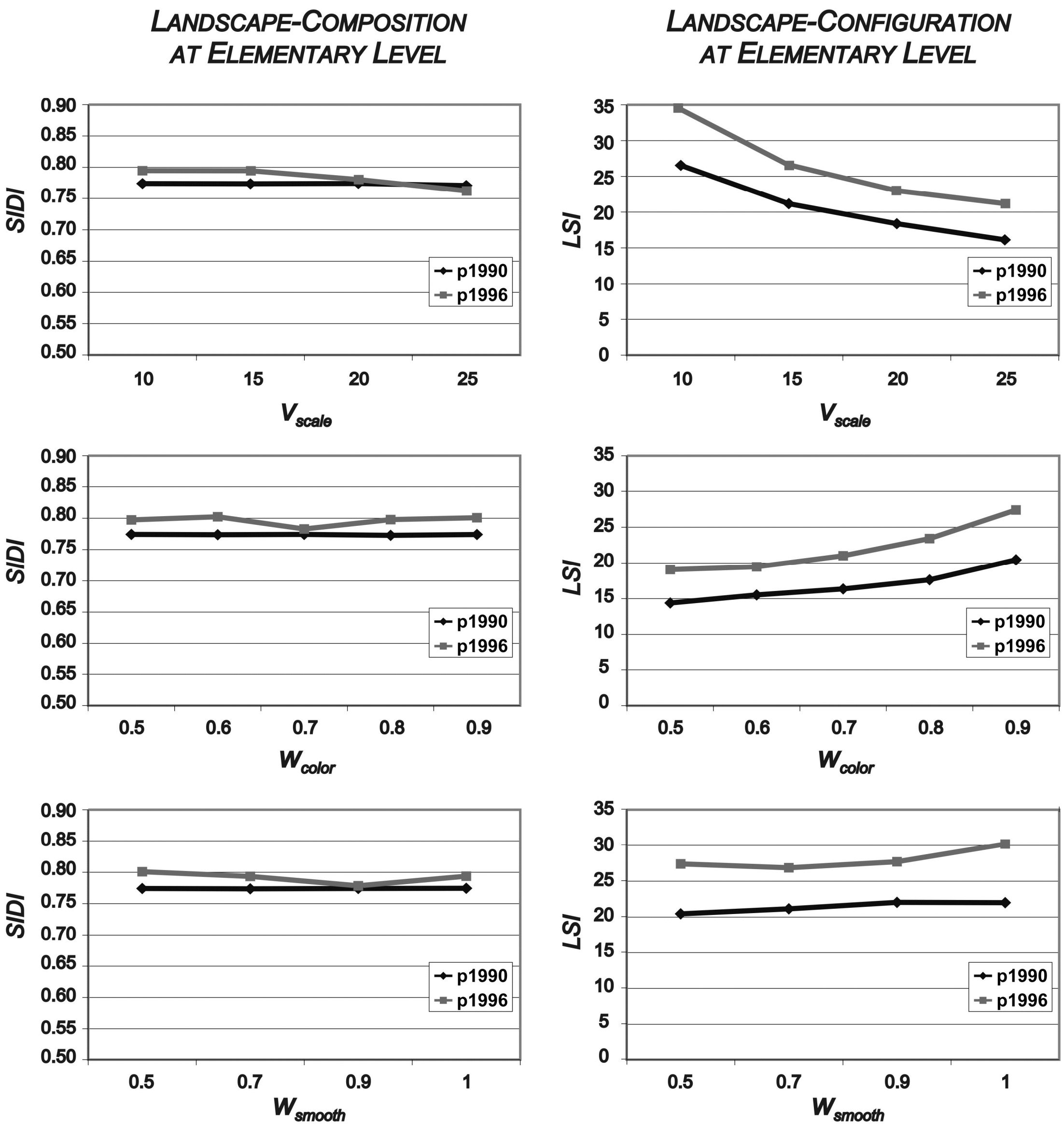


Figure 4.13: Landscape-composition at elementary level expressed in Simpson's Diversity Index (SIDI) and landscape-configuration at elementary level expressed in Landscape Shape index (LSI) for different settings of the three segmentation parameters break-off value vscale, color weighting wcolor and smoothness weighting wsmooth in patch-segmentation.

4.7 Conclusions

4.7.1 Effect of segmentation parameters

From the results of the sensitivity analysis investigating the effect of the three segmentation parameters (i.e., break-off value v_{scale}, color weighting w_{color} and smoothness weighting w_{smooth}) on four output aspects of created elementary objects (i.e., extent of under-segmentation, patch-classification accuracy, forest area, and variability and arrangement of forest cover and forest cover pattern) four conclusions can be drawn:

I

In patch-segmentation, lowest under-segmentation was obtained for both images at small break-off values and high color weightings. Small break-off values v_{scale} led to small elementary objects reducing the possibility of under-segmentation. High color weightings w_{color} led to a large contribution of the local spectral heterogeneity measure, which reduced the spectral variance of elementary objects within a land cover class. The lower this spectral variance, the less under-segmentation. From a patch-classification point of view, under-segmentation would cause larger patch-classification problems in heterogeneous environments because of an increasing spectral variance within a land cover class. However, with similar parameter settings, the more heterogeneous p1996 image showed less under-segmentation than the p1990 image. The higher standard deviations for the p1996 image reduced the growing of elementary objects. The smoothness weighting parameter w_{smooth} did not affect under-segmentation. It only fine-tuned the shape of the elementary objects.

II

No conclusions could be made regarding the parameter settings that provided the highest accuracy in patch-classification, despite application of the standard approach (i.e., using per-pixel classified images to assess classification accuracy of segmented images). It seemed that the *KHAT* metric addressed differences in spatial aggregation levels when applying this standard approach (a per-pixel spatial model assessing a patch spatial model). Therefore, reconsideration of applying the standard approach is needed for spatially heterogeneous environments to assess patch-classification accuracy. These environments require a measure addressing both composition and configuration.

III

The two spatial aggregation levels (i.e., elementary and per-pixel) gave a different forest change scenario when comparing their forest area figures. Regarding the difficulties for practicing agriculture in peatswamp forests, the deduced change scenario at elementary level was more likely than at per-pixel level. This underlines the need to define meaningful spatial objects (see Chapter 3).

IV

The most spatially heterogeneous image and the most spatially fragmented land cover class showed most sensitivity for differences in parameter settings of the segmentation algorithm when comparing the derived forest area figures. This is in line with results obtained from the four landscape pattern metrics. Generally, patch-segmentation settings mainly affected configuration at both the class-level and the landscape-level. Class-fragmentation and landscape-heterogeneity increased for small break-off values v_{scale}, high color weightings w_{color} and high smoothness weightings w_{smooth} for both images of the Pelangkaraya study area. Small v_{scale} values led to small elementary objects. With increasing spatial heterogeneity, elementary objects became even smaller because of their high standard deviations. High w_{color} weightings led to higher importance of standard deviations rather than object geometry. With increasing spatial heterogeneity, standard deviations specifically increased and thus segmented elementary objects became even smaller. High w_{smooth} weightings led to higher importance of object-borders rather than object-compactness. With increasing spatial heterogeneity, compactness kept elementary objects larger and thus they can become smaller with higher smoothness weightings. Finally, patch-segmentation settings hardly affected composition. This means that spatial heterogeneity could be segmented using different parameter settings *without* thematically loosing information. Only very fragmented land cover classes showed compositional differences. This was most likely due to spectral overlap.

4.7.2 Patch-segmentation settings

The selected settings of the three segmentation parameters in patch-segmentation are given in Table 4.6. The resulting elementary objects were used as input to continue the LCM classification at composite level (Chapter 5 and Chapter 6).

Table 4.6: Selected parameter settings in patch-segmentation to create elementary objects as input for the next two chapters (and used in Figure 3.9).

Segmentation parameter	*Symbol*	*Input setting*
Break-off value	v_{scale}	*10*
Color weighting	w_{color}	*0.9*
Smoothness weighting	w_{smooth}	*0.9*

A small break-off value of v_{scale} 10 was chosen to avoid under-segmentation. The latter would cause patch-classification problems (i.e., increasing spectral overlap of several land cover classes). In addition, the KHAT could not provide information on the impact of under-segmentation on patch-classification accuracy (see previous section). A high color weighting was chosen to additionally reduce under-segmentation. Both configuration measures at class-level and at landscape-level showed highest values when color weighting was set at v_{color} 0.9. A high smoothness weighting was chosen to fine-tune the two forest classes logged forest (LF) and heavily logged forest (HLF). Both classes showed a configuration peak at class-level when the smoothness weighting was set at v_{smooth} 0.9 (see NP results). In addition, both images showed a similar composition at this weighting (see SIDI results).

The above mentioned patch-segmentation settings were selected under the assumption that similar settings should be chosen for both images and that the required minimum spatial aggregation level of the elementary objects was related to the required analysis resolution (see Chapter 3, section 3.4). In fact, the selected settings were suitable for the p1990 image assuming that the required minimum spatial aggregation level is met. To really obtain a similar spatial aggregation level for the more heterogeneous p1996 image (compared to the p1990 image), however, both configuration and composition should be the same for both images. The Landscape Shape Index (*LSI*) measures configuration, whereas the Simpson's Diversity Index (*SIDI*) measures composition. These measures indicated that a break-off value of v_{scale} 15 and a color weighting of v_{color} 0.7 for the more heterogeneous p1996 image would give a similar spatial aggregation level. Fortunately, both images showed similar trends applying the investigated parameter settings. As such, this will ease the interpretation of the next two chapters.

References

Abeyta, A. & Franklin, J. (1998). The accuracy of vegetation stand boundaries derived from image segmentation in a desert environment. Photogrammetric Engineering and Remote Sensing 64(1):59-66.

Aronoff, S. (1982a). Classification accuracy: A user approach. Photogrammetric Engineering and Remote Sensing 48(8):1299-1307.

Aronoff, S. (1982b). The map accuracy report: A user's view. Photogrammetric Engineering and Remote Sensing 48(8):1309-1312.

Baatz M. & Schäpe A. (2000). Multiresolution segmentation, an optimisation approach for high quality multi-scale image segmentation. In: Strobl J, Blaschke T., & Griesebner, G. (eds). Angewandte Geographische Informationsverarbeitung XII, Wichmann Verlag, Heidelberg, 12-23.

Baatz, M., Heynen, M., Hofman, P., Lingenfelder, I., Mimler, M., Schäpe, A., Weber, M. & Willhauck, G. (2002). eCognition User Guide 3.0: Object oriented image analysis. Definiens Imaging GmbH, München, Germany.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry & Remote Sensing 58:239-258.

Bishop, Y.M.M., Feinberg, S.E. & Holland, P.W. (1975). Discrete multivariate analysis: Theory and practice. MIT Press, Cambridge, Massachusetts.

Blaschke, T. & Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. Geoinformation Systems 6:12-17.

Bogaert, J., Hecke, P. van, Salvador-van Eysenrode, D. & Impens, I. (2000). Landscape fragmentation assessment using a single measure. Wildlife Society Bulletin 28:875–881.

Burnett, C. & Blaschke, T. (2003). A multi-scale segmentation/object relationship modelling methodology for landscape analysis. Ecological Modelling 168(3):233-249.

Chuvievo, E. (1999). Measuring changes in landscape pattern from satellite images: Short-term effects of fire on spatial diversity. International Journal of Remote Sensing 20:2331-2346.

Cohen, J. (1960). A coefficient of agreement for nominal scales. Educational and Psychological Measurement 20(1):37-40.

Congalton, R.G. & Mead, R.A. (1983). A quantitative method to test for consistency and correctness in photointerpretation. Photogrammetric Engineering and Remote Sensing 49(1):69-74.

Crosetto, M., Tarantola, S. & Saltelli, A. (2000). Sensitivity and uncertainty analysis in spatial modelling based on GIS. Agriculture, Ecosystems & Environment 81(1):71-79.

Dorren, L.K.A., Maier, B. & Seijmonsbergen, A.C. (2003). Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. Forest Ecology and Management 183:31-46.

Droesen, W.J. (1999). Spatial modelling and monitoring of natural landscapes with cases in the Amsterdam Waterworks Dunes. PhD Thesis Wageningen Agricultural University, Ponsen & Looijen, Wageningen.

Easton, V.J. & McColl, J.H. (1997). Statistics glossary (version 1.1). Centre for Applied Statistics, Web version revised and updated, September 1997 by Stuart G. Young. At http://www.cas.lancs.ac.uk/glossary_v1.1/main.html, accessed October 14, 2003.

FAO (2001). The Global Forest Resources Assessment 2000 (FRA 2000), FAO Forestry Paper 140. At http://www.fao.org/forestry/fo/fra/main/index.jsp, accessed November 5, 2003.

Fisher, P.F. & Pathirana, S. (1990). The evaluation of fuzzy membership of land cover classes in the suburban zone. Remote Sensing of Environment 34:121-132.

Foody, G.M. (1992). On the compensation for change agreement in image classification accuracy assessment. Photogrammetric Engineering and Remote Sensing 58(10):1459-1460.

Foody, G.M. (1994). Ordinal-level classification of sub-pixel tropical forest cover. Photogrammetric Engineering and Remote Sensing 60(1):61-65.

Foody, G.M. (1996). Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. International Journal of Remote Sensing 17(7):1317-1340.

Forman, R. T. T., & Godron, M. (1986). Landscape ecology. Wiley, New York.

Forman, R.T.T. (1995). Land mosaics: The ecology of landscapes and regions. Cambridge University Press, Cambridge.

Gurney, C.M. & Townshend, J.R.G. (1983). The use of contectual information in the classification of remotely sensed data. Photogrammetric Engineering and Remote Sensing 49(1):55-64.

Gustafson, E.J. (1998). Quantifying landscape spatial pattern: What is the state of the art. Ecosystems 1:143-156.

Gustafson, E.J., & Parker, G.R. (1992). Relationships between landcover proportion and indices of landscape spatial pattern. Landscape Ecology 7:101-110

Hay, G., Blaschke, T., Marceau, D. & Bouchard, A. (2003). A comparison of three image-object methods for the multiscale analysis of landscape structure. ISPRS Journal of Photogrammetry & Remote Sensing 57:327-345.

Hudson, W.D. & Ramm, C.W. (1987). Correct formulation of the kappa coefficient of agreement. Photogrammetric Engineering and Remote Sensing 53(4):421-422.

Jaeger, J.A.G. 2000. Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. Landscape Ecol. 15:115-130.

Jensen, J.R., Cowen, D., Narumalani, S. & Halls, J. (1997). Principles of change detection using digital remote sensor data. In: J.L. Star, J.E. Estes, K.C. McGwire (Eds), Integration of Geographic Information Systems and Remote Sensing, Cambridge University Press, Cambridge, pp. 37-54.

JRC (2005). A forum on sensitivity analysis. European Commission, Institute for systems, informatics and safety (ISIS) and Joint Research Centre (JRC). At http://sensitivity-analysis.jrc.cec.eu.int/default2.asp?page=news, accessed March 23, 2005.

Kenk, E., Sondheim, M. & Yee, B. (1988). Methods for improving accuracy of thematic mapper ground cover classifications. Canedian Journal of Remote Sensing 14(1):17-31.

Kettig, R.L. & Landgrebe, D.A. (1976). Classification of multispectral image data by extraction and classification of homogeneous objects. IEEE Transactions on Geoscience and Remote Sensing, 1:19-26.

Key. J.R., Maslanik, J.A. & Barry, R.G. (1989). Cloud classification from satellite data using a fuzzy sets algorithm: A polar example. International Journal of Remote Sensing 10(12):1823-1842.

Lee, S.U., Chung, S.Y., & Park R.H. (1990). A comparative performance study of several global thresholding techniques for segmentation. Computer Vision Graphics and Image Processing 52:171-190.

Li, H., & Reynolds, J.F. (1993). A new contagion index to quantify spatial patterns of landscapes. Landscape Ecology 8:155-162.

Luque, S., Pekkarinen, A. & Tomppo, E. (2002). Improved methods for biodiversity assessment: Comparison of spatial landscape metrics by pixel and image segment based approaches. ForestSAT Symposium, Heriot Watt University, Edinburgh, August 5-9, 2002,10 pp.

McGarigal, K., Cushman, S.A., Neel, M.C. & Ene, E. (2002), FRAGSTATS: Spatial pattern analysis program for categorical maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. At www.umass.edu/landeco/research/fragstats/fragstats.html, accessed April16, 2004.

McGarigal, K., & McComb, W.C. (1995). Relationships between landscape structure and breeding birds in the Oregon Coast Range. Ecological Monographs 65:235-260.

McGarigal, K., & Marks, B.J. (1995). FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. General Techinical Report PNW-GTR-351, USDA Forest Service, Pacific Northwest Research Station, Portland.

Molenaar, M. & Cheng, T. (2000). Fuzzy spatial objects and their dynamics. ISPRS Journal of Photogrammetry and Remote Sensing 55(3):164-175.

Musick, H.B. & Grover, H.D. (1991). Image textural measures as indices of landscape pattern. In Turner, M.G. & Gardner, R.H. (Eds), Quantitative methods in landscape ecology, Springer-Verlag, New York, 289-307.

Neubert, M. & Meinel, G. (2003): Evaluation of segmentation programs for high resolution remote sensing applications. In: Schroeder, M., Jacobsen, K. & Heipke, C. (Eds), Procedings of the Joint ISPRS/EARSeL Workshop "High Resolution Mapping from Space 2003", Hannover, Germany, October 6-8, 2003, CD-ROM, 8 S.

Obbink, M.H. (1992). PODINS Ground Survey I and II. National Forest Inventory UTF/INS/066/INS, Back to Office Report (BTOR6). Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Obbink, M.H. (1993). Manual on operational digital image analysis for land cover/land use mapping. National Forest Inventory UTF/INS/066/INS, Working Document No. 6. Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H. & Graham, R.L. (1988). Indices of landscape pattern. Landscape Ecology 1:153-162.

Palubinskas, G., Lucas, R.M., Foody, G.M. & Curran, P.J. (1995). An evaluation of fuzzy and texture-based classification approaches for mapping regenerating tropical forest classes from Landsat-TM data. International Journal of Remote Sensing16(4):747-759.

Richards, J.A. (1986). Remote sensing digital image analysis: An introduction. Springer-Verlag, Berlin.

Ritters, K.H., O'Neill, R.V., Hunsaker, C.T., Wickham, J.D., Yankee, D.H., Timmins, S.P.. Jones, K.B., & Jackson, B.L. (1995). A factor analysis of landscape pattern and structure metrics. Landscape Ecology 10:23-40.

Ryherd, S. & Woodcock, C. (1996). Combining spectral and texture data in the segmentation of remotely sensed images. Photogrammetric Engineering and Remote Sensing 62:181-194.

Sande, C.J. van der, Jong, S.M. de & Roo, A.P.J. de (2003). A segmentation and classification approach of IKONOS-2 imagery for land cover mapping to assist flood risk and flood damage assessment. International Journal of Applied Earth Observation and Geoinformation 4:217–229.

Simpson, E.H. (1949). Measurement of diversity. Nature 163:688.

Stein. A. & Beurs, K. de (2004). Complexity measures to quantify semantic accuracy in segmented Landsat images. International Journal of Remote Sensing 26:2937-2951.

Story, M. & Congalton, R.G. (1986). Accuracy assessment: A user’s perpective. Photogrammetric Engineering and Remote Sensing 52(3):397-399.

Stuckens, J, Coppin P.R. & Bauer, M.E. (2000). Integrating contextual information with per-pixel classification for improved land cover classification. Remote Sensing of Environment 71(3):282-296.

Tilton, J.C. (1998). Image segmentation by region growing and spectral clustering with a natural convergence criterion. Proceedings of the 1998 International Geoscience Remote Sensing Symposium (IGARSS’98), 6–10 July 1998, Seattle, WA, 1766–1768.

Tischendorf, L. (2001). Can landscape indexes predict ecological processes consistently? Landscape Ecology 15:235-254.

Tortura, R. (1978). A note on sample size estimation for multinominal populations. The American Statistician 32(3):100-102.

Turner, M.G. (1990). Spatial and temporal analysis of landscape patterns. Landscape Ecology 4:21-30.

Turner, M.G. & Gardner, R.H. (Eds)(1991). Quantitative methods in landscape ecology. Springer-Verlag, New York.

Urban, D.L., O'Neill, R.V. & Shugart Jr, H.H. (1987). Landscape ecology: A hierarchical perspective can help scientist understand spatial patterns. BioScience 37:119-127.

Wang, F. (1990a). Fuzzy supervised classification of remote sensing images. IEEE Transactions on Geoscience and Remote Sensing 28(2):194-201.

Wang, F. (1990b). Improving remote sensing image analysis through fuzzy information representation. Photogrammetric Engineering and Remote Sensing 56(8):1163-1169.

Wang, L., Sousa, W.P. & Gong, P. (2004). Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. International Journal of Remote Sensing 25(24):5655-5668.

Zadeh, L.A. (1965). Fuzzy sets. Information and Control 8:338-353.

Zhang, Y.J. (1996). A survey on evaluation methods for image segmentation. Pattern Recognition 29(8):1335-1346.

Zhang, Y.J. & Gerbrands, J.J. (1994). Objective and quantitative segmentation evaluation and comparison. Signal Processing 39(1-2):43-54.

CHAPTER 5

PATCH-MOSAIC CLASSIFICATION

"Logica brengt je van A naar B. Verbeelding brengt je overal"

"Logic will get you from A to B. Imagination will take you everywhere"

Albert Einstein (1879-1955)

5.1 Introduction

After creating elementary objects (Chapter 4), composite objects are created in LCM classification based on functional generalization according to the Aggregate-Mosaic Theory (Chapter 3). This chapter describes the application of this theory for creating composite objects with specific focus on the effect of upscaling thresholds in patch-mosaic classification (Figure 5.1). Patch-mosaic classification defines the thematic content of the composite objects. Composite objects are groups of neighboring elementary objects that can contain different land cover classes, but represent together the same single land cover mosaic (LCM) class (i.e., patch-mosaics). Similar to creating elementary objects, only the combination of thematic and geometric information can define the composite objects. This requires two main processes that are classification and segmentation. At composite level, these two main processes are called *patch-mosaic classification* and *patch-mosaic segmentation*. Patch-mosaic classification (thematic abstraction) precedes patch-mosaic segmentation (geometric abstraction), because partonomy is the driving factor in functional generalization. It classifies the different land cover classes at elementary level (i.e., patches) to the same single LCM class at composite level (i.e., thematic upscaling). Patch-mosaic segmentation defines the geometric extent of the composite objects. It groups at composite level the neighboring elementary objects having a similar LCM class (i.e., patch-mosaic).

This chapter mainly focuses on patch-mosaic classification, leaving Chapter 6 for discussing patch-mosaic segmentation. This chapter, therefore, specifically studies two upscaling parameters by means of a sensitivity analysis. These parameters are the *minimum-area (MA)* quantifying the LCM parameter 'area', and the *shared-border* (*BN*) quantifying the LCM parameter 'mixture' (see Chapter 3). The sensitivity analysis studies the effect these two parameters have on three output aspects of created composite objects (i.e., LCM classification accuracy at composite level, forest area, and variability and arrangement of forest cover and forest cover pattern). The results of the sensitivity analysis are used to evaluate their significance on creating composite objects and to define which upscaling thresholds are used as input to study the patch-mosaic segmentation.

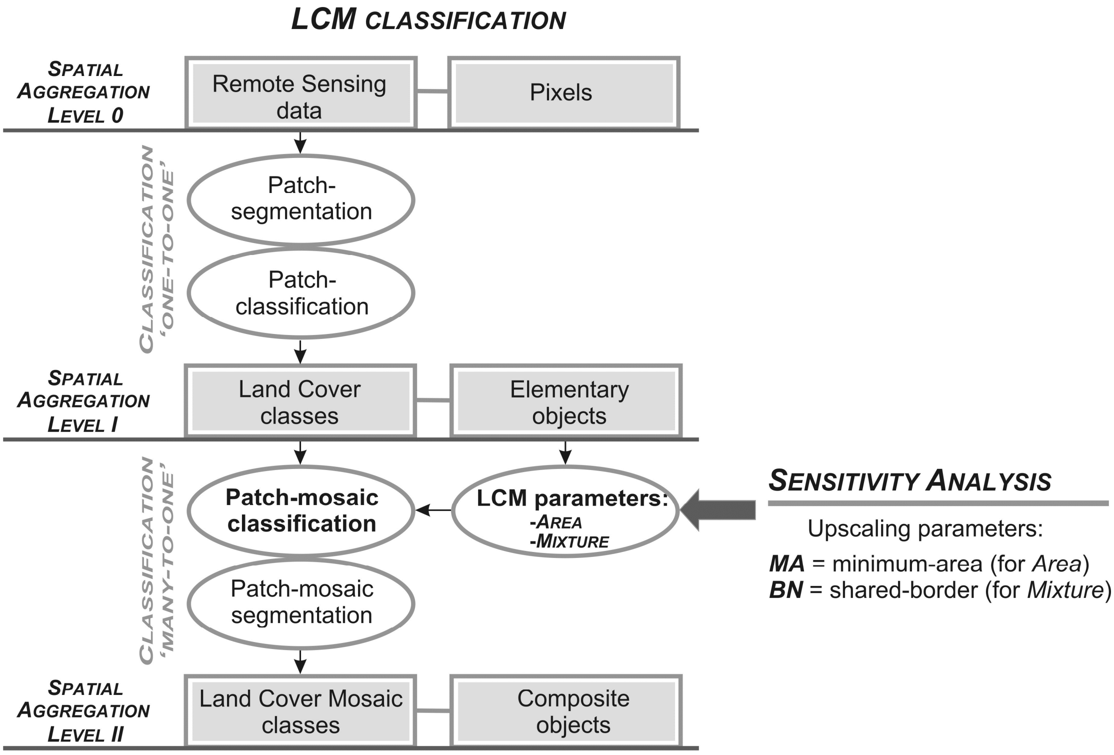


Figure 5.1: A sensitivity analysis on patch-mosaic classification in LCM classification for thematically upscaling elementary objects into composite objects.

Creating composite objects requires elementary objects. This chapter uses the elementary objects that have come out as most useful during the sensitivity analysis in Chapter 4 (section 4.7.2 for details on the patch-segmentation settings, and section 4.3 for details on the patch-classification method). Details and rationale of patch-mosaic classification as well as the LCM classes used at the composite level are described in section 5.2. Briefly, the used segmentation process in patch-mosaic segmentation is presented in section 5.3 (Chapter 6 presents four different segmentation processes that can be applied in patch-mosaic segmentation). Next, section 5.4 provides details and rationale of the used upscaling thresholds and the classification scheme, both used in the sensitivity analysis. Five evaluation metrics have been used to compare the LCM classification results at composite level. They cover the standard remote sensing accuracy metric *KHAT* and four landscape pattern metrics as applied in landscape ecology. The details and rationale of these five evaluation metrics have been described in Chapter 4. Regarding the findings of Chapter 4, a new reference was selected to calculate KHAT. This reference is described in section 5.5. After that, section 5.6 presents and discusses the results of the sensitivity analysis. Finally, in section 5.7 conclusions are drawn related to the effect of the two upscaling parameters

(*MA* and *BN*) in LCM classification and their selected threshold values to be used in Chapter 6.

5.2 Patch-mosaic classification method

Patch-mosaic classification quantitatively identifies the LCM class for each elementary object through estimating its membership to predefined spatial aggregation classes. This process requires at least two upscaling parameters in order to quantify the two LCM parameters *mixture* and *area* for which the decision rules are defined in the spatial aggregation classes (Chapter 3, section 3.3). This thesis selected two upscaling parameters, which are *minimum-area MA* and *shared-border BN*. Minimum-area *MA* quantifies the LCM parameter *area* and estimates the spatial size of each elementary object. Shared-border *BN* quantifies the LCM parameter *mixture* and estimates the relative border of an elementary object to the LCM classes of its neighboring elementary objects. Consequently, patch-mosaic classification operates both at elementary level to estimate minimum-area *MA* and at composite level to estimate shared-border *BN*. Such a truly multi-scaled process (Chapter 2, sections 2.2.4 and 2.3.3) requires two hierarchy types: a classification hierarchy to relate thematic classes within each aggregation level, and an aggregation hierarchy to relate both aggregation levels (Chapter 2, section 2.3.1). After estimating both minimum-area *MA* and shared-border *BN*, the elementary objects are classified into the LCM class that showed the highest membership. Summarized, the patch-mosaic classification consists of six steps:

1. Compromise on spatial aggregation classes with the end-user and define the necessary *LCM classes* (section 5.2.1).
2. Select at least two *upscaling parameters* to quantify the two LCM parameters *mixture* and *area*. This thesis selected minimum-area *MA* and shared-border *BN* (section 5.2.2).
3. Define *threshold values* for the upscaling parameters based on the decision rules on *mixture* and *area* as defined for the compromised spatial aggregation classes (section 5.2.3).
4. Define a classification hierarchy at elementary level to enable thematic *specialization* (Figure 5.2, arrow A) and estimate *area* for each elementary

object, which is the minimum-area *MA* of an elementary object per land cover class (section 5.2.4).

5. Define an aggregation hierarchy to enable *spatial generalization* (Figure 5.2, arrow B) and estimate *mixture* for each elementary object (Figure 5.2 arrow C&D), which is the shared-border *BN* of an elementary object with the LCM classes of neighboring elementary objects (section 5.2.5).
6. Estimate for each elementary object the LCM class having the highest *membership* based on step 4 and 5 and continue with patch-mosaic segmentation (Chapter 6).

For iterative classifications like the patch-mosaic classification (see arrow B, C & D in Figure 5.2), the classification process can become very unstable, because the classification result of each neighboring elementary object affects the classification result of other elementary objects. Therefore, simulated annealing was used to handle such classification instabilities. Simulated annealing is an optimization algorithm, originating from statistical physics. It was developed independently by Kirkpatric *et al.* (1983) and by Cerny (1985). Other names for the same algorithm include Monte Carlo annealing, probabilistic hill climbing, statistical cooling and stochastic relaxation (Aarts & Korst, 1989; Groenigen & Stein, 1998). The optimization process involves simulating the evolution of a physical system as it cools and anneals into a state of minimum energy (Park et al., 2004). A major property of simulated annealing is its insensitivity to local extremes. Therefore, it is a useful method to solve classification problems where an anticipated global minimum is hidden in many local minima (Aarts & Korst, 1989). Patch-mosaic classification uses simulated annealing to randomly change the computed membership of elementary objects to a LCM class, taking into account the membership values of all LCM classes (details are presented in Appendix 5.1).

5.2.1 LCM classes

According to the Aggregate-Mosaic Theory, defining LCM classes means defining spatial aggregation classes that are linked to end-users. For demonstration purposes, this thesis selected the forestry minister of a country as end-user. This means that forest cover information must be described at the aggregation level of forest types (Chapter 3, section 3.3).

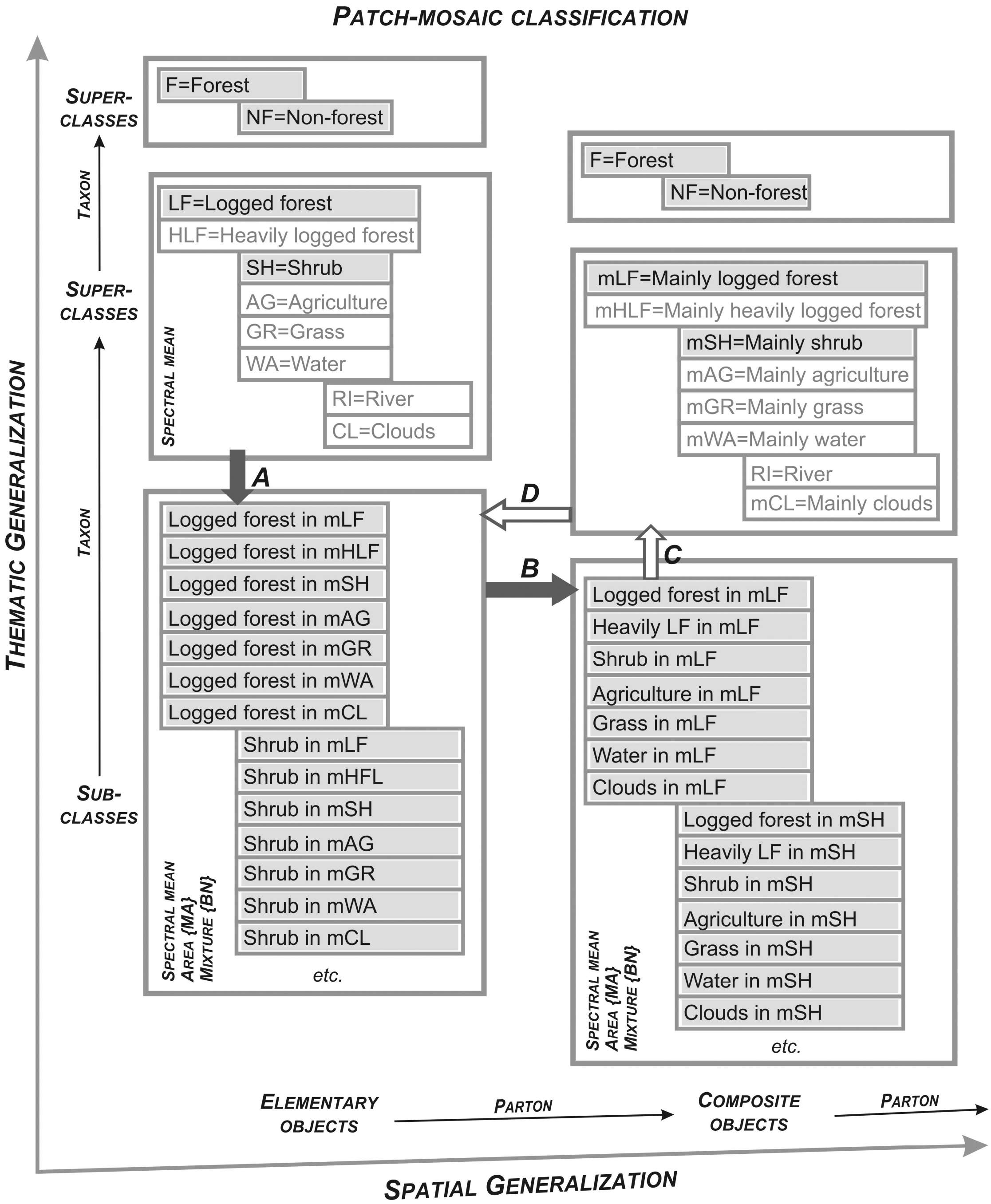


Figure 5.2: Thematic specialization at elementary level (A) and spatial generalization from elementary level to composite level (B requiring C & D) in patch-mosaic classification.

The most generic spatial aggregation class to describe a forest type is a LCM class consisting of one dominant land cover class with any combination of other minor land cover classes. Such LCM classes are often used in cartographic map representations to eliminate spatial objects that are smaller than the minimum mapping unit (Yee et al., 1986; Kenk et al., 1988). These classes are based on their geometric size only because of a visualization problem (Chapter 2, section 2.3.1). The LCM classes used in the Aggregate-Mosaic Theory are based on functional relationships because of a spatial modeling problem. Although this difference in problem setting, selecting a LCM class being a generic spatial aggregation class has the advantage that it can be easily examined. This is useful for demonstrating and assessing the use of a new approach like patch-mosaic classification. Therefore, land cover classes having an *area* smaller than a certain threshold value at elementary level should become part of a larger (generic) LCM class at composite level (whereas *mixture* defines which LCM class). Having selected seven areal land cover classes at the elementary level and one linear land cover class (i.e., river) will therefore result in seven generic (areal) LCM classes at the composite level and one linear LCM class. The seven generic (areal) LCM classes are called *mainly logged forest, mainly heavily logged forest, mainly shrub, mainly grass, mainly agriculture, mainly water, and mainly clouds*. The linear LCM class 'river' remains 'river' at composite level, because not all thematic classes of interest at composite level are necessarily spatially heterogeneous. Details of the eight LCM classes are given in Table 5.1.

Table 5.1: Description of LCM classes at composite level.

No.	*Land cover mosaic (LCM) class*	*Abbre-viation*	*Description*
1	*Mainly logged forest*	*mLF*	*Area covered with logged forest including small areas that are covered with any other land cover type or clouds.*
2	*Mainly Heavily logged forest*	*mHLF*	*Area covered with heavily logged forest including small areas that are covered with any other land cover type or clouds.*
3	*Mainly shrub*	*mSH*	*Area covered with shrub including small areas that are covered with any other land cover type or clouds.*
4	*Mainly agriculture*	*mAG*	*Area covered with agriculture including small areas that are covered with any other land cover type or clouds.*
5	*Mainly grass*	*mGR*	*Area covered with grass including small areas that are covered with any other land cover type or clouds.*
6	*Mainly water*	*mWA*	*Area covered with water including small areas that are covered with any other land cover type or clouds.*
7	*Mainly clouds*	*mCL*	*Area covered with clouds including small areas that are covered with any other land cover type.*
8	*River*	*RI*	*Area covered with only the land cover class river.*

The term 'mainly' in the LCM class name refers to predominance of one land cover type. Although clouds typically cannot be considered as a land cover type, during patch-mosaic classification they are considered a LCM class, i.e., mainly clouds. The advantage of such a concept is that small clouds will 'disappear' as it will be part of a LCM class. Only clouds that are larger than the threshold for upscaling parameter minimum-area *MA* will remain (under the condition that it meets the upscaling parameter shared-border *BN*). Handling cloud cover is a major issue in optical remote sensing (Addink & Stein, 1999; Carvalho, 2001). Patch-mosaic classification provides an appealing solution to handle small clouds.

5.2.2 Upscaling parameters

This thesis selected only one upscaling parameter for each LCM parameter. Increasing the number of upscaling parameters is only necessary if a selected parameter would show limited applicability. The two selected upscaling parameters in patch-mosaic classification are:

- Minimum-area *MA* to quantify the LCM parameter *area*.
- Shared-border *BN* to quantify the LCM parameter *mixture*.

Minimum-area (MA) estimates the spatial size of the elementary objects (i.e., patch-size) in patch-mosaic classification. It is defined as the true area covered by one pixel times the number of pixels forming an elementary object with [0; scene size] as value range (Baatz et al., 2000). If the area of an elementary object is smaller than a selected threshold value, then this elementary object is classified to the LCM class surrounding this elementary object (under the condition that it meets the shared-border criteria). If the area is larger than the threshold value, then this elementary object itself becomes a LCM class and is classified accordingly. For example, an elementary object that contains the land cover class 'shrub' will be classified into the LCM class 'mainly logged forest' if its area is smaller than the threshold value for minimum-area *MA* and it is surrounded by the LCM class 'mainly logged forest'. However, this shrub object will be classified into the LCM class 'mainly shrub' if its area is larger than the threshold value for minimum-area *MA*.

Shared-border (BN) estimates the relative shared border of elementary objects to neighboring elementary objects containing LCM classes in patch-mosaic classification. It is defined as the ratio of 'the border of an elementary object shared with a defined neighboring elementary object' to 'the total border length of that elementary object with [0;1] as value range' (Baatz et al., 2000). If the relative shared border of an elementary object to neighboring elementary objects containing LCM classes is larger than a selected threshold value, then this elementary object is classified into the LCM class sharing the largest relative border (under the condition that it meets the minimum-area criteria). If the relative border to any LCM class is smaller than the threshold value, then this elementary object itself becomes a LCM class and is classified accordingly. For example, an elementary object that contains the land cover class 'shrub' shares a border with three LCM classes like 'mainly logged forest' (20%), 'mainly shrub' (20%), and 'mainly agriculture' (60%). This shrub object will be classified into the LCM class 'mainly agriculture' if its relative shared border is larger than the threshold value for shared-border *BN* (under the condition that it meets the threshold value for minimum-area *MA*). However, this shrub object will be classified into 'mainly shrub' if the largest relative shared-border is smaller than the threshold value for shared-border *BN*.

5.2.3 Fuzzy threshold values

For natural phenomena like heterogeneous vegetation, exact definitions for the two threshold values on minimum-area *(MA)* and shared-border *(BN)* are hardly possible. In addition, the description of each LCM class is typically based on qualitative criteria like 'area', and 'small areas'. These qualitative criteria are generally used in thematic class descriptions; they do not make any reference to exact boundary definitions. As such, using fuzzy logic is more appealing than using Boolean logic. The advantage of fuzzy logic is that it can formalize reasoning with inexact boundary information; it allows partial membership of several *fuzzy sets*. A fuzzy set is a set of which the boundaries are characterized by transition zones that are not necessarily crisp or abrupt like in Boolean logic (Zadeh, 1965). The latter excludes the possibility of a geographical entity simultaneously belonging to other classes. With fuzzy logic, a geographical entity is no longer described by the probability of belonging to one sharply defined class, but by the possibility of belonging to overlapping classes, for which the boundaries are not sharply defined (Hootsman, 1996). Therefore, this thesis used fuzzy sets to define the threshold values for the two upscaling parameters.

Membership functions describe the transition zones of the boundaries of the fuzzy sets. In the example of patch-mosaic classification, membership functions define the relation between the threshold values of the two upscaling parameters and the membership value μ $(0 \leq \mu \leq 1)$ to express parameter fulfillment. These membership values, or possibility values, describe the degree of membership on a continuous range $[0,1]$, where 0 indicates that the object does not belong to any LCM class, and 1

that it definitely belongs to a specific LCM class (see also Chapter 4, section 4.2.2). The range of threshold values with possibility values between 0 and 1 is the transition zone of a membership function. Methods for constructing membership functions can be data-driven or expert-driven. The latter are also known as semantic import models (Burrough & Mc Donnell, 1998). In this chapter, membership functions are constructed on the basis of expert-knowledge to include the end-user domain. Expert-driven membership functions require specification of three characteristics (see also Figure 5.3). These three characteristics are called:

- Function parameters
- Symmetry types
- Function conditions

Function parameters specify membership functions, which consist of three function parameters; they are called cross-over points, dispersion values, and mathematical functions. Cross-over points are the boundary values of fuzzy sets that correspond to a possibility value of 0.5 (member). They equal the conventional Boolean boundary value. Cross-over points are indicated as *a1* or *a2* in Figure 5.3. Dispersion values characterize the range between a cross-over point and the nearest boundary value of fuzzy sets that receives the absolute member value 1 (full-member). Small dispersion values indicate steeper slopes of the membership function, and thus less fuzzy transition between 0 (non-member) and 1 (full-member). For dispersion values equal to 0 the membership functions are defined as crisp, thus conventional Boolean logical rules are applicable. Dispersion values are indicated as *d1* or *d2* in Figure 5.3. Mathematical functions describe the transition zones of membership functions. Although many functions exist, a function can only be implemented if it is relevant for the application domain. Hootsman (1996) distinguished three types of mathematical functions in a study on soil and land evaluation: linear (e.g., Bortolan & Degani, 1985), curved (e.g., Dombi, 1990), and S-shaped (e.g., Zadeh, 1965, 1971; Zimmerman & Zysno, 1985; Svarovski, 1987). He concluded that a S-shaped function best represents a natural continuous behavior, because of its lack of breakpoints. In addition, the cross-over point in S-shaped functions is also the inflection point between a convex and a concave part causing the largest change in possibility values near the cross-over point. As the cross-over point equals the conventional Boolean boundary value, changes in possibility values should be detected in any case (Hootsman, 1996). Therefore, in this thesis, the *S-shaped* mathematical function was selected to describe the transition zones of the boundaries of the two fuzzy sets (i.e., the upscaling parameters minimum-area *MA* and shared-border *BN).*

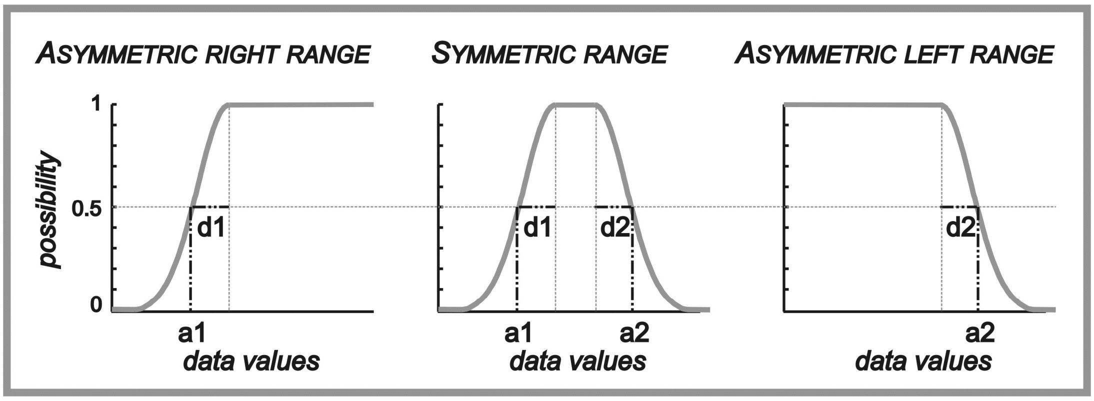


Figure 5.3: Graphic example of membership functions indicating cross-over point (a1, a2) and dispersion value (d1,d2) for a S-shaped transition zone (adapted from Hootsman, 1996).

Symmetry types specify the behavior of membership functions. For continuously scaled data, membership functions consist of three symmetry types that are asymmetric right range, asymmetric left range, and symmetrical range (Hootsman, 1996). The asymmetric left range with cross-over point *a2* and dispersion value *d2* suits the upscaling parameter minimum-area *MA,* because this upscaling parameter is used to quantify if the area of an elementary object *is smaller* than a selected cross-over point. The general notation to describe this symmetry type is:

$$m(x) = \begin{cases} 0 \text{ for } x > a2 + d2 \\ f(x) \text{ for } a2\text{-}d2 \le x \le a2 + d2 \\ 1 \text{ for } x < a2 - d2 \end{cases} \qquad (5.1)$$

The asymmetric right range with cross-over point *a1* and dispersion *d1* suits the upscaling parameter shared-border *BN*, because this upscaling parameter is used to estimate whether the largest relative shared-border of an elementary object to neighboring LCM classes *is larger* than a selected cross-over point. The general notation to describe this symmetry type is:

$$m(x) = \begin{cases} 0 \text{ for } x < a1 - d1 \\ g(x) \text{ for } a1\text{-}d1 \leq x \leq a1 + d1 \\ 1 \text{ for } x > a1 + d1 \end{cases} \tag{5.2}$$

Function conditions specify the syntax of membership functions to represent the classification condition. Function conditions can be single, combined or nested. A single function expresses that the membership value (or possibility value) of an elementary object to a LCM class equals the membership value of the upscaling parameter for that elementary object, given the fuzzy set of that upscaling parameter as described in the membership function. Formally defined:

$$\mu_{\text{LCM class}} (\text{elementary object}) = \mu_{\text{fuzzy set}} (\text{upscaling parameter (elementary object)}) \tag{5.3}$$

Combined function conditions are connected by logical operators like "and", "or", or "not". A combined function expresses that the membership value (or possibility value) of an elementary object to a LCM class equals the logical operation of the membership value of upscaling parameter *MA* for that elementary object (given the fuzzy set of the upscaling parameter *MA* as described in the membership function), and the membership value of upscaling parameter *BN* for that elementary object (given the fuzzy set of the upscaling parameter *BN* as described in the membership function). Formally defined:

$$\mu_{\text{LCM class}} (\text{elementary object}) = \text{operator} (\mu_{\text{fuzzy set A}} (\text{upscaling parameter } MA \text{ (elementary object)}), \mu_{\text{fuzzy set B}} (\text{upscaling parameter } BN \text{ (elementary object)})) \tag{5.4}$$

Nested function conditions allow a hierarchy in the fulfillment of the membership functions of the upscaling parameters. A nested function expresses that the membership value (or possibility value) of an elementary object to a LCM class equals the logical operation of the membership value of that elementary object to a land cover (LC) class, and the membership value of the upscaling parameter for that elementary object, given the fuzzy set of that upscaling parameter as described in the membership function. Formally defined:

$\mu_{\text{LCM class}}$ (elementary object) = operator ($\mu_{\text{LC class}}$ (elementary object), $\mu_{\text{fuzzy set}}$ (upscaling parameter (elementary object))) (5.5)

In patch-mosaic classification, the function condition specifies whether an elementary object belongs to a LCM class. The function condition to fulfill the membership of a LCM class is a nested fulfillment of (a) the land cover type at elementary level, and (b) the combined fulfillment of the two upscaling parameters minimum-area *MA* and shared-border *BN*. Formally expressed:

μ_{LCMclass} (elementary object) = *and(min)* (μ_{LC} (elementary object), ($\mu_{\text{fuzzy set A}}$ (upscaling parameter *MA* (elementary object)), $\mu_{\text{fuzzy set B}}$ (upscaling parameter *BN* (elementary object)))

(5.6)

The fuzzy logical *'and'* operator is used, because an elementary object should fulfill all conditions in order to belong to a LCM class. This operator gives the intersection of the two fuzzy sets and uses the minimum function (min), which equals the minimum value of the individually calculated memberships.

5.2.4 Thematic specialization

Thematic specialization ads attribute information to superclasses via defining subclasses and necessarily moves down a classification hierarchy (Chapter 2, section 2.3.1). Patch-mosaic classification uses thematic specialization to specify for the superclasses at elementary level their spatial context at composite level. Subsequently, the derived subclasses at elementary level contain three attributes: the inherited spectral mean of their superclass (to quantify its land cover class; Chapter 4, section 4.3.1), and the two spatial context attributes minimum-area *MA* (to quantify *area*) and shared-border *BN* (to quantify *mixture*). The superclasses at elementary level are the eight land cover classes defined in Chapter 4. For generic spatial aggregation classes, the number of heterogeneous LCM classes at composite level defines the number of subclasses per superclass at elementary level. Having selected seven heterogeneous LCM classes at the composite level (i.e., the *mainly* classes, section 5.2.1) will therefore result in seven subclasses per superclass at elementary level. This gives a total of 49 subclasses at elementary level. These subclasses are denoted as {*land cover* *class* in *LCM class*} to explicitly relate the subclasses' names to the composite level. Table 5.2 provides an example of a superclass at elementary level with its seven subclasses (see also Figure 5.2).

Table 5.2: Thematic specialization: an example of a superclass with its seven subclasses in the classification hierarchy at elementary level.

Class Type	*Superclass at elementary level*	*Subclass at elementary level*
Class Name	*Logged-forest*	*Logged forest in mainly logged forest*
		Logged forest in mainly heavily logged forest
		Logged forest in mainly shrub
		Logged forest in mainly agriculture
		Logged forest in mainly grass
		Logged forest in mainly water
		Logged forest in mainly clouds
Attribute information	*Radiometric Landsat TM bands 1345*	*Land cover class*
		Upscaling parameter minimum-area MA
		Upscaling parameter shared-border BN

5.2.5 Spatial generalization

Spatial generalization functionally relates elementary objects into composite objects and necessarily moves up in an aggregation hierarchy (Chapter 2, section 2.3.1). Patch-mosaic classification uses spatial generalization to functionally relate subclasses at elementary level with similar spatial context at composite level into superclasses at composite level (i.e., LCM classes at the spatial aggregation level of forest types, see section 5.2.1). Consequently, all subclasses occur both at elementary level and at composite level. They only differ in how they are thematically generalized to the superclasses at each level: similar spectral mean at elementary level, similar spatial context at composite level (attributes minimum-area *MA* and shared-border *BN*). Subsequently, the superclasses at composite level (i.e, the LCM classes) do not have any own attributes. They only exist on behalf of their subclasses. Table 5.3 provides an example of a LCM class at composite level based on the seven subclasses with similar spatial context at composite level (see also Figure 5.2).

Table 5.3: Spatial generalization: an example of a superclass at composite level based on its seven subclasses with similar spatial context at composite level in the aggregation hierarchy.

Class Type	*Superclass at composite level*	*Subclass at composite level*
Class Name	*Mainly logged-forest*	*Logged forest in mainly logged forest* *Heavily logged forest in mainly logged forest* *Shrub in mainly logged forest* *Agriculture in mainly logged forest* *Grass in mainly logged forest* *Water in mainly logged forest* *Clouds in mainly logged forest*
Attribute information	-	*Land cover class* *Upscaling parameter minimum-area MA* *Upscaling parameter shared-border BN*

5.3 Patch-mosaic segmentation method

This thesis distinguishes four different patch-mosaic segmentation processes to group elementary objects into composite objects (see Chapter 6, section 6.1). This chapter uses the *lc-driven* segmentation process to investigate the two upscaling parameters minimum-area *MA* and shared-border *BN*. This patch-mosaic segmentation process was selected, because it is conventionally used in remote sensing (Yee et al., 1986; Kenk et al., 1988). *Lc*-driven segmentation starts with grouping, at elementary level, adjacent elementary objects that contain similar land cover classes. This creates small and large elementary objects. After patch-mosaic classification, this patch-mosaic segmentation process ends with grouping adjacent elementary objects that contain similar LCM classes to create the composite objects. Yee et al. (1986) and Kenk et al. (1988) thematically regarded the small spatial objects *minor* land cover classes and the larger spatial objects *dominant* land cover classes. They both recoded those minor land cover classes to the dominants. The patch-mosaic classification does not recode the small and large elementary objects into dominant land cover classes. Instead, it classifies both small and large elementary objects to defined spatial aggregation classes (i.e., the LCM classes denoted as *mainly* classes). Although thematically the conventional use differs from the patch-mosaic classification, its geometric extent at composite level is similar. Therefore, the *lc-driven* segmentation process is suitable to study a new approach like patch-mosaic classification.

5.4 Sensitivity analysis

A sensitivity analysis was performed to get more insight in the significance and the effect of the threshold values of the two upscaling parameters minimum-area *MA* and shared-border *BN* (input factors) on created composite objects. This chapter deals with three output variances of the composite objects. These are LCM classification accuracy at composite level, forest area at composite level, and variability and arrangement of forest cover and forest cover pattern at composite level. The reason to study these three output variances are:

- LCM classification accuracy at composite level indicates the patch-mosaic classification performance at composite level. The classified composite objects are used as input to study patch-mosaic segmentation at composite level (Chapter 6).
- Forest area is an easily understood baseline parameter that provides the first indication of the relative importance of forests in a country or region (FAO, 2001).
- Variability (composition) and arrangement (configuration) of forest cover and forest cover pattern are essential indicators of change processes in tropical rainforest areas.

A total of 46 patch-mosaic classifications were carried out on two Landsat TM images of the Pelangkaraya study area. Section 5.4.1 provides the details and reasoning of the used upscaling thresholds, whereas section 5.4.2 explains the classification scheme of the sensitivity analysis.

5.4.1 Upscaling thresholds

Fuzzy sets are used to describe the threshold values of the two upscaling parameters minimum-area *MA* and shared-border *BN* (see section 5.2.3). In the sensitivity analysis, only the sensitivity of the two cross-over points *a1* and *a2* of the membership functions of both upscaling parameters were analyzed. They indicate the actual threshold values of the two upscaling parameters. The dispersion values *d1* and *d2* were not assessed. They indicate the fuzziness in threshold definition. Although it would be scientifically interesting, the impact of threshold values are the objective of the sensitivity analysis, not the decision theory (*Boolean-logic vs. fuzzy-logic*). For completeness, Table 5.4 provides the settings for the three function parameters (i.e., cross-over point, dispersion value and mathematical function) as used in the sensitivity analysis. Fourteen different cross-over points for minimum-area *MA* were selected; they ranged from 5 ha to 18800 ha. These thresholds were chosen according to the spatial size of the spatial objects present in the classified images, from the smallest elementary object up to the largest composite object. In addition, the values should also include the minimum-area of tree-covered land that should be considered as 'forest'. For Papua New Guinea this was about 100 ha (Lund, 1999). Two values close to both extremes of the range were chosen to check the assumption that classification results generated with thresholds beyond the extremes would be identically to classification results generated using the extremes. The remaining ten values were ranged between these two extremes to get sufficient insight in the sensitivity of this upscaling parameter. The dispersion value for minimum-area *MA* was set at 5 ha (5% of a Papua New Guinea forest according to Lund, 1999).

Table 5.4: Selected thresholds for the two upscaling parameters in the sensitivity analysis.

Upscaling Parameter	*Symbol*	*Membership function parameter*		
		Cross-over point	*Dispersion value*	*Mathematical Function (Zadeh, 1965)*
Minimum-area in ha	*MA*	*5, 5.5, 15, 25, 50, 100, 150, 200, 250, 300, 350, 400, 15000, 18800*	*5*	*S-shape*
Shared-border [0:1]	*BN*	*0.35, 0.45, 0.55, 0.65, 0.75, 0.85*	*0.05*	*S-shape*

Six different values for shared-border *BN* were selected; they ranged from 0.35 to 0.85, meaning that the relative shared-border should be at least respectively 35% and 85% of the total border length. A relative shared-border smaller than 35% was not considered to have a strong link with a neighboring elementary object. Therefore, *BN* values below 0.35 were not investigated. Very heterogeneous environments seldomly embed elementary objects to their full extent in neighboring objects. Therefore, shared-border *BN* values above 0.85 were not investigated in the sensitivity analysis. The dispersion value for shared-border *BN* was set at 0.05 (5%).

5.4.2 Upscaling scheme

Both upscaling parameters *MA* and *BN* need a setting for all three membership function parameters to enable execution of the patch-mosaic classification process. Analyzing all combinations of the cross-over points as presented in Table 5.4 would result in 84 patch-mosaic classifications per image. In case of a large number of inputs, a screening exercise should be performed to select the subset of the best explanatory factors (JRC, 2005). Therefore, not all combinations of the cross-over points were analyzed. Instead, an upscaling scheme was constructed after some preliminary testing. First, the cross-over points of minimum-area *MA* were studied, keeping the cross-over point of shared-border *BN* constant at 0.55. The value 0.55 was chosen to balance between a not too loose adjacency of elementary objects, and a possible adjacency of elementary objects in a heterogeneous environment. Second, the cross-over points of shared-border *BN* were studied keeping the cross-over point of minimum-area *MA* constant at 150 ha. The value of 150 ha was chosen to definitely meet the criteria on minimum-area of tree-covered land that should be considered as 'forest' in a tropical environment (Lund, 1999). Third, interaction between the two parameters was studied for three different thresholds of each upscaling parameter. The values 15, 150, and 15000 were chosen for minimum-area *MA*, and the values 0.45, 0.55 and 0.65 were chosen for shared-border *BN*. This upscaling scheme and the thresholds for the cross-over points are presented in Table 5.5.

Table 5.5: Upscaling scheme of the sensitivity analysis.

Upscaling parameters	*Upscaling parameter threshold*		*Number of patch-mosaic classification runs*
	MA in ha	*BN range 0;1*	
Minimum-area MA	*MA*	*0.55*	*14*
Shared-border BN	*150*	*BN*	*5 additional*
Interaction MA x BN	*15, 150, 15000*	*0.45, 0.55 0.65*	*4 additional*
Total			*23*

5.5 Reference data

Reference data is needed to calculate *KHAT*. The reference data should provide the expected LCM classification result at composite level to define which set of thresholds of the two upscaling parameters in patch-mosaic classification is the most accurate. Unfortunately, field data at the required spatial aggregation level was not available for the Pelangkaraya study area (see Chapter 1, section 1.6). This means that assessing the best set of thresholds defining the thematic content of composite objects can only be evaluated indirectly by means of assessing upscaling differences (i.e., LCM classification ‘accuracy’). A common approach in remote sensing is to use classification results of finer resolution data to assess classification results of coarser resolution data (Foody, 2002). Similarly, less spatially aggregated classification results (patches) could be used to assess more spatially aggregated classification results (patch-mosaics). This means that a classification result at elementary level could be used to assess the LCM classification results at composite level. Therefore, this chapter presents the use of a (patch) classification result at elementary level as reference to calculate all similarity matrices (Figure 5.4). This reference was chosen, because it is spatially more detailed, it includes spatial context, and it covers the same time span (see also Chapter 4, Figure 4.5). A spatially more detailed reference is required to analyze the often many and small LCM classification variations as a result of threshold differences of the two upscaling parameters in patch-mosaic classification. Spatial context is required, because classifying composite objects is based on spatial context; a per-pixel based classification is less suitable (see Chapter 4, section 4.7.1). Same time span is important for areas with many vegetation changes in a short time frame. With this reference, the *KHAT* metric could be used to evaluate significant differences between parameter thresholds.

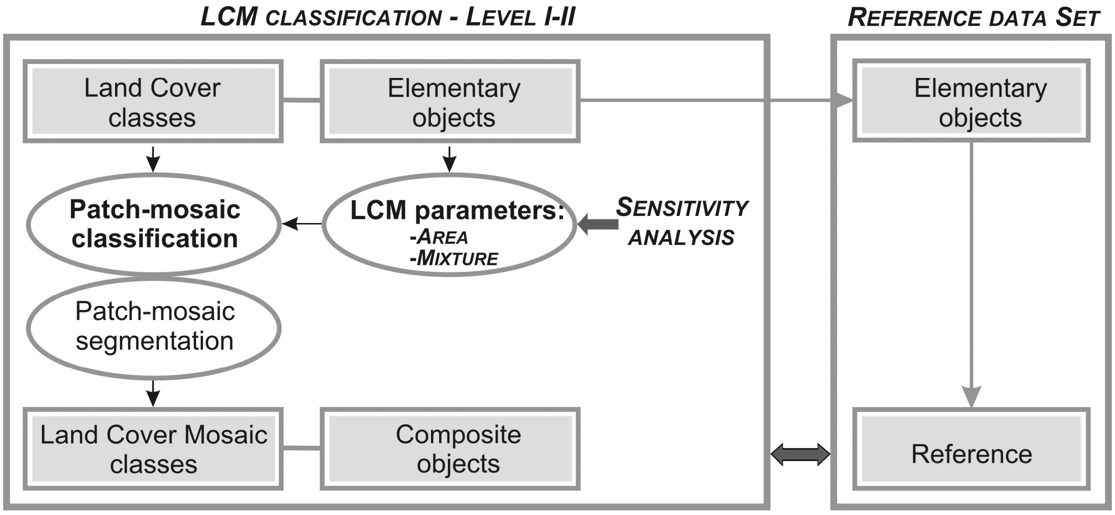


Figure 5.4: Reference data to evaluate the LCM classification results at composite level for different thresholds of the two upscaling parameters in patch-mosaic classification.

5.6 Results & discussion

5.6.1 LCM classification accuracy at composite level

Figure 5.5 (p1990 image) and Figure 5.6 (p1996 image) each show four LCM classification results at composite level for different thresholds of the two upscaling parameters in patch-mosaic classification. Both figures clearly show that the LCM classes were less fragmented when increasing the threshold for minimum-area *MA* or decreasing the threshold for shared-border *BN*. For both images, the KHAT metric showed a similar trend of this decreasing fragmentation (Figure 5.7). However, the selected thresholds had more effect on the more fragmented p1996 image than on the p1990 image. This is demonstrated by the higher level of agreement of the p1990 image for both the upscaling parameters. The more heterogeneous p1996 image contained a larger number of small elementary objects compared with the p1990 image (see Appendix 5.2 for full details). Consequently, more elementary objects fulfilled the threshold values and obtained the LCM class of adjacent elementary objects. Not surprisingly, lowest fragmentation was obtained when selecting high values for minimum-area *MA* and low percentages for shared-border *BN*. In such cases, many elementary objects met both threshold values of the two upscaling parameters and an increasing number obtained the LCM class of adjacent elementary objects. This could result in very low *KHAT* values (addressing differences in spatial aggregation levels) as is shown in both interaction figures of Figure 5.7. In addition, shared-border *BN* has more impact with increasing threshold for minimum-area *MA*. In such a situation, more elementary objects were aggregated into LCM classes at composite level and decreased subsequently image fragmentation. Finally, identical *KHAT* values were obtained for the two minimum-area *MA* thresholds close to the extremes, as expected (see section 5.4.1). This means that the patch-mosaic classification process performed as intended.

From the Z statistics presented in Appendix 5.3 it was evident that the majority of minimum-area *MA* threshold values and all shared-border *BN* threshold values resulted in significantly different patch-mosaic classifications at the 0.05 probability level (> 1.96) for both the images. Specifically, the more dissimilar the thresholds, the higher the Z values. However, no significant difference occurred for the p1990 image between MA_{100} and MA_{150}, MA_{200} and MA_{250}, and MA_{300} and MA_{350}. For the p1996 image a similar 'pattern' occurs, but with a small shift of 50 ha, that is, no significant difference occurred between MA_{150} and MA_{200}, MA_{250} and MA_{350}, MA_{350} and MA_{400}. This ‘pattern’ shift is probably due to differences in fragmentation at elementary level (see Chapter 4, section 4.7.2).

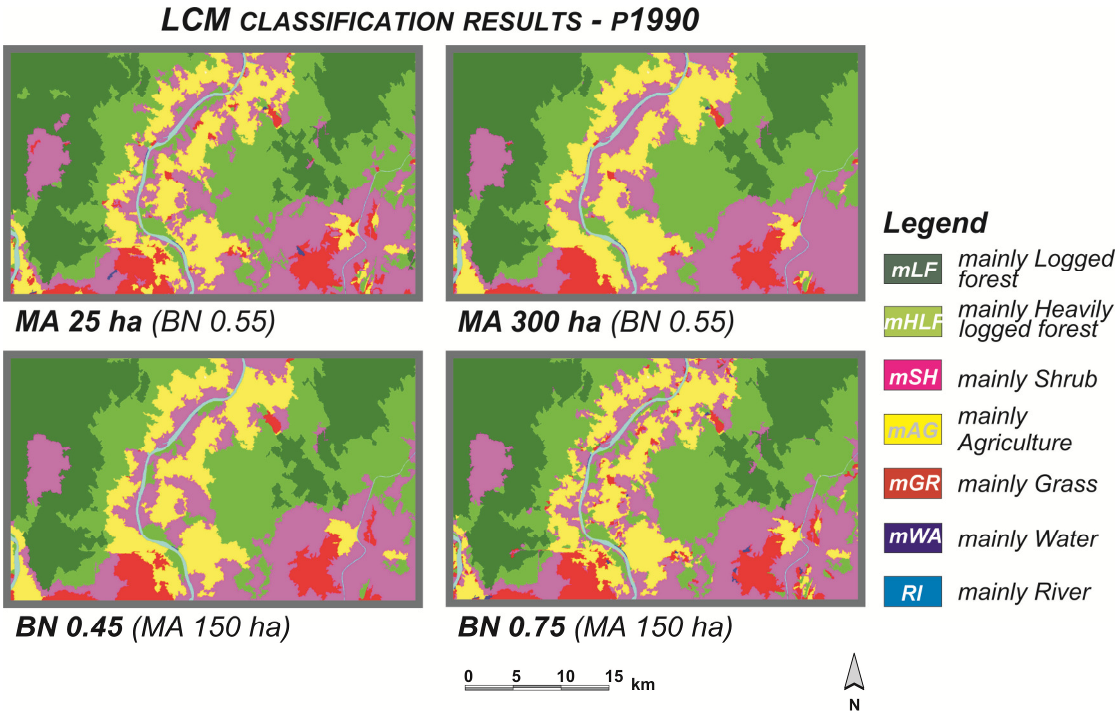


Figure 5.5: LCM classification results at composite level for different threshold combinations of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification; p1990 image.

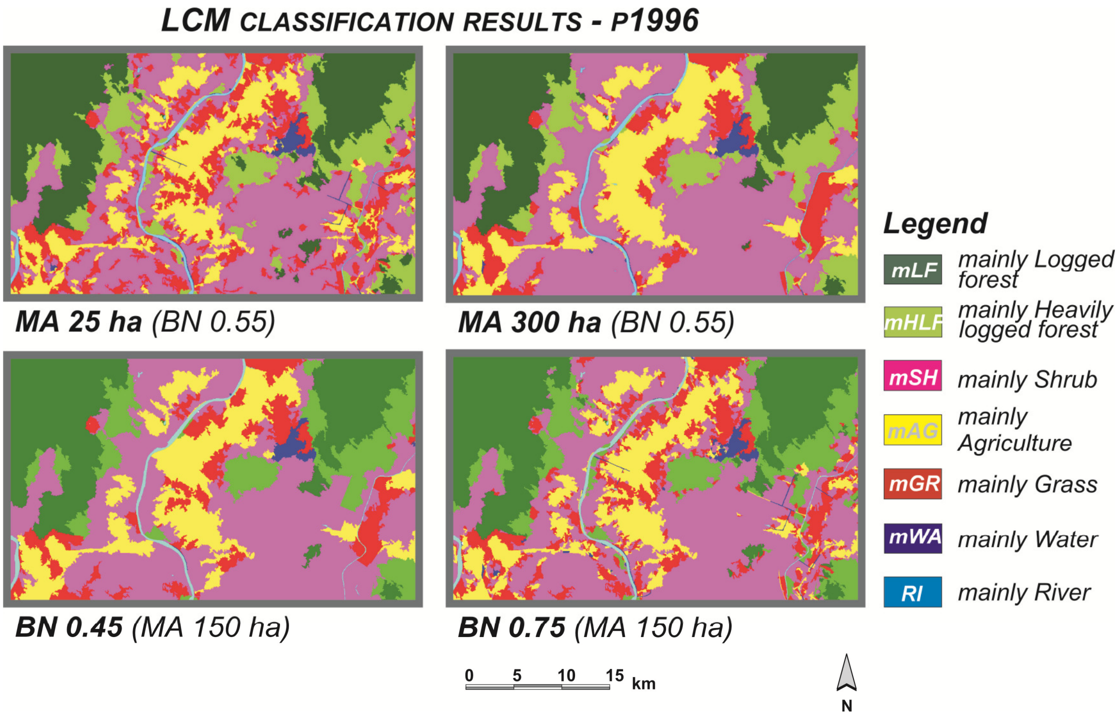


Figure 5.6: LCM classification results at composite level for different threshold combinations of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification; p1996 image.

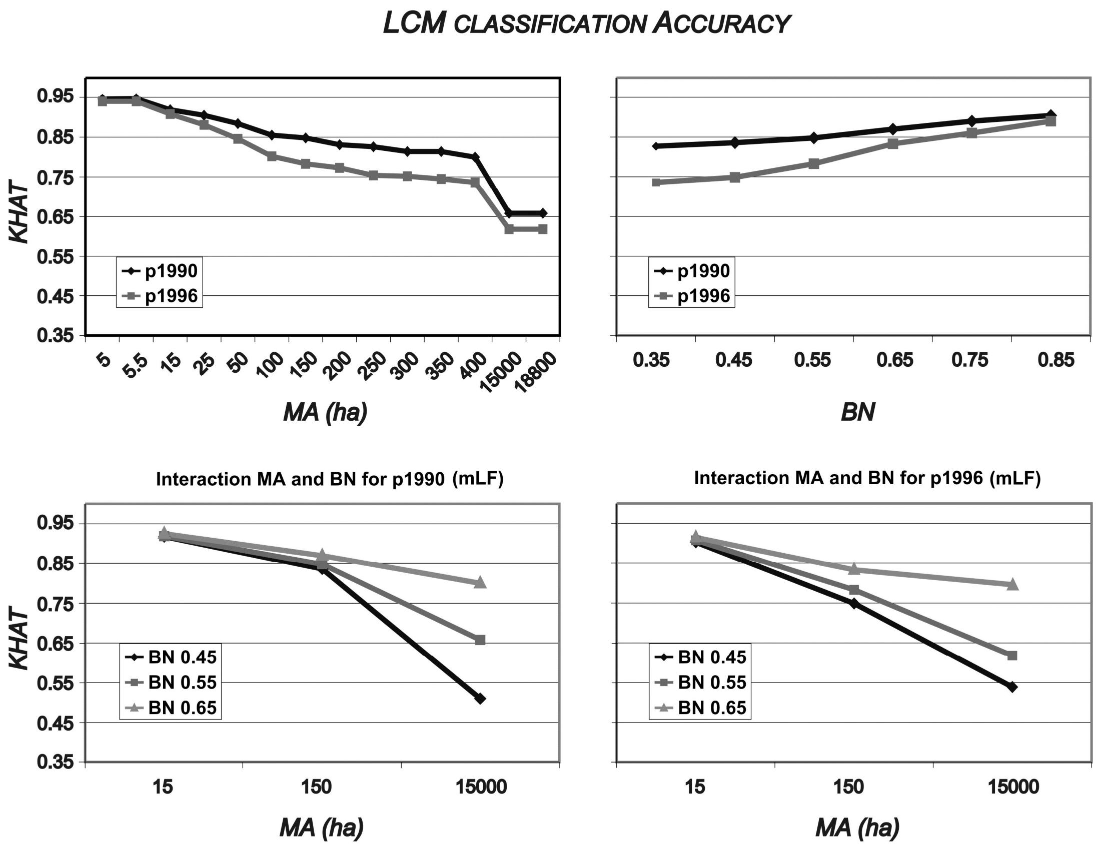


Figure 5.7: LCM classification accuracy at composite level expressed in KHAT values for different thresholds of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification.

Table 5.6 provides the range of maximum Z values for the two upscaling parameters minimum-area *MA* and shared-border *BN*. Both images showed similar significant differences when changing threshold values for minimum-area *MA*. Both images differed, however, when changing threshold values for shared-border *BN*. The more heterogeneous p1996 image showed larger significant differences between LCM classification results at composite level, specifically when lowering the shared-border *BN* percentages. Adjacent elementary objects will differ more likely with increasing spatial heterogeneity.

Table 5.6: Range of maximum Z values.

TM image	*Upscaling parameter*	
	Minimum-area MA	*Shared-border BN*
p1990	*24 - 28*	*7 – 15*
p1996	*24 - 28*	*16 – 24*

5.6.2 Forest area

Table 5.7 shows an overview of the cover percentages of the eight tropical LCM classes after patch-mosaic classification including all 23 different threshold combinations per image. It provides also the cover percentages of the eight land cover classes of the reference data. As such, forest area can be examined at two different spatial aggregation levels (i.e., elementary level versus composite level). Both forest vegetation classes showed similar sensitivity towards the two upscaling parameters *MA* and *BN* comparing the standard deviations of the two images. However, the standard deviations of shrub vegetation and grass vegetation were much larger in the more heterogeneous p1996 image. As such, spatially fragmented land cover classes were more sensitive for the chosen thresholds of the two upscaling parameters than less-fragmented land cover classes like agriculture.

Comparing LCM classification results at composite level with patch-classification results at elementary level, the p1990 image showed almost no PLAND differences, while the more heterogeneous p1996 image showed PLAND differences for heavily logged forest vegetation and shrub vegetation. At composite level, the heavily logged forest vegetation decreased, while the shrub vegetation increased. Spatially, this means that the shrub vegetation surrounded (or enclosed) the heavily logged forest vegetation. Concerning land use, more agricultural areas were abandoned leading to an increase of shrub vegetation, and more heavily logged forest was burned to maintain agricultural production. At composite level the problem of deforestation was more severe than at elementary level.

5.6.3 Variability and arrangement of forest cover

Figure 5.8 shows the Percentage of Landscape *PLAND* of the three LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF), and mainly shrub (mSH). The latter class has been included, because it depicts the problem of practicing agriculture in tropical peatswamp forests. The figure clearly shows that the two upscaling parameters *MA* and *BN* did not affect class-composition of forest vegetation in both the images, except for high minimum-area values (*MA* > 400 ha). In the latter case, *BN* should be set at 0.45 for the p1990 image and 0.65 for the p1996 image to maintain class-compositions for MA > 400 ha (see interaction figures). The two upscaling parameters, however, affected the proportional abundance of shrub vegetation for the spatially more heterogeneous image. Specifically, shrub increased between MA_{25} and MA_{150} (and $MA > 400$ ha) and decreased with increasing values for shared-border (BN > 0.55). Finally, whether the proportional abundance of forest vegetation is independent of the two upscaling parameters also depends on the patch-segmentation settings at elementary level. However, using a low break-off value in patch-segmentation ($v_{scale}10$) substantially decreased the possibility that the two land cover classes heavily logged forest and shrub posed spectral overlap problems at elementary level.

Table 5.7: LCM classification results at composite level (for different thresholds of the two upscaling parameters in patch-mosaic classification) versus patch-classification results at elementary level (reference data) expressed in proportional abundance (i.e., PLAND mean and standard deviation).*

p 1990 image					p 1996 image				
composite level N=23			elementary level N=1		composite level N=23			elementary level N=1	
LCM class	PLAND mean	PLAND sd	LC class	PLAND	LCM Class	PLAND mean	PLAND SD	LC class	PLAND
mLF	25.51	1.89	LF	25.13	mLF	21.26	2.43	LF	21.25
mHLF	26.99	2.08	HLF	27.65	mHLF	12.25	2.38	HLF	16.30
mSH	24.95	0.52	SH	24.60	mSH	38.20	3.60	SH	33.99
mAG	15.44	0.96	AG	14.77	mAG	14.40	0.74	AG	14.53
mGR	5.62	0.79	GR	6.13	mGR	11.60	2.57	GR	11.40
mWA	0.18	0.14	WA	0.37	mWA	1.00	0.13	WA	1.17
RI	1.32	0.02	RI	1.35	RI	1.29	0.03	RI	1.29
mCL	0.00	0.00	CL	0.00	mCL	0.00	0.00	CL	0.00

**PLAND figures presented in this table at elementary level are slightly different compared with Table 4.5 in Chapter 4. This is mainly due to differences in parameter settings in patch-segmentation. This table used a break-off value v_{scale} of 10 while Table 4.5 used a v_{scale} of 15.*

Figure 5.9 shows the Number of Patches *NP* for the three LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF), and mainly shrub (mSH) for different thresholds of the two upscaling-parameters *MA* and *BN* in patch-mosaic classification. The figure clearly shows that both upscaling parameters affected class-configuration in both the images. For the entire range of the two upscaling parameters, fragmentation in the p1996 image was higher compared with the p1990 image. Only the LCM class mainly heavily logged forest was less fragmented in the p1996 image because of its enormous reduction. The two upscaling parameters mostly affected the LCM class mainly shrub (mSH), while mainly logged forest (mLF) was little affected. As such, the more fragmented a LCM class is, the larger its sensitivity for the two upscaling parameters will be. Generally, the three LCM classes appeared less fragmented for both images when either minimum-area *MA* increased or shared-border *BN* decreased. Specifically, the reduction in fragmentation is largest when selecting a threshold value for minimum-area *MA* that is larger than 100 ha and a threshold value for shared-border *BN* that is smaller than 0.55.

5.6.4 Variability and arrangement of forest cover pattern

Figure 5.10 shows the Simpson's Diversity Index *SIDI* for different thresholds of the two upscaling parameters *MA* and *BN* including all eight LCM classes. The figure clearly shows that the two upscaling parameters did not affect the relative proportions of the eight LCM classes in the p1990 image. For the more heterogeneous p1996 image, however, SIDI decreased at larger minimum-area *MA* areas and at smaller shared-border *BN* percentages. Such a small diversity decrease means that dominance of one or a few land cover classes slightly increased. Combining SIDI and PLAND, this slightly increasing dominance can be explained. At larger minimum-area *MA* areas, shrub vegetation showed a remarkable PLAND increase. At smaller shared-border *BN* percentages, the class shrub slightly increased. As such, a constant SIDI and a constant PLAND means that the LCM classes have their own specific composition in the landscape. Nevertheless, for parameter thresholds having effect on certain LCM classes, like shrub vegetation, SIDI quantified this compositional change. Combining both composition measures, it can be concluded that shrub vegetation, which depicts the problem of practicing agriculture in tropical peatswamp forests, contributed significantly to the change in SIDI and thus plays an important role in the underlying change process. This means that between 1990 and 1996 forest was not depleted due to logging practices, but due to agricultural practices.

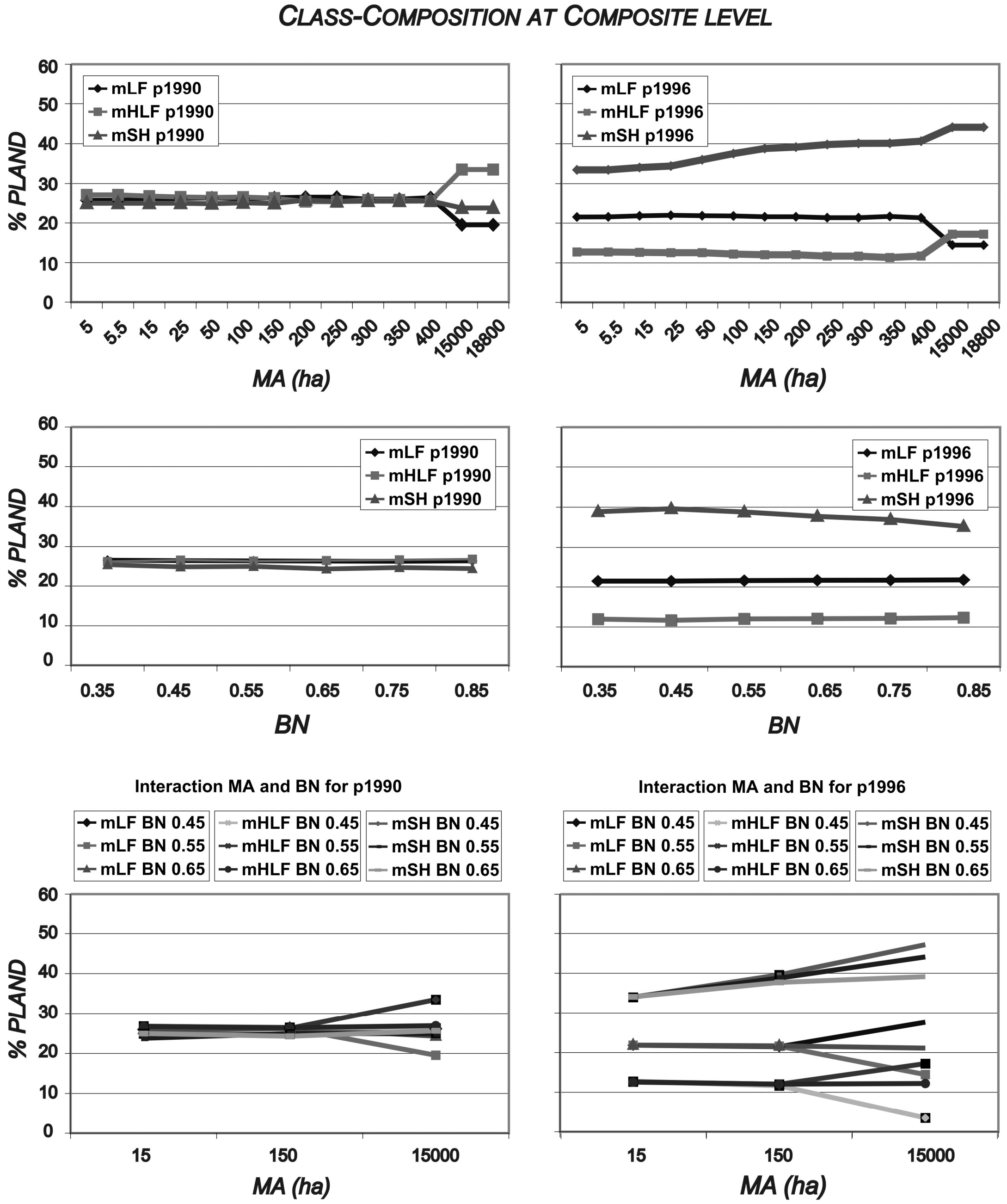


Figure 5.8: Class-composition of the LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF) and mainly shrub (mSH) expressed in Percentage of Landscape (%PLAND) for different thresholds of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification.

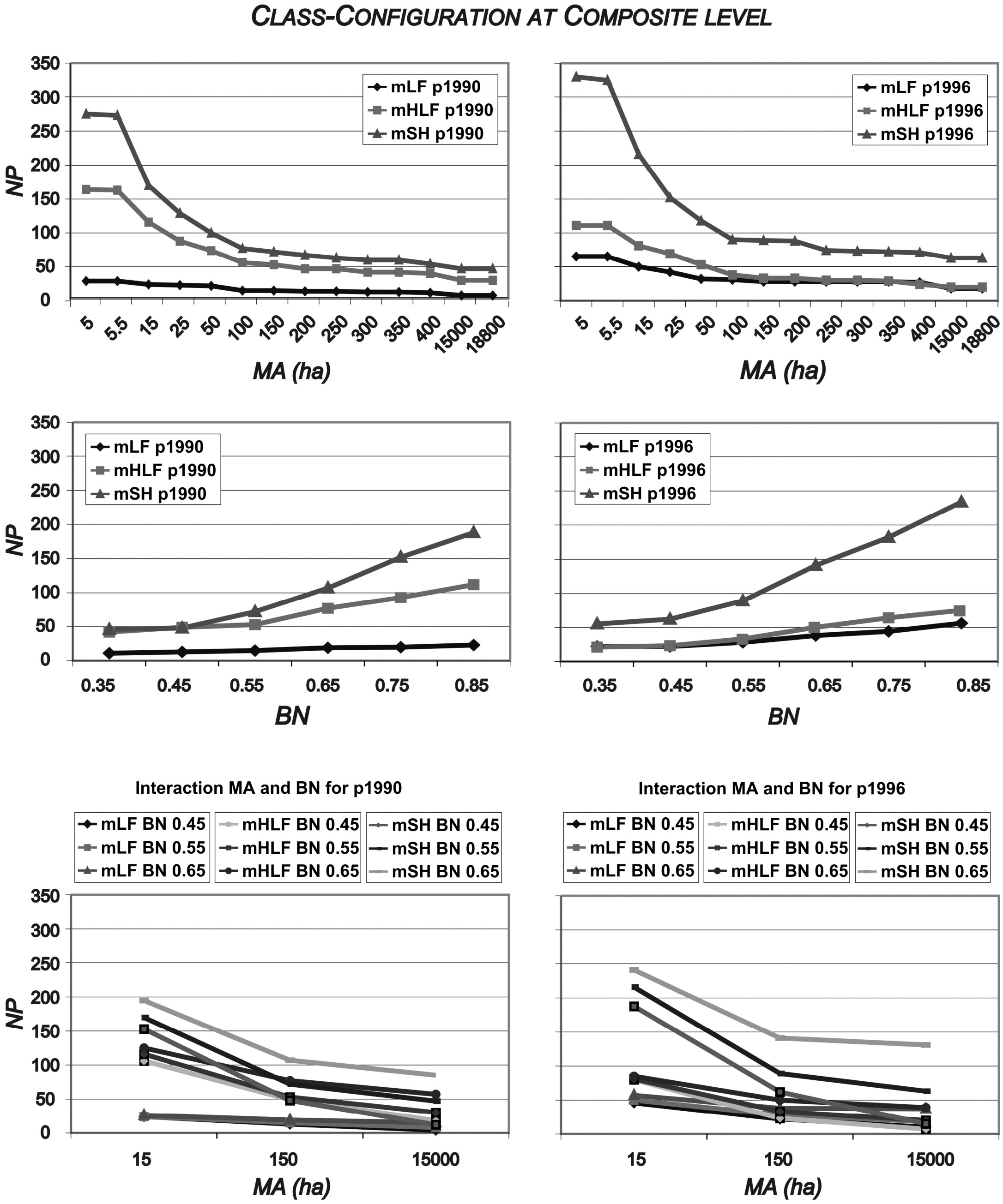


Figure 5.9: Class-configuration of the three LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF) and mainly shrub (mSH) expressed in Number of Patches (NP) for different thresholds of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification.

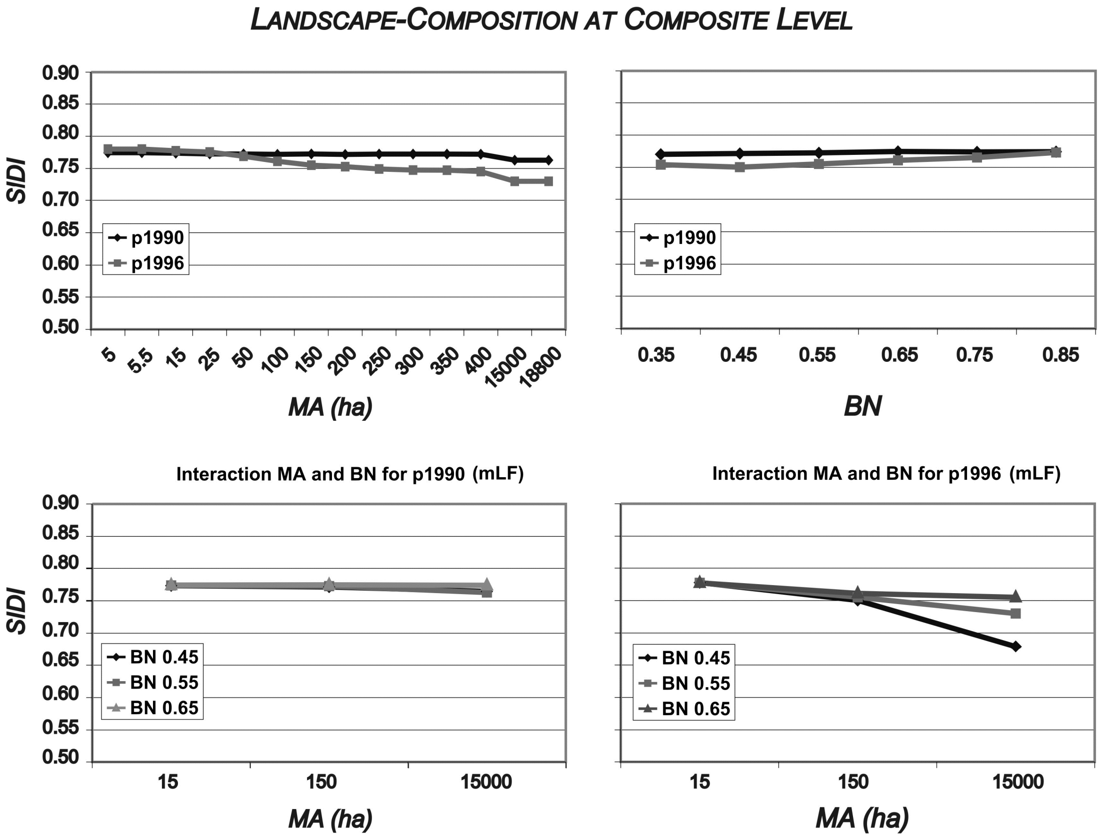


Figure 5.10: Landscape-composition expressed in Simpson's Diversity Index (SIDI) for different thresholds of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification.

Finally, Figure 5.11 shows the Landscape Shape Index *LSI* for different thresholds of the two upscaling parameters including all eight LCM classes. The figure clearly shows that the two upscaling parameters affected the perimeter-to-area ratio for both images. The *LSI* decreased at larger minimum-area *MA* areas and at lower shared-border *BN* percentages. At those thresholds the composite objects (i.e., the patch-mosaics) became larger and spatial heterogeneity decreased. Obviously, the *LSI* for the more heterogeneous p1996 image was higher than for the p1990 image, but both images showed similar trends for the two upscaling parameters.

5.7 Conclusions

5.7.1 Effect of upscaling parameters

From the results of the sensitivity analysis investigating the effect of the two upscaling parameters minimum-area *MA* and shared-border *BN* on three output aspects of created composite objects (i.e., LCM classification accuracy at composite

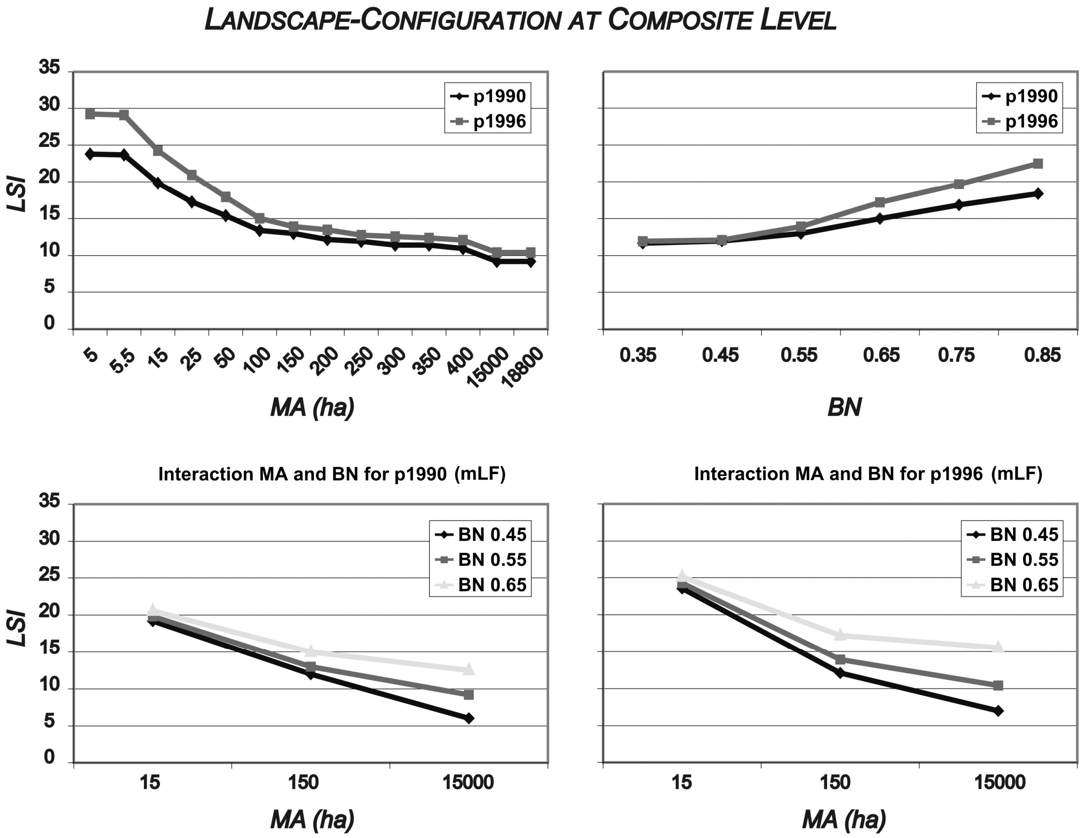


Figure 5.11: Landscape-configuration expressed in Landscape Shape Index (LSI) for different thresholds of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification.

level, forest area, and variability and arrangement of forest cover and forest cover pattern), four conclusions can be drawn:

I

Both Landsat TM images of the Pelangkaraya study area showed similar trends towards both upscaling parameters: a decreasing *KHAT* for higher minimum-area *MA* thresholds and for lower shared-border *BN* thresholds. As such, expanding thresholds led to increasing generalization of spatial entities. The *KHAT* (addressing differences in spatial aggregation levels) depicted this trend. The spatially heterogeneous p1996 image was more sensitive when changing both thresholds. Heterogeneous environments contained more elementary objects, while adjacent elementary objects appeared more dissimilar, resulting in a larger variety of possible LCM classes at composite level. For all minimum-area *MA* thresholds smaller than 100 ha and for all shared-border *BN* thresholds lower than 0.65, the patch-mosaic classifications were significantly different. No conclusions could be drawn regarding thresholds that provided the highest accuracy in patch-mosaic classification because of a lack of field data at the required spatial aggregation level.

II

The two spatial aggregation levels (i.e., elementary and composite) gave a similar forest change scenario when comparing their forest area figures. At composite level, however, the problem of practicing agriculture in peatswamp forest was more severe (i.e., more shrub vegetation, less heavily logged forest vegetation). Deforestation and its underlying change process was best highlighted at composite level.

III

The two upscaling parameters *MA* and *BN* mainly affected configuration. Specifically, spatially heterogeneous images (e.g., p1996 image) and spatially fragmented vegetation (e.g., shrub vegetation) were most sensitive for threshold differences. Similarly to the *KHAT* findings, class-fragmentation and landscape-heterogeneity decreased for higher minimum-area *MA* thresholds and for lower shared-border *BN* thresholds. In such cases, more elementary objects obtained the LCM class of adjacent elementary objects. Remarkably, the two upscaling parameters hardly affected composition when configuration was affected for both the images. Only very fragmented and abundant vegetation like shrub vegetation showed composition differences. As such, spatial heterogeneity can be functionally generalized using different upscaling thresholds *without* loosing thematic information. This is a major improvement compared with commonly used geometry-driven generalizations that either cause distortion of cover type proportions or cause disaggregation of spatial patterns (for details and literature see Chapter 2, section 2.3.2).

IV

Finally, the landscape composition metric at the landscape-level *SIDI* was a useful index to quantify changes in land cover mosaics in addition to the commonly used landscape composition metric at the class-level *PLAND*. SIDI provided the area range at which a striking diversity change occurred, whereas PLAND indicated the vegetation class most likely involved (i.e., shrub vegetation).

5.7.2 Patch-mosaic classification thresholds

The selected thresholds of the two upscaling parameters *MA* and *BN* in patch-mosaic classification are given in Table 5.8. These upscaling thresholds are used to study patch-mosaic segmentation at composite level (Chapter 6). Such a study requires upscaling thresholds having a similar effect on configuration. Differences in patch-mosaic segmentation results can then be accredited to the selected segmentation process at composite level. In addition, similar thresholds for both images are required regarding the definition of spatial aggregation classes (see Chapter 3, section 3.3).

Table 5.8: Selected thresholds in patch-mosaic classification to create thematically composite objects as input for Chapter 6.

Upscaling parameter	*Symbol*	*Input setting*
Minimum-area	*MA*	*150 ha*
Shared-border	*BN*	*0.55*

A minimum-area *MA* of 150 ha was chosen, because it is the threshold closest to the required minimum-area of 100 ha as defined in forest definition for tropical countries (see Chapter 1). Both images showed a similar effect on configuration for this threshold *(LSI p1990 ≈ LSI p1996).*

A shared-border *BN* of 0.55 was chosen, because this is the threshold closest to the one for which both images showed a similar effect on configuration, while maintaining a similar effect on composition. Evaluating all five evaluation metrics in detail, the configuration metric *KHAT* would go for a *BN* setting of 0.65. At this setting, however, the composition metric *PLAND* showed a decreasing shrub area in the p1996 image. Both configuration metrics *NP* and *LSI* would go for a *BN* setting of 0.45. However, the composition metric *SIDI* showed the largest interaction for this setting in the p1996 image, especially with increasing *MA*.

References

Aarts, E. & Korst, J. (1989). Simulated annealing and Boltzmann machines: A stochastic approach to combinatorial optimization and neural computing. John Wiley & Sons, New York.

Addink, E.A. & Stein, A. (1999). A comparison of conventional and geostatistical methods to replace clouded pixels in NOAA-AVHRR images. International Journal of Remote Sensing 20(5):961-977.

Baatz, M. & Schäpe, A. (2000). Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation. In: Strobl, J. & Blaschke, T. (eds), Angewandte geographische informationsverarbeitung, Vol. XII, AGIT-Symposium, Salzburg, Herbert Wichmann Verlag, Karlsruhe, 12–23.

Bortolan, G. & Degani, R. (1985). A review of some methods for ranking fuzzy subsets. Fuzzy Sets and Systems 15:1-19.

Burrough, P.A. & Mc Donnell, R.A. (1998). Principles of geographical information systems. Oxford University Press, Oxford.

Carvalho, L.M. (2001). Mapping and monitoring forest remnants: A multi-scale analysis of spatio-temporal data. PhD Thesis Wageningen University, The Netherlands.

Cerny, V. (1985). Thermo-dynamical approach to the travelling salesman problem: An efficient simulation algorithm. Journal of Optimization Theory and Applications 45:41-51.

Dombi, J. (1990). Membership function as an evaluation. Fuzzy Sets and Systems 35:1-21.

FAO (2001). The Global Forest Resources Assessment 2000 (FRA 2000), FAO Forestry Paper 140. At http://www.fao.org/forestry/fo/fra/main/index.jsp, accessed November 5, 2003.

Groenigen, J.W. van & Stein, A. (1998). Constrained optimisation of spatial sampling using continuous simulated annealing. Journal of Environmental Quality 27:1078-1086.

Hootsman, R.M. (1996). Fuzzy sets and series analysis for visual decision support in spatial data exploration. PhD Thesis, Utrecht University, The Netherlands.

JRC (2005). A forum on sensitivity analysis. European Commission, Institute for systems, informatics and safety (ISIS) and Joint Research Centre (JRC). At http://sensitivity-analysis.jrc.cec.eu.int/ default2.asp? page=news, accessed March 23, 2005.

Kenk, E., Sondheim, M. & Yee, B. (1988). Methods for improving accuracy of thematic mapper ground cover classifications. Canadian Journal of Remote Sensing 14(1):17-31.

Kirkpatrick, S., Gelatt, C. D. Jr. & Vecchi, M.P. (1983). Optimization by simulated annealing. Science 220:671-680.

Lund, H.G. (1999). Forest classification: A definitional quagmire. In: The world's natural forests and their role in global processes, Khabarovsk, Russia, 17 p. At http://home.att.net/~gklund /quagmire.htm, accessed November 7, 2003.

Park, N.-W., Chi, K.-H. & Kwon, B.-D. (2004). Application of object-based multiresolution segmentation to classification of remote sensing data. In: Proceedings of the 2001 International Symposium on Remote Sensing, October 31 - November 2, 2001, Seogwipo, South Korea. At http://ksrs.or.kr/PROCEED/2001int /p_d_1.htm, accessed June 14, 2005.

Svarovski, S.G. (1987). Usage of linguistic variable concept for human operator modelling. Fuzzy Sets and Systems 22:107-114.

Yee, B., Kenk, E., Turpin, D. & Sondheim, M. (1986). A context based technique for smoothing of digital thematic maps. Proceedings of Graphics/Vision Interface '86, Vancouver, British Columbia, 26-30 May, 279-283.

Zadeh, L.A. (1965). Fuzzy sets. Information and Control 8:338-353.

Zadeh, L.A. (1971). Quantitative Fuzzy Semantics. Information Sciences 3:159-176.

Zimmerman, H.J. & Zysno, P. (1985). Quantifying vagueness in decision models. European Journal of Operational Research 22:148-158.

CHAPTER 6

PATCH-MOSAIC SEGMENTATION

"Wat een rups het einde noemt, noemt de wereld een vlinder"

"What a caterpillar calls the end, the world calls a butterfly"

Jalal ad-Din Rumi (1207-1273)

6.1 Introduction

After studying patch-mosaic classification (Chapter 5), patch-mosaic segmentation can be studied in the LCM classification process. Patch-mosaic segmentation defines the geometric extent of the composite objects when upscaling elementary objects into composite objects based on functional generalization according to the Aggregate-Mosaic Theory (Chapter 3). Patch-mosaic segmentation groups at composite level the neighboring elementary objects having a similar LCM class (i.e., resulting from the patch-mosaic classification). Such a grouping is not univocal. This chapter specifically studies four possible patch-mosaic segmentation methods, they are called *lc*-driven, *lcm*-driven, *data*-driven, and *wavelet*-driven (Figure 6.1).

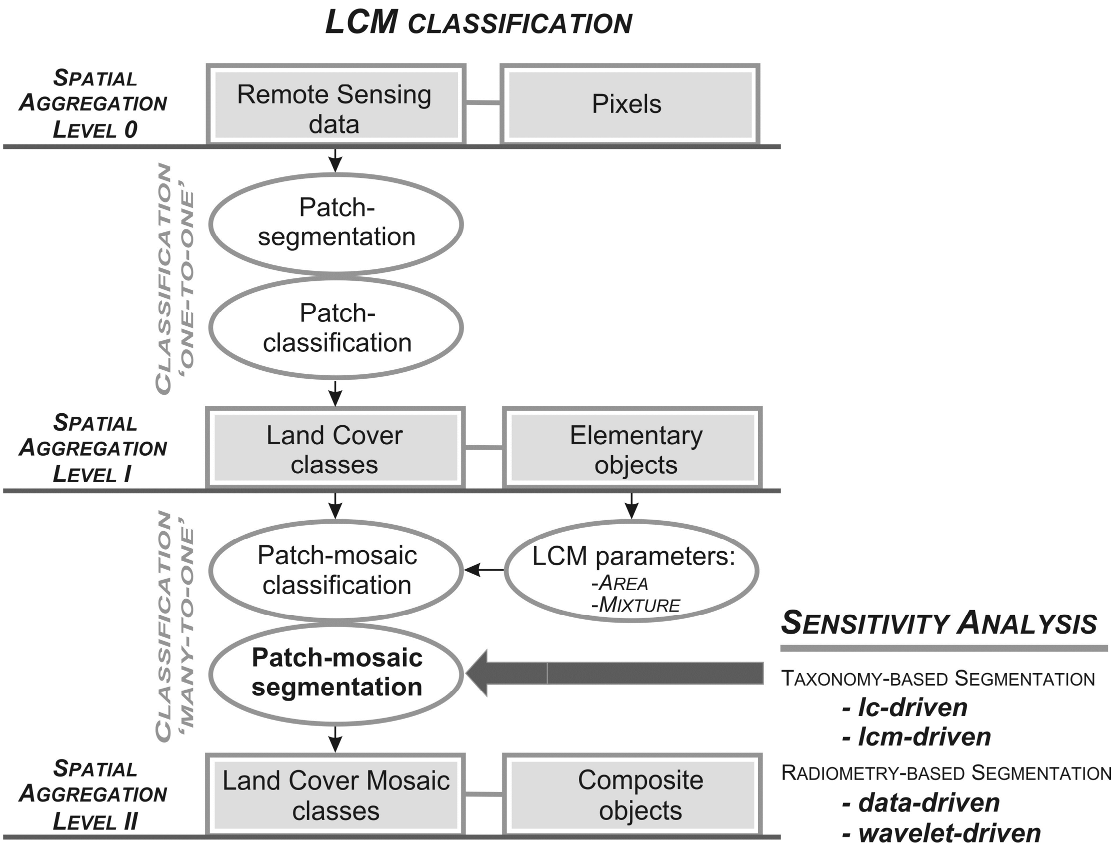


Figure 6.1: A sensitivity analysis on patch-mosaic segmentation in LCM classification for geometrically upscaling elementary objects into composite objects.

These four methods are based on two general segmentation approaches. The first approach is segmentation based on class similarity, further referred to as *taxonomy-based* segmentation. The second one is segmentation based on radiometric similarity, further referred to as *radiometry-based* segmentation. Taxonomy-based segmentation uses the taxonomy of a classification hierarchy. Adjacent spatial objects are grouped if they belong to the same (super)class (Richardson, 1993; Bregt and Bulens, 1996). Having two classification hierarchies in a LCM classification, the (super)classes can be either the land cover classes at elementary level or the land cover mosaic (LCM) classes at composite level. This chapter investigates the use of both taxonomies. Patch-mosaic segmentation using the taxonomy at elementary level is land cover driven, and therefore called *lc*-driven. Patch-mosaic segmentation using the taxonomy at composite level is land cover mosaic driven, and thus called *lcm*-driven.

Radiometry-based segmentation uses segmentation algorithms with thresholds indicating the similarity of radiometric information between pixels (for literature see Chapter 2, section 2.3.6.). Adjacent pixels are grouped if their radiometric information falls within the thresholds. Using remote sensing data, radiometric similarity can be based either on original image data (e.g., Landsat TM bands) or on transformed image data (e.g., applying spectral filters, spatial filters, principal component analysis, band rationing, tasseled cap transformation, color space transformation, fourier transformation, and wavelet transformation). This chapter investigates patch-mosaic segmentation using original image data and using wavelet-transformed image data. Original image data was chosen, because such data are mainly used in all kinds of operational mapping programmes (Srinivasan, 1992; FAO, 2000). Wavelet-transformed image data was chosen, because such data decomposes original image data at interrelated spatial scales (Mallat, 1989 and 1998; Chui, 1992; Daubechies, 1992; Foufoula Georgiou and Kumar, 1994; Chapter 2, section 2.3.7). Such a decomposing could suit radiometric segmentation at composite level, because it specifically decomposes vegetation structure at different spatial aggregation levels (Chapter 2, section 2.3.5). Patch-mosaic segmentation using the radiometry of original image data is called *data*-driven. Patch-mosaic segmentation using the radiometry of wavelet-transformed image data is called *wavelet*-driven. Investigating two differently scaled image data leads to the following hypothesis:

> *Patch-mosaic segmentation using image data that are decomposed at interrelated spatial aggregation levels better resembles human knowledge to create composite objects than patch-mosaic segmentation using original image data.*

Upscaling elementary objects into composite objects based on functional generalization requires a thematic abstraction before a geometric abstraction (Chapter 2, section 2.3.2). Subsequently, each of the four patch-mosaic segmentation methods should be preceded by a patch-mosaic classification (Chapter 5). The patch-mosaic classification applied in this Chapter used a minimum-area *MA* of 150 ha and a shared-border *BN* of 0.55 for the thresholds of the two functional upscaling parameters (for rationale see Chapter 5, section 5.7.2). It also used the seven 'mainly' LCM classes (i.e, mainly logged forest, mainly heavily logged forest, mainly shrub, mainly agriculture, mainly grass, mainly water, mainly cloud, and the class river; Chapter 5, section 5.2.1).

The details of the four patch-mosaic segmentation methods are described in section 6.2. Similarly to Chapter 5, five evaluation metrics are used to compare the LCM classification results at composite level. These metrics cover the standard remote sensing accuracy metric *KHAT* and four landscape pattern metrics as applied in landscape ecology (details and rationale see Chapter 4, section 4.5). Reference data is needed to apply *KHAT*. The rationale of the selected reference is described in section 6.3. This section also describes the details on three manual interpretation results, because manual segmentation and classification (also based on functional relationships at composite level) is common practice in operational mapping programmes (NFI, 1993; FAO, 2000). Next, section 6.4 presents and discusses all the LCM classification results at composite level (digital) and the manual interpretation results (manual). Finally, in section 6.5 conclusions are drawn related to the two spatial modeling approaches (digital and manual) and the four patch-mosaic segmentation methods as developed in this Chapter.

6.2 Patch-mosaic segmentation methods

6.2.1 Lc-driven segmentation

The lc-driven patch-mosaic segmentation method is, in fact, a conventional post-processing method in remote sensing (Yee et al., 1986; Kenk et al., 1988; see also Chapter 5, section 5.3). This method starts with grouping at elementary level all adjacent elementary objects that contain similar land cover classes. As such, it creates small and large elementary objects. After the patch-mosaic classification (Chapter 5), this segmentation method ends with grouping at composite level all adjacent elementary objects that contain similar LCM classes. Subsequently, the sequence of this functional upscaling process is *(1) patch-mosaic segmentation I, (2) patch-mosaic classification* and *(3) patch-mosaic segmentation II* (Figure 6.2). Such a sequence differs slightly from the definition of functional generalization that consists of a thematic abstraction preceding a geometric abstraction (Chapter 2, section 2.3.6). The patch-mosaic segmentation I, however, is in fact a geometric abstraction after thematic abstraction at *elementary* level. It could, therefore, be denoted as a *patch-*segmentation II finishing a true functional generalization when upscaling from neighboring pixels to elementary objects (Chapter 4). This requires the condition that homogeneity is a special case of heterogeneity (Chapter 3).

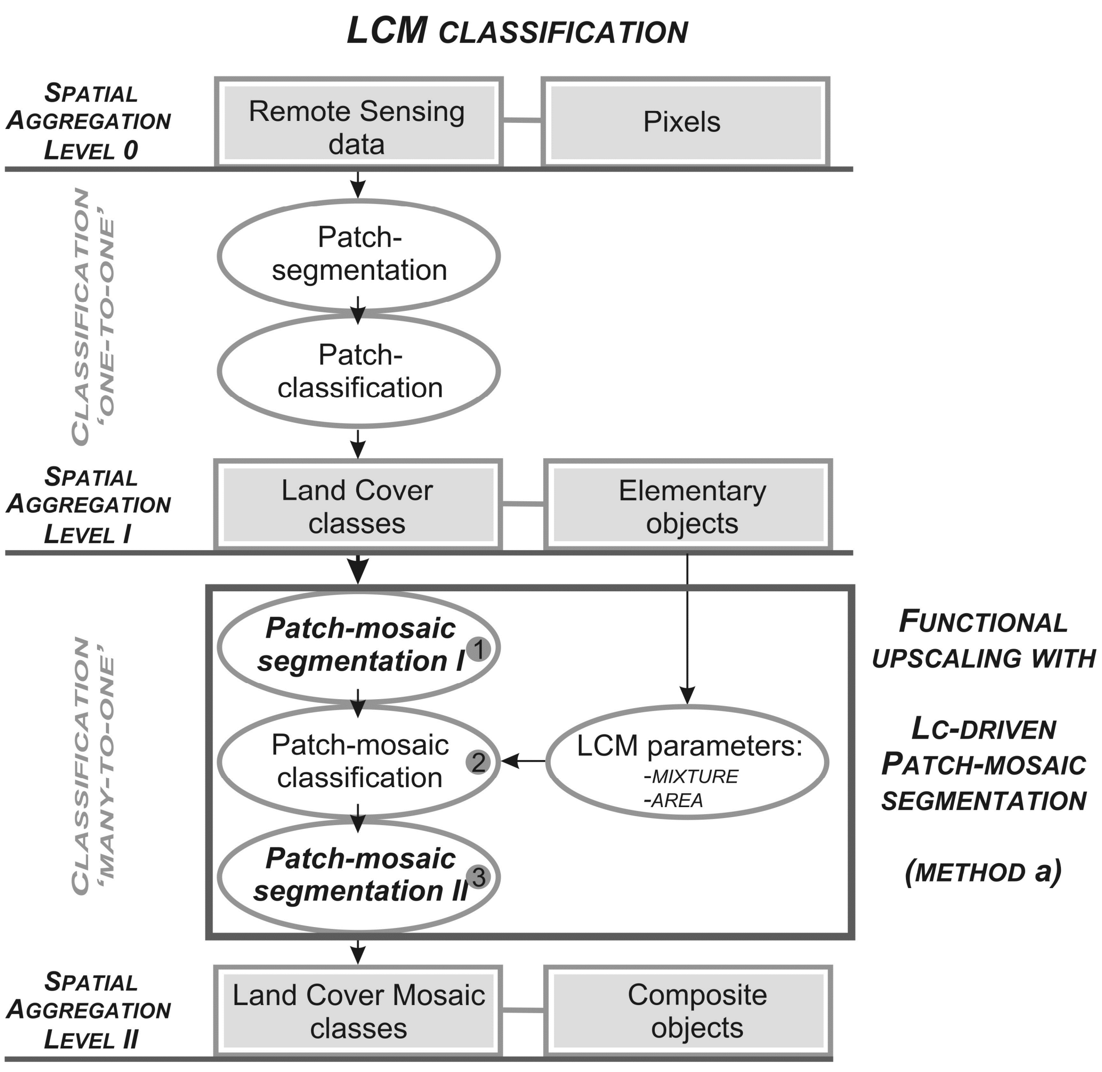


Figure 6.2: Functional upscaling in LCM classification with lc-driven patch-mosaic segmentation (also referred to as method a).

6.2.2 Lcm-driven segmentation

The lcm-driven patch-mosaic segmentation method groups at composite level all adjacent elementary objects that contain similar LCM classes. The sequence of this functional upscaling process is *(1) patch-mosaic classification* and *(2) patch-mosaic segmentation* (Figure 6.3). This is a sequence truly based on functional generalization conform its definition (Chapter 2, section 2.3.6).

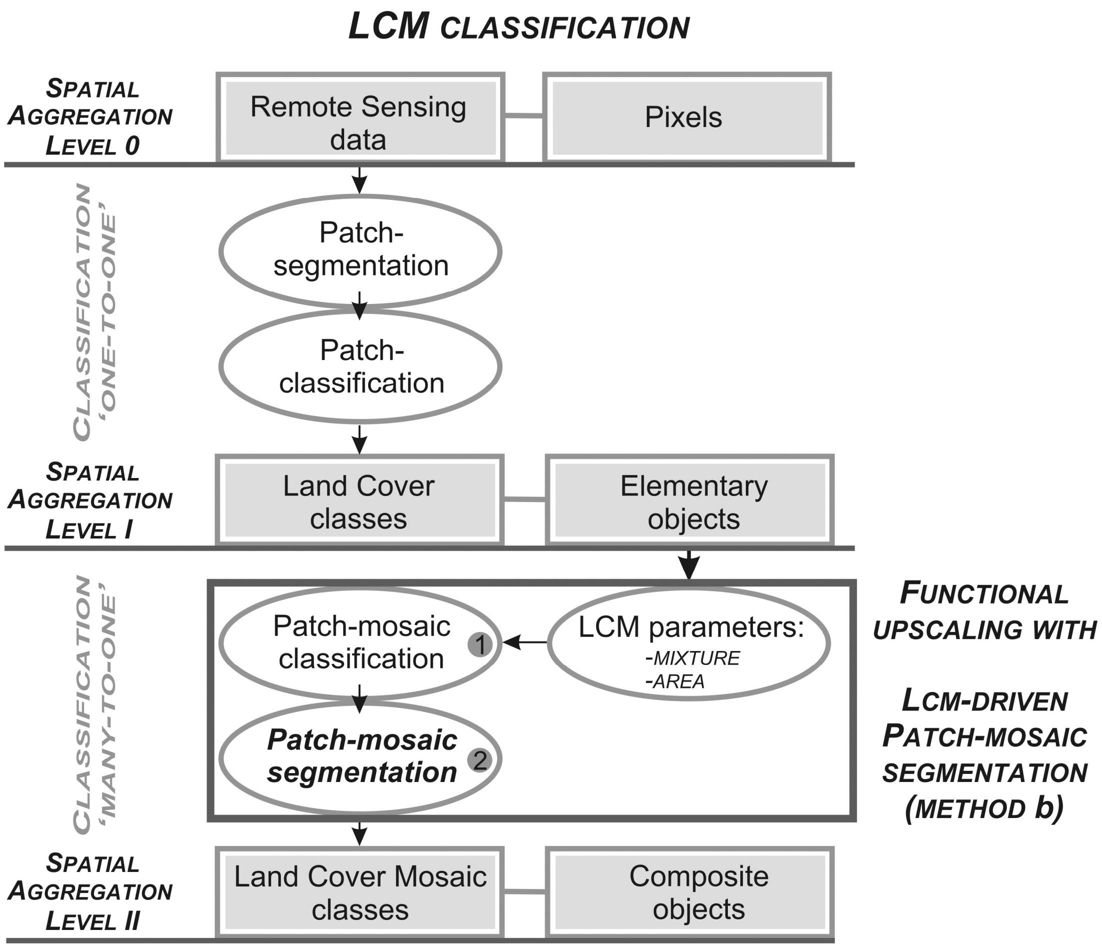


Figure 6.3: Functional upscaling in LCM classification with lcm-driven patch-mosaic segmentation (also referred to as method b).

6.2.3 Data-driven segmentation

The data-driven patch-mosaic segmentation method first pre-indicates the geometric extent of composite objects. Next, an (additional) thematic decision rule assigns the final LCM classes (based on the LCM classes resulting from the patch-mosaic classification) to the pre-indicated geometric extent of the composite objects. The data-driven segmentation method ends with grouping all adjacent composite objects that contain similar LCM classes. Subsequently, the sequence of this functional upscaling process is *(1) patch-mosaic classification, (2) patch-mosaic segmentation I, (3) additional classification,* and *(4) patch-mosaic segmentation II* (Figure 6.4). Such a sequence can be regarded as a ‘stepwise’ functional generalization.

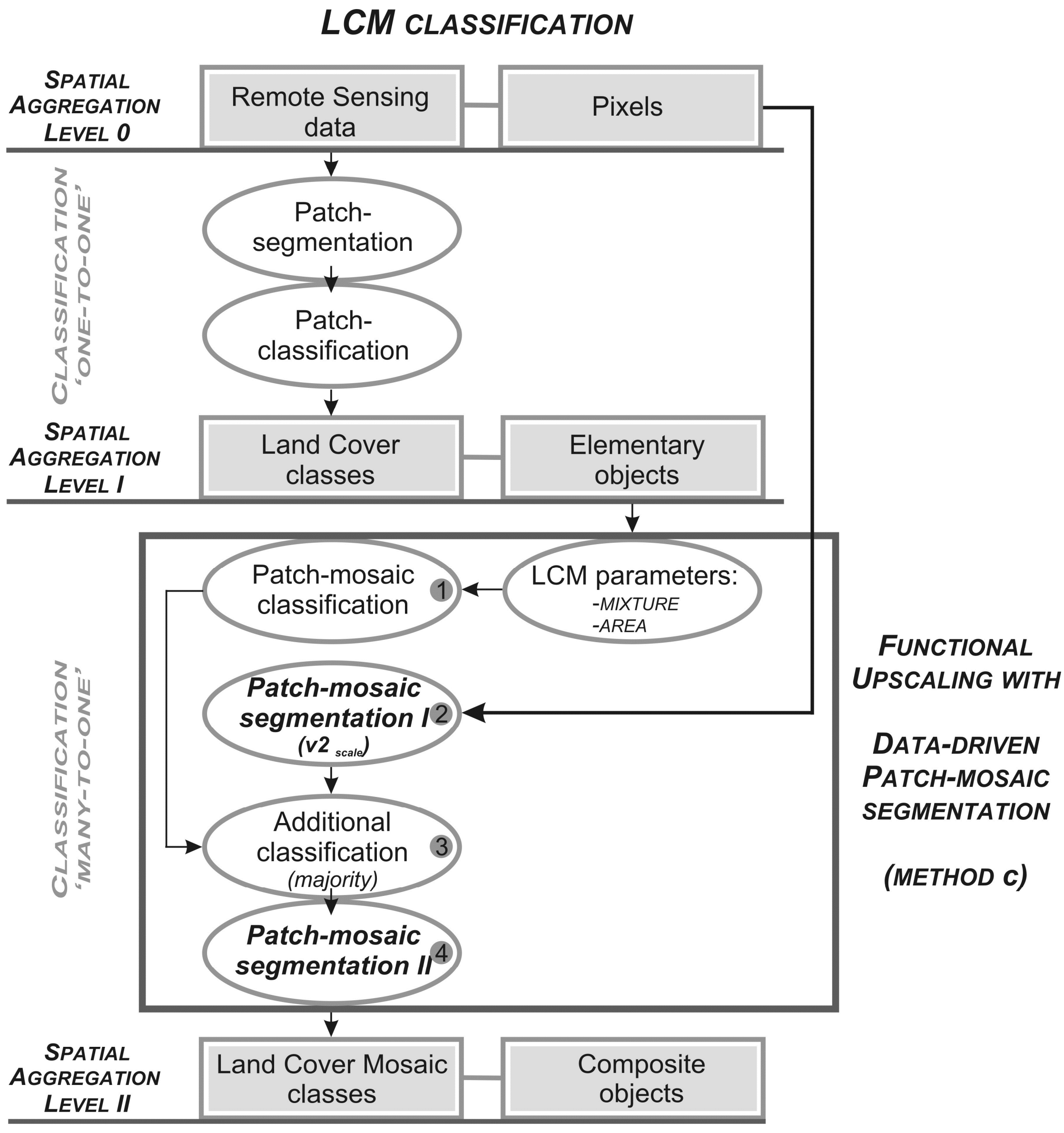


Figure 6.4: Functional upscaling in LCM classification with data-driven patch-mosaic segmentation (also referred to as method c).

Pre-indication of the geometric extent requires explicit expert knowledge on spatial aggregation levels in relation to thematic definitions (Chapter 3). The current explicit knowledge is that the composite objects are at a higher spatial aggregation level than the elementary objects. The break-off value v_{scale} using the eCognition segmentation algorithm (Chapter 4, section 4.2.1) is specifically denoted to the average size of spatial objects. Therefore, the selected threshold settings for the break-off value when creating composite objects *($v2_{scale}$)* should be larger compared with creating elementary objects *($v1_{scale}$)*. With $v1_{scale}$ set at 10, four different settings for $v2_{scale}$ were selected: 20, 40, 80 and 160 (the two other segmentation parameters, color weighting w_{color} and smoothness weighting w_{smooth}, remained both at 0.9). These $v2_{scale}$ values were chosen as a 2^x*-function* of the initial $v1_{scale}$ value. Formally expressed:

$$v2_{scale} = v1_{scale} \,.\, 2^x, \quad x \in N,\ N=\{1, 2, 3, 4\},\ \text{with } v1_{scale}=10 \tag{6.1}$$

For *N=1*, the nature of created composite objects is still elementary (see section 4.4.1). This means that if the patch-mosaic classification results do not differ significantly from the patch-classification results, then LCM classification is meaningless. For *N>4*, the number of composite objects is drastically reduced to only a few spatial objects with no semantic meaning on forest cover and forest cover pattern. Therefore, *N* was not investigated above a value of 4.

A majority decision rule was used as the additional thematic decision rule to assign final LCM classes to the pre-indicated geometric extent of the composite objects. This rule was chosen, because it is a generally accepted post-processing strategy in per-pixel classifications. The majority rule calculates the majority (area-wise) of a thematic class in a certain area. At composite level, this means that the final LCM class for a composite object is the LCM class with the 'largest relative area' in that composite object. The definition of *largest-relative-area* was based on fuzzy sets (see Chapter 5, section 5.2.3). The membership function describing the transition zone of the boundaries of the fuzzy set is asymmetric right range with cross-over point *a1*, dispersion *d1*, and mathematical equation *f(x)*. The three function parameters were set according to a true interpretation of majority: *a1*=0.4, *d1*=0.1, and *f(x)*=S-shaped. This means that if a LCM class comprises half of the composite object, then it is a full member of the fuzzy set. However, a lower largest-relative-area does not mean that the LCM is not a member of the fuzzy set 'majority', but it obtains a membership (or possibility) value in the range [0,1]. The final LCM class of a composite object is the LCM class with the highest possibility value for that composite object. The function condition of this decision rule is a single fulfillment to majority.

6.2.4 Wavelet-driven segmentation

The wavelet-driven patch-mosaic segmentation method follows exactly the data-driven method, with two additions. First, a discrete wavelet transform (Chapter 2, section 2.3.7) was used to guide the pre-indication of the geometric extent of the composite objects (see section 6.1). Second, a quantitative measure was used to select the scale level (i.e., decomposed image band) with the highest image quality per Landsat TM band. Subsequently, the sequence of this functional upscaling process is *(1) patch-mosaic classification, (2) wavelet transformation, (3) image quality evaluation, (4) patch-mosaic segmentation I, (5) additional classification* and *(6) patch-mosaic segmentation II* (Figure 6.5). This sequence can be regarded again as a stepwise functional generalization with step (2) and (3) as pre-processing steps of the patch-mosaic segmentation I.

The 2D extension of the 'à trous' algorithm with a linear spline (1/4, 1/2, 1/4) was used as the discrete wavelet transform to decompose the original Landsat TM bands. The number of scale levels J was set at 7. This number of levels was chosen to definitely obtain broad features that are relevant in the case of creating composite objects (i.e., 60 m when $j=1$ up to 3840 m when $j=7$). A graphic example applying this algorithm is presented in Figure 2.19 of Chapter 2, section 2.3.7.

The MITRE Image Quality Measure (IQM) was used as the quantitative measure to select the scale level (i.e., decomposed image band) with the highest image quality per Landsat TM band. Being developed for the U.S. Government, in particular for the USAir Force and the FBI, this measure was chosen because of its use in reconnaissance applications, forensic applications (fingerprints), image compression applications, and medical applications (MITRE, 2000). Good results with this measure were also obtained in multi-resolution data fusion using wavelet transforms (Muhammad et al., 2002a, 2002b; Acerbi et al., 2004). The IQM computes image quality (spatial and spectral information) based on the two-dimensional spatial requency power spectrum of an image (Nill & Bouzas, 1992). This spectrum is the square of the magnitude of the Fourier transform of an image. It contains information on sharpness, contrast, and detail rendition of the image, which are components of image quality (Nill, 2003).

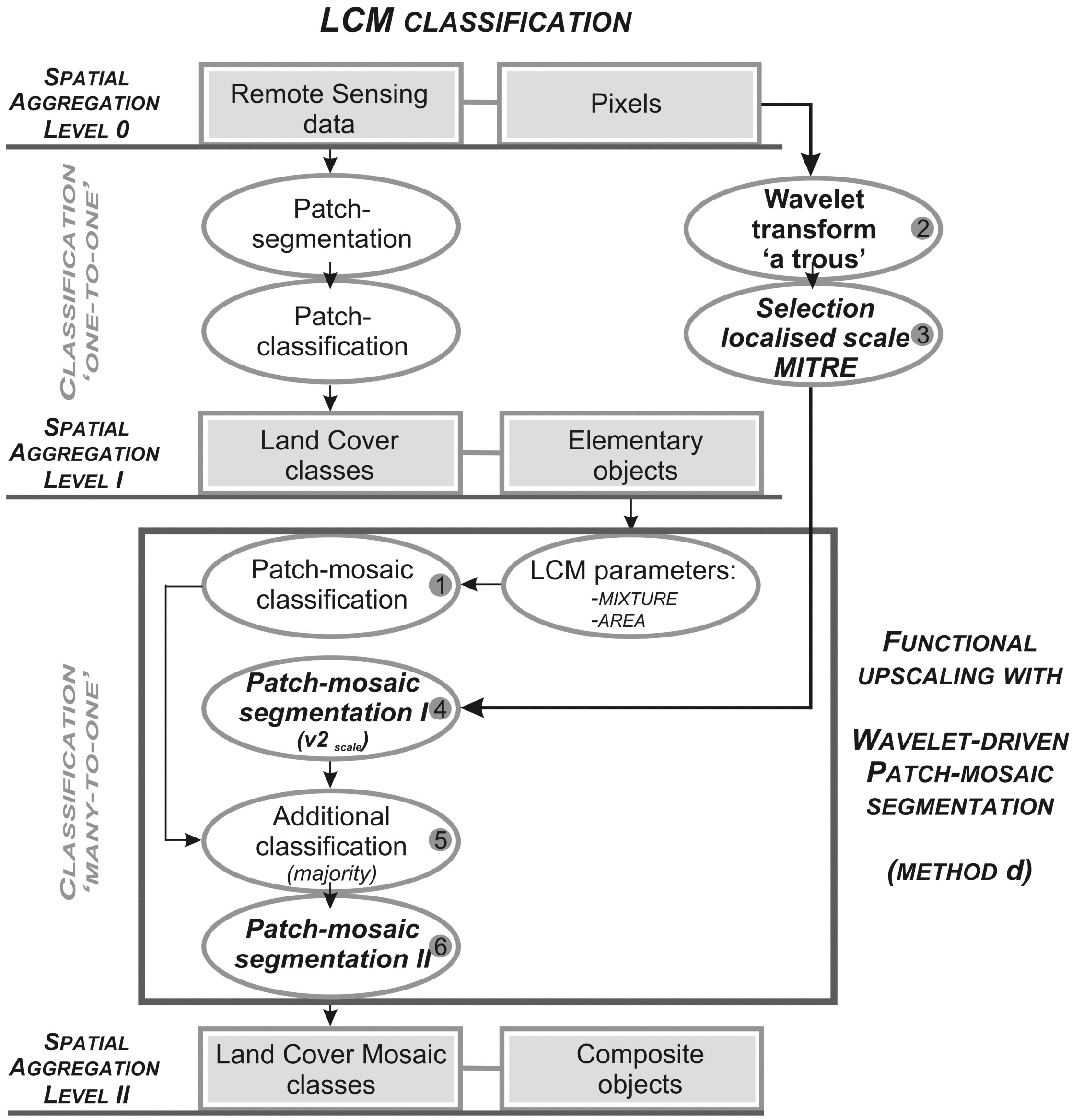


Figure 6.5: Functional upscaling in LCM classification with wavelet-driven patch-mosaic segmentation (also referred to as method d).

This power spectrum is normalized for image brightness and weighted for a visual response function. The brightness normalization allows inter-comparison between images with different average gray levels. The visual weights align image quality with what humans perceive as 'quality'. If a significant noise level is detected, a modified Wiener noise filter is applied to the spectrum. The spectrum is finally normalized for image size (in pixels) and weighted for a direction-dependent scale factor. The noise filter compensates for the power spectrum's sensitivity to noise. The scale factor converts the power spectrum's inherent scale-independency to scale-dependency. The output Image Quality factor, 'IQ', is the sum of the weighted power spectrum values. Formally expressed:

$$IQ = \frac{1}{M^2} \sum_{\theta} \sum_{\rho} S(\theta_1) W(\rho) A^2(T\rho) P(\rho, \theta) \tag{6.2}$$

with M^2 is the digital image size in pixels, $S(\theta_1)$ is the directional image scale parameter, $W(\rho)$ is the modified Wiener noise filter, $A^2(T\rho)$ is the modulation transfer function of the human visual system, $P(\rho,\theta)$ is the brightness normalized image power spectrum, and ρ,θ is the spatial frequency in polar coordinates. For detailed information on each component, see Nill & Bouzas (1992). The image with a low IQ contains less spatial and spectral information than an image with a high IQ. To run this quality measure, three data files are needed: a preference data file containing the settings for the MITRE Image Quality Measure (see Appendix 6.1), an auxiliary data file containing the information on the original image data (see Appendix 6.2), and the image data file containing the original image data (i.e., Landsat TM bands). This study compared the IQs of the wavelet-transformed images (smooths and details) per Landsat TM band to the IQ of each original Landsat TM band. The images with the highest IQ were subsequently used as input for patch-mosaic segmentation I (Table 6.1). Apparently, these were all smooth images but of different scale levels *J* comparing the spectral bands. The more fragmented p1996 image required more decomposing (a larger number of scale level *J*) to obtain a highest IQ compared to the p1990 image.

Table 6.1: Wavelet-transformed Landsat TM bands containing best spatial and spectral information as selected with MITRE's highest IQ test (the number behind smooth refers to scale level J; see Appendix 6.3 for full details).

LANDSAT TM band	*HighestIQ test p1990 Image / J*	*Localized scale*	*HighestIQ test p1996 Image / J*	*Localized scale*
1	*smooth 4*	*480 m*	*smooth 6*	*1920 m*
3	*smooth 1*	*60 m*	*smooth 3*	*240 m*
4	*smooth 6*	*1920 m*	*smooth 7*	*3840 m*
5	*smooth 5*	*960 m*	*smooth 5*	*960 m*

6.3 Reference data & approaches in spatial object modeling

Reference data is needed to calculate *KHAT*. The reference data should provide the expected segmentation result at composite level to define which patch-mosaic segmentation method is the most accurate when classifying spatially heterogeneous environments. Such environments, however, show composite objects that are often thematically complex (see discussion Chapter 2, section 2.2.5). This means that composite objects do not necessarily have exact boundary information. In fact, boundaries often do not exist in the field but are the result of *spatial object modeling*. Therefore, the geometric extent of composite objects can only be evaluated indirectly by means of assessing functional upscaling differences. Such an evaluation was already performed in the previous chapter. Subsequently, this chapter used the same digital reference as described in Chapter 5, section 5.5. It is the patch-classification result at elementary level. With this reference, the *KHAT* metric could be used to evaluate significant differences between the four patch-mosaic segmentation methods.

An alternative indirect way to evaluate the four patch-mosaic segmentation methods is to investigate another spatial modeling approach that also requires segmentation at composite level. Such a spatial modeling approach is offered by manual image interpretation, a common practice in operational mapping programmes (NFI, 1993; FAO, 2000). A key difference between the two spatial modeling approaches is the way how composite objects are created (Figure 6.6).

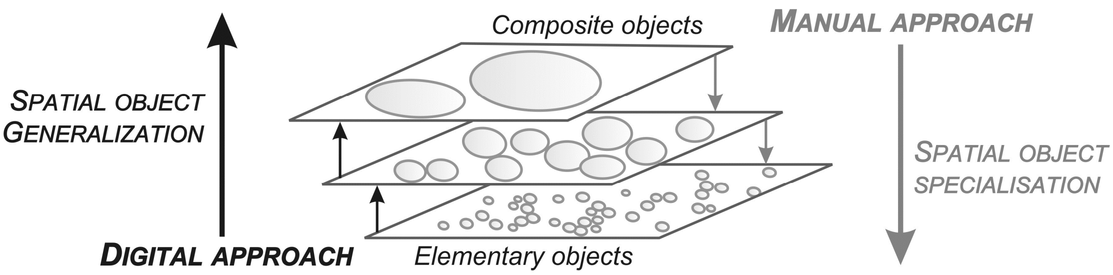


Figure 6.6: A digital (bottom-up) approach versus a manual (top-down) approach in spatial object modeling for creating composite objects.

A digital approach obtains the composite objects via *spatial-generalization* (see Chapter 2, section 2.3.1 for detailed information). This is a bottom-up approach that first identifies primitives or elementary objects, and subsequently identifies more general composite objects, up to composite objects with the desired thematic description at the required spatial aggregation level. A manual approach obtains the composite objects via *spatial-specialization*. This is a top-down approach that first identifies general composite objects, and subsequently identifies more detailed composite objects, down to composite objects with the desired thematic description at the required spatial aggregation level. Manual approaches are also based on expert knowledge including a-priori knowledge and general image information like shadow, texture, size, shape and orientation of spatial objects as well as (functional) relations between composite objects (Richards & Xiuping Jia, 1999; Abkar, 1999). Although manual approaches often cause interpretation inaccuracies (João, 1998), they still outperform standard digital approaches (e.g., Mas & Ramirez, 1996). Moreover, the spatial information obtained from manual approaches is easier to use in a qualitative sense (Richards & Xiuping Jia, 1999). This research used a manual spatial modeling approach to obtain an expert's view on LCM classification at composite level for a spatially heterogeneous forest area. It assumed that experts knew the end-users' requirements regarding the required spatial aggregation level for interpretation results at composite level.

Three tropical forestry experts were asked to manually segment and classify the two Landsat TM images of the Pelangkaraya study area. Although a higher number could have provided additional statistical information, three experts were regarded to be sufficient. Similar to the digital approach, the forestry minister of a country was selected as end-user (Chapter 5, section 5.2.1). Therefore, hardcopies of false-colour composites of original Landsat TM bands 453 (in RGB including histogram-based contrast enhancement) of the p1990 image and the p1996 image were provided at scale 1:160,000. At this scale, the smallest spatial entity that can be manually mapped was 10 ha considering a minimum mapping unit of 2mm x 2mm. This area was regarded sufficient with respect to the defined LCM classes. A spectral legend was provided for the eight land cover classes (1) logged forest, (2) heavily logged forest, (3) shrub, (4) agriculture, (5) grass, (6) water, (7) cloud and (8) river. This means that the legend did not specify or indicate the level of spatial aggregation. Transparencies were superimposed on top of the hardcopies. A black marker (0.6 mm) was used for the delineation of the spatial (composite) objects, and a green marker for labelling the spatial (composite) objects. The manual interpretation results obtained from the three experts were scanned and rasterized into 30-meter pixels to obtain spatially the same digital format as the digital approaches (i.e., LCM classification results at composite level).

Similar to the digital approaches, the manual geometric extent of composite objects can only be evaluated indirectly by means of assessing functional upscaling differences. Therefore, the patch-classification result at elementary level was again used as reference to calculate all similarity matrices (Chapter 5, section 5.5). With this reference, the evaluation measure *KHAT* could be used to evaluate significant differences between the two spatial modeling approaches (Figure 6.7).

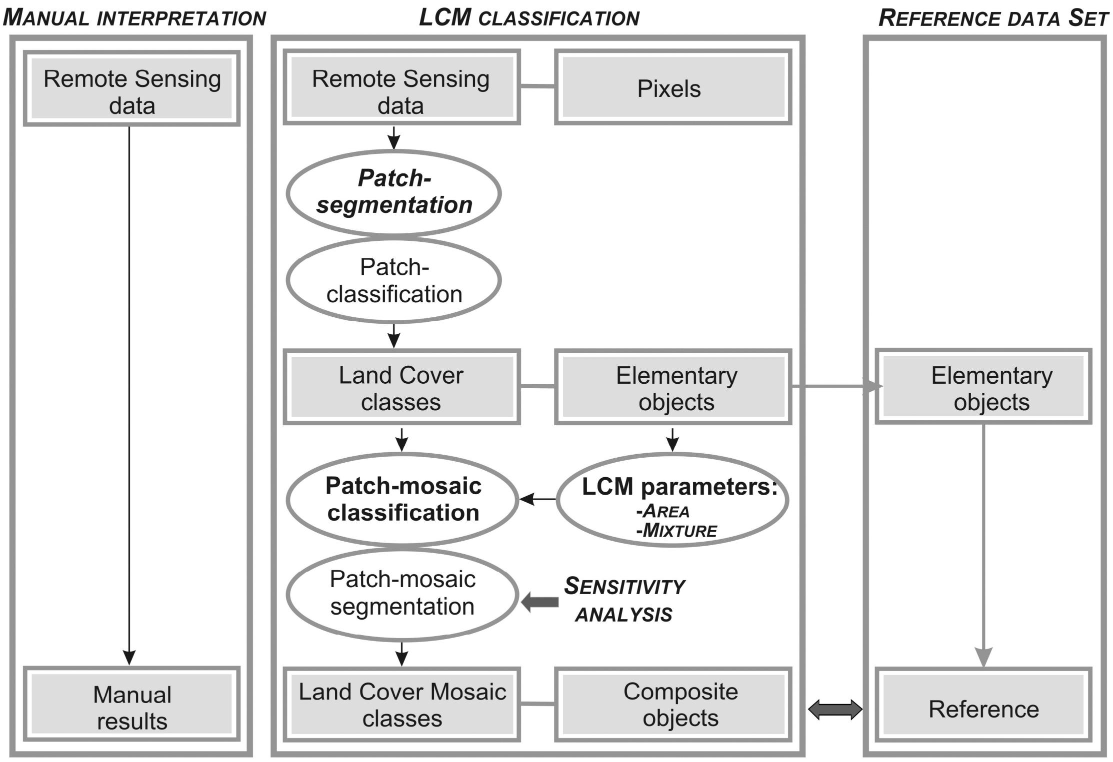


Figure 6.7: Reference data to evaluate the digital LCM classification results and the manual interpretation results at composite level.

6.4 Results & discussion

6.4.1 LCM classification accuracy

Figure 6.8 (p1990 image) and figure 6.9 (p1996 image) show all the LCM classification results at composite level applying the four patch-mosaic segmentation methods. Both figures clearly show that the LCM classes were less fragmented applying the two radiometry-based segmentation methods (*c* and *d*) compared to the two taxonomy-based segmentation methods (*a* and *b*), especially when increasing the break-off value. The *lc*-driven patch-mosaic segmentation (method *a*) showed highest agreement with the reference (i.e., patch-classification result at elementary level, section 6.3). One reason could be that this conventionally used segmentation method has the underlying assumption of homogeneity (i.e., distinguishing major and minor classes, see Chapter 5, section 5.3). Such an assumption would not force a large generalization progress in a spatially heterogeneous environment.

Figure 6.10 shows the manual interpretation results of the three tropical forestry experts (i.e., *I-1*, *I-2*. and *I-3)* for both the p1990 image and the p1996 image. Obviously, large differences exist in assigning the land cover (mosaic) classes. Specifically non-forest classes caused confusion.

The *KHAT* metric showed the reduction in fragmentation of the LCM classes in the digital results, but did not show the major confusion in assigning non-forest classes in the manual results (Figure 6.11). Probably, interpretation confusion did not affect the resulting spatial aggregation level. The finer classification detail of manual *I-1* increased the *KHAT* of the p1996 image compared with the two other manual results. Generally, the manual results showed *KHAT* values that were most similar to radiometry-based segmentation results with large break-off values (i.e., *c160* and *d160* for the p1990 image, and *d160* for the p1996 image). Both images showed a similar trend towards the four patch-mosaic segmentation methods, except for the p1996 image applying data-driven patch-mosaic segmentation with largest break-off value (*c160*). Applying this combination (method and setting), probably, a disconnection occurs between the geometric extent of composite objects and their thematic content. The used wavelet transform seemed to restore this relation. Generally, the four patch-mosaic segmentation methods had more effect on the spatially more heterogeneous p1996 image (lower *KHAT*) than on the p1990 image.

From the Z statistics presented in Appendix 6.4 it was evident that many digital results were significantly different at the 0.05 probability level for both the images. Specifically, the two taxonomy-based segmentation methods were significantly different, and the two radiometry-based segmentation methods were different when applying a different break-off value. For the p1990 image, however, there was no significant difference between the two radiometry-based segmentation methods when applying an identical break-off value (i.e., *c40=d40, c80=d80, and c160=d160).* For the spatially more heterogeneous p1996 image, only *c80* was not significantly different to *d80.*

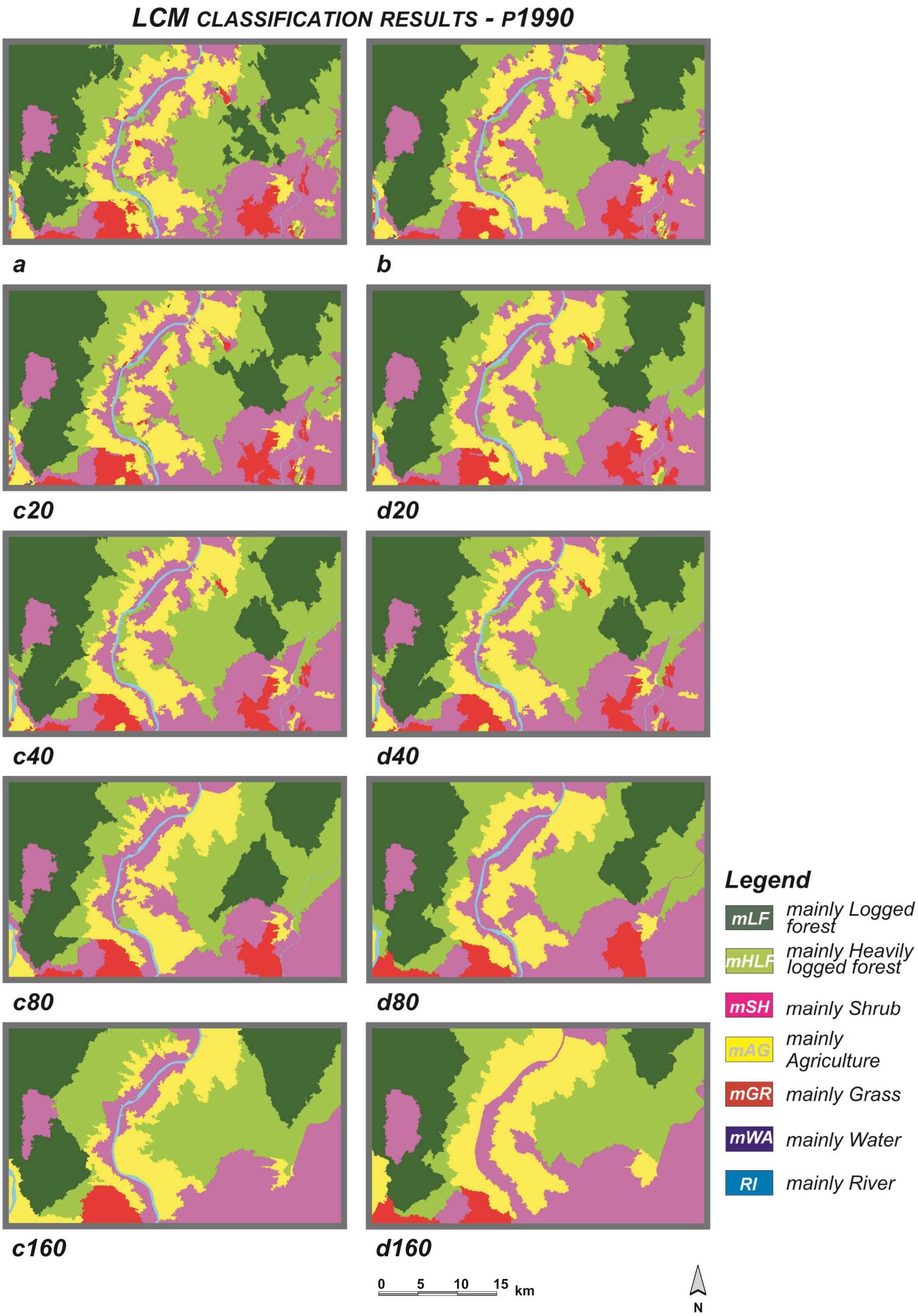


Figure 6.8: LCM classification results at composite level for the four patch-mosaic segmentation methods: lc-driven (a), lcm-driven (b), data-driven (c), and wavelet-driven (d); p1990 image. The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation.

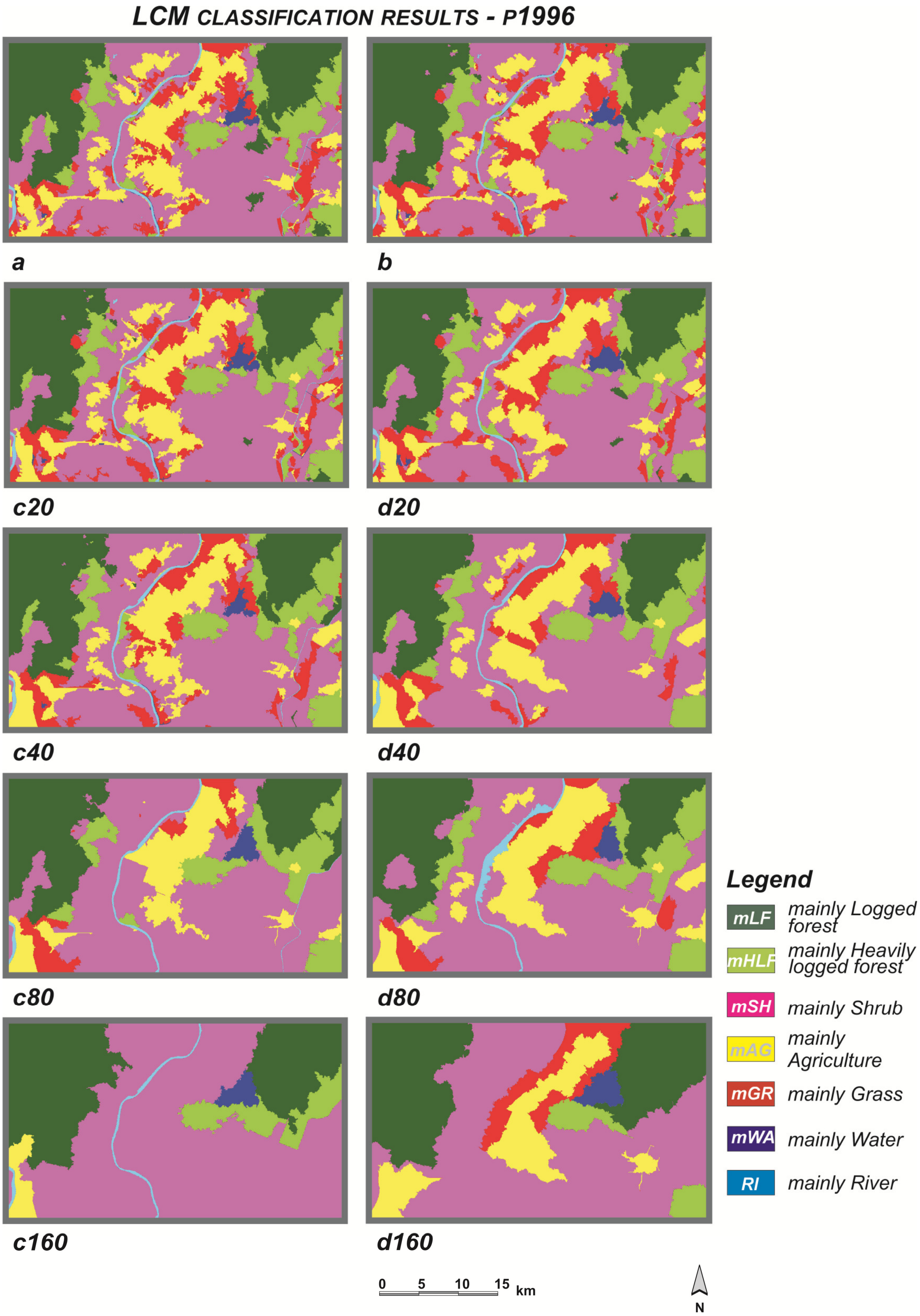


Figure 6.9: LCM classification results at composite level for the four patch-mosaic segmentation methods: lc-driven (a), lcm-driven (b), data-driven (c), and wavelet-driven (d); p1996 image. The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation.

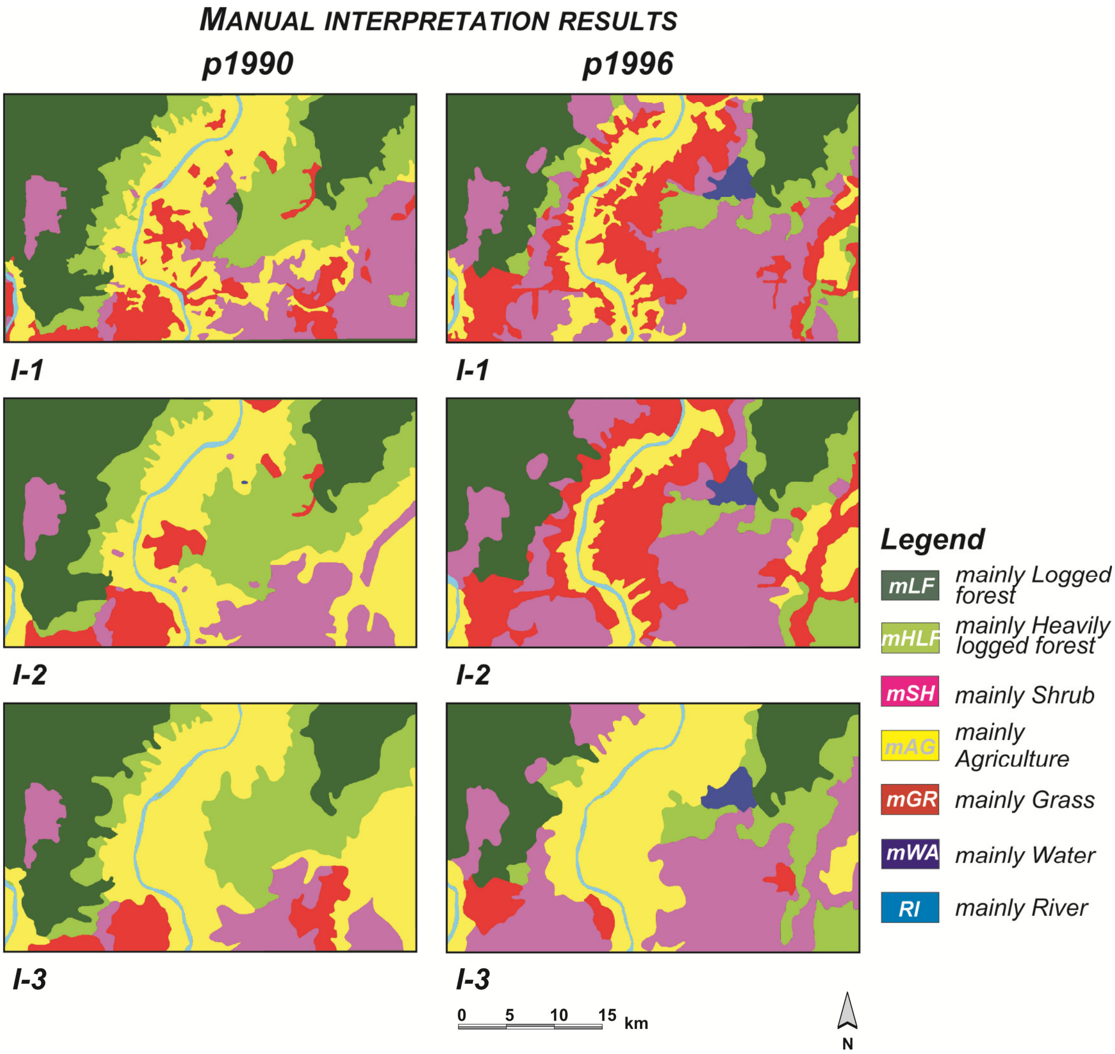


Figure 6.10: Manual interpretation results of the three tropical forestry experts I-1, I-2, and I-3 for the two Landsat TM images p1990 and p1996.

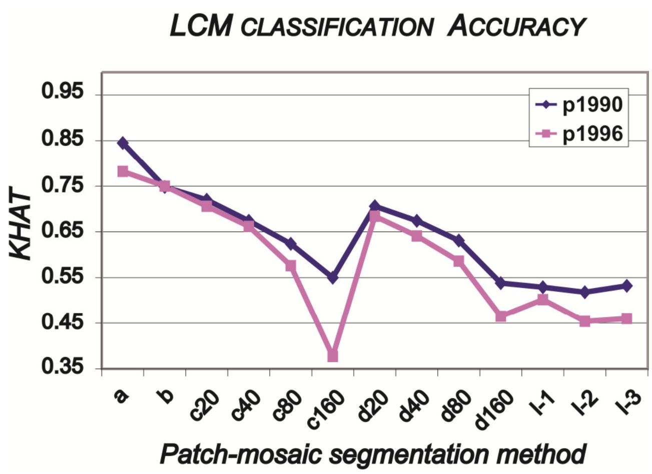


Figure 6.11: LCM classification accuracy expressed in KHAT values for the four patch-mosaic segmentation methods (a, b, c, and d) and for the three manual interpretation results (I-1, I-2, and I-3). The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation (figure displayed in line graphs for visual clarity).

From the Z statistics it can also be concluded that all manual results were not significantly different at the 0.05 probability level for both images, except *I-1* for the p1996 image. Regarding the findings of the two previous chapters, this means that their spatial aggregation levels were not significant different. Experts apparently create composite objects at a similar spatial aggregation level. They know the required level of detail when interpreting an image at a certain map scale. Finally, when comparing the digital results versus the manual results, only the wavelet-driven functional upscaling *d160* was not significantly different from the manual results of *I-1* and *I-3* for the 1990 image, and *I-2* and *I-3* for the p1996 image. Unfortunately, small linear features like the two rivers disappeared when applying this upscaling method. A solution for preserving such linear features could be to include more steps in the upscaling process, for example, elementary objects, lower level composite objects, final level composite objects.

6.4.2 Forest area

Table 6.2 shows an overview of the proportional abundance of the eight tropical LCM classes for the digital LCM classification results and the manual interpretation results. Comparing the standard deviations of the digital results (p1990 image versus p1996 image), all vegetation classes for the p1996 image showed higher standard deviations than for the p1990 image. Similar to findings in Chapter 4 (section 4.6.3), the spatially more heterogeneous p1996 image was more sensitive for the four patch-mosaic segmentation methods than the spatially homogeneous p1990 image. Most spectacular is the drastically increase of the standard deviation of shrub vegetation. Considering the findings in Chapter 5 (section 5.6.2), shrub vegetation seemed to be most spatially fragmented and thus most sensitive for patch-mosaic segmentation methods. This finding necessitates the need for quantifying spatial heterogeneity at different spatial aggregation levels to suit end-users' need (i.e., which shrub belongs to what process? Chapter 3).

Comparing the two spatial modeling approaches (digital versus manual), three interesting findings need to be mentioned. First, the manual interpretation results showed largest variations in the standard deviation for the p1990 image, while the digital classification results showed largest variations in the standard deviation for the p1996 image. The larger the entities to be classified, the larger the impact of manual (thematic) interpretation errors. The more fragmented an image, the more the impact of (digital) spatial aggregation levels. Second, both spatial modeling approaches showed relatively similar cover percentages for both forest vegetation classes (mLF and mHLF), but dissimilar cover percentages for non-forest vegetation classes (mSH, mAG and mGR). For both the images, the manual results showed striking lower cover percentages for shrub vegetation (mSH), which went along with a substantially higher area for agriculture and grass vegetation. This major confusion may have occurred in assigning shrub vegetation and agriculture after delineating the composite objects. Even in the field, a distinction between shrub vegetation and agriculture was often hard to make. Third, both modeling approaches at composite level agreed on the underlying change scenario. They revealed the abandoning of agricultural areas, leading to a striking increase of shrub vegetation and the burning of heavily logged forest vegetation for (maintaining) agricultural production.

Table 6.2: Digital (LCM classification) results versus manual interpretation results at composite level expressed in proportional abundance (i.e., PLAND mean and standard deviation).

	p1990 image				*p1996 image*			
LCM Class	*Digital N=10*		*Manual N=3*		*Digital N=10*		*Manual N=3*	
	PLAND mean	*PLAND sd*	*PLAND mean*	*PLAND sd*	*PLAND mean*	*PLAND sd*	*PLAND mean*	*PLAND sd*
mLF	*25.89*	*2.27*	*26.73*	*0.35*	*22.75*	*3.05*	*22.16*	*1.28*
mHLF	*25.80*	*1.61*	*21.05*	*2.24*	*10.52*	*2.91*	*11.10*	*0.70*
mSH	*25.80*	*1.21*	*14.15*	*4.86*	*43.53*	*6.98*	*29.12*	*1.73*
mAG	*16.31*	*1.25*	*28.01*	*5.84*	*12.85*	*3.94*	*18.61*	*1.95*
mGR	*4.83*	*1.03*	*7.62*	*2.12*	*8.03*	*3.86*	*15.80*	*2.95*
mWA	*0.03*	*0.05*	*0.01*	*0.01*	*1.04*	*0.29*	*1.32*	*0.06*
RI	*1.27*	*0.09*	*1.38*	*0.02*	*1.16*	*0.43*	*1.33*	*0.04*
mCl	*0.09*	*0.26*	*1.06*	*0.79*	*0.13*	*0.26*	*0.56*	*0.04*

6.4.3 Variability & arrangement of forest cover

Figure 6.12 shows the Percentage of Landscape *PLAND* and the Number of Patches *NP* of the three LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF), and mainly shrub (mSH). The figure clearly shows that the four patch-mosaic segmentation methods did not affect class-composition of forest and shrub vegetation in either of the two images, except for radiometry-based segmentation methods with largest break-off value (specifically *c160* and *d160*). At large break-off values a disconnection occurs, probably, between the geometric extent of composite objects and their thematic content. The figure also shows that the more a vegetation class is spatially fragmented (like shrub vegetation), the larger its proportional abundance fluctuates. In such cases, functional upscaling using wavelet-driven patch-mosaic segmentation seemed to guide a balance between geometric extent and thematic content (e.g., compare *c80* and *d80*, and *c160* and *d160* for the shrub class). This means that class-composition is more constant if a wavelet transform is included in radiometry-based segmentation methods, specifically for spatially fragmented vegetation.

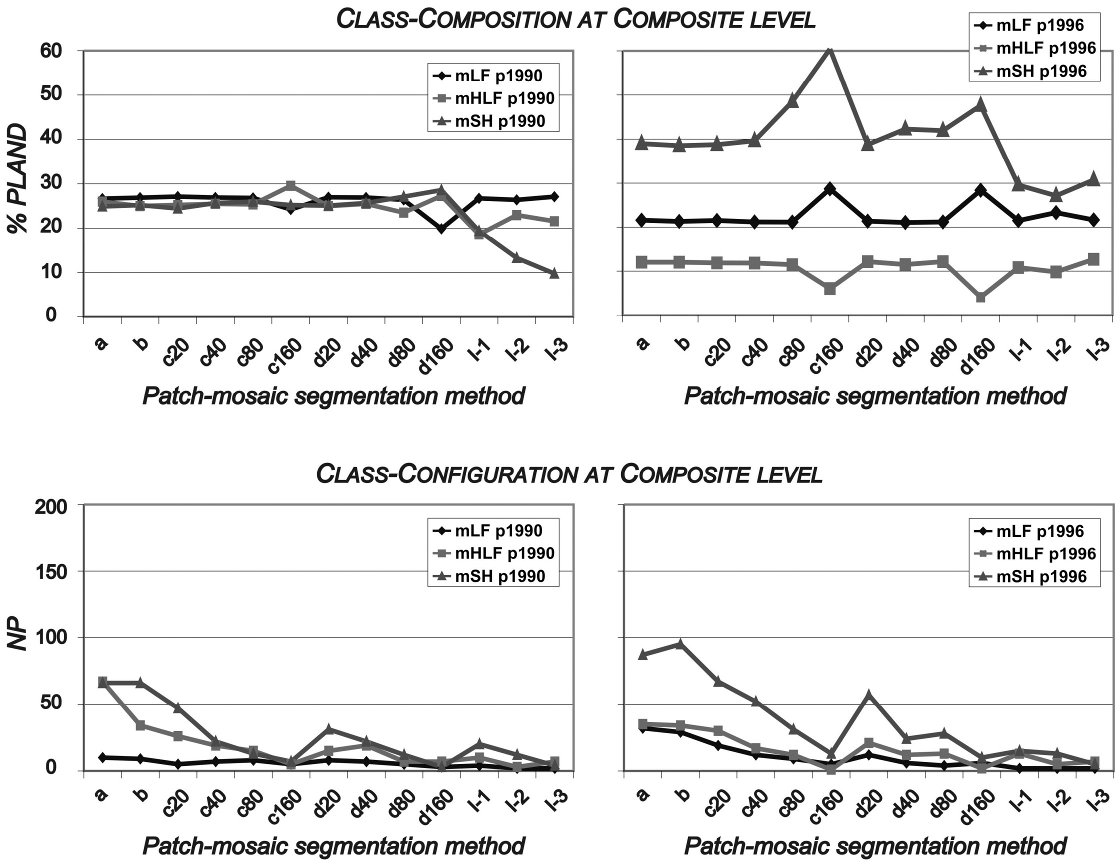


Figure 6.12: Class-composition expressed in Percentage of Landscape (PLAND) and class-configuration expressed in Number of Patches (NP) of the LCM classes mainly logged forest (mLF), mainly heavily logged forest (mHLF) and mainly shrub (mSH) for the four digital patch-mosaic segmentation methods (a, b, c, and d) and the three manual interpretation results (I-1, I-2, and I-3). The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation (figure displayed in line graphs for visual clarity).

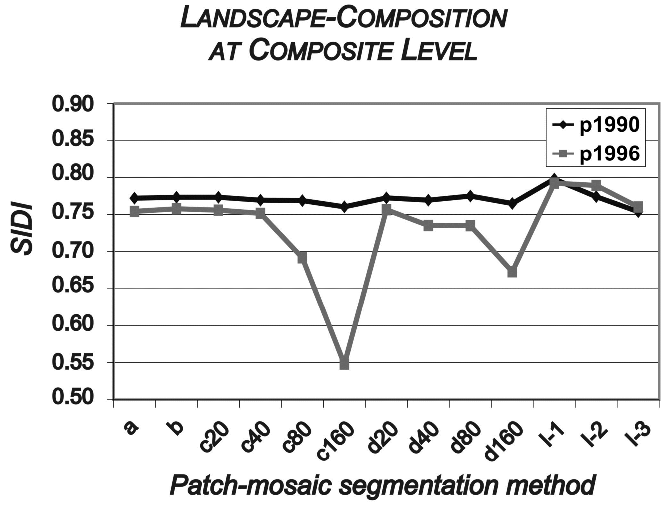
The manual interpretation results showed about a similar proportional abundance (PLAND) for the two forest vegetation classes for both images. For the p1990 image, however, they showed a dissimilar proportional abundance for shrub vegetation.

Interpretation confusion of small (heterogeneous) composite objects less influenced interpretation results than interpretation confusion of large (homogeneous) composite objects. This may explain the large differences in class-composition between the three manual interpretation results for the more homogeneous p1990 image. Not surprisingly, the largest confusion occurred between shrub vegetation and agriculture. Even in the field, this distinction was often hard to make (see also section 6.4.2).

Figure 6.12 also clearly shows that the four patch-mosaic segmentation methods differently affected class-configuration of the three vegetation classes for both images. Again, the more spatially fragmented a vegetation class is, the more its extent of fragmentation is affected in patch-mosaic segmentation. Generally, class-configuration was highest for the taxonomy-based segmentation methods (*a* and *b*), and decreased with increasing break-off values for the radiometry-based segmentation methods (*c* and *d*). As such, the geometric extent of composite objects was larger in radiometry-based segmentation methods. The figure also shows that wavelet-driven functional upscaling forced a reduction in fragmentation to a certain level. A sharp decrease occurred in the number of patches at *d40* for shrub vegetation in the p1996 image using wavelet-driven patch-mosaic segmentation, while remaining the same at *d80* compared to data-driven patch-mosaic segmentation. This means that class-configuration is more constant if a wavelet transform is included in radiometry-based segmentation methods, specifically for spatially fragmented vegetation. The p1990 image showed also such a decrease in the number of patches, but at *d20*. This difference in break-off value comparing the two images is probably related to differences in localized scales. The mean spatial size of composite objects was 855 m in the p1990 image, and 1740 m in the p1996 image (see Table 6.1). Class-configuration of the manual interpretation results tended to be most similar with radiometry-based segmentation methods, especially with large break-off values. Finally, the third manual result (*I-3*) showed lowest fragmentation of the three vegetation classes.

6.4.4 Variability & arrangement of forest cover pattern

Figure 6.13 shows the Simpson's Diversity Index *SIDI* and the Landscape Shape Index *LSI* for the four different patch-mosaic segmentation methods. The figure clearly shows that landscape diversity remained relatively constant for all digital methods in the p1990 image. This means that the relative proportions of the eight LCM classes did not change. For the more fragmented p1996 image, however, landscape diversity showed a striking decrease for the patch-mosaic segmentation methods *c80*, *c160* and *d160*, and showed some decrease for *d40* and *d80*.



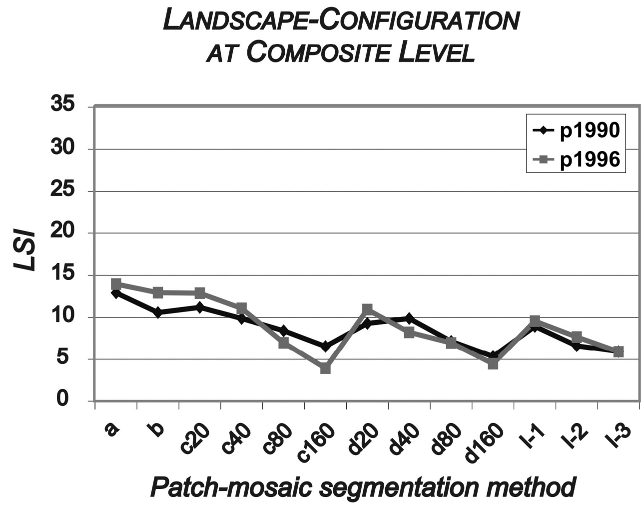


Figure 6.13: Landscape-composition expressed in Simpson's Diversity Index (SIDI) and landscape-configuration expressed in Landscape Shape Index (LSI) for the four digital patch-mosaic segmentation methods (a, b, c and d) and the three manual interpretation results (I-1, I-2, I-3). The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation (figure displayed in line graphs for visual clarity).

This diversity decrease means that dominance of one or several LCM classes increased. Combining the landscape-composition metric SIDI and the class-composition metric PLAND, this increasing dominance can be explained. For the patch-mosaic segmentation methods *c80*, *c160* and *d160* the proportional abundance of shrub vegetation increased remarkably. As such, a constant SIDI and a constant

PLAND means that the LCM classes have their own specific composition in the landscape. Nevertheless, for patch-mosaic segmentation methods having effect on certain classes, like shrub vegetation, SIDI quantified this compositional change. SIDI also quantified the small increase in PLAND of shrub vegetation for the two patch-mosaic segmentation methods *d40* and *d80* (p1996 image).

Including a wavelet transform in radiometry-based segmentation remarkably reduced the large landscape diversity drop of *c160* and it seemed again to guide a balance between geometric extent and thematic content of composite objects (compare *c40* with *d40*, and *c80* with *d80*). These findings indicate a relation between thematic content and geometric extent of composite objects. The dramatic dip of SIDI was a result of increasing the geometric extent while maintaining the same thematic content. Using a majority rule to link thematic content with geometric extent of composite objects implicitly assumed the existence of a dominant LCM class. Without any relation between geometric extent and thematic content such a dominance cannot be detected. In fact, the geometric extent increased too much when applying large break-off values. The resulting large composite objects should actually be related to the thematic content of higher level composite objects. This means that the geometric extent of composite objects cannot be unlimitedly enlarged. There must be a relation between thematic and geometric characteristics. Therefore, functional upscaling elementary objects into composite objects is geometrically restricted as a result of thematic constraints (i.e., semantics).

Figure 6.13 also clearly shows that the landscape-composition metric SIDI depicted the major confusion in assigning non-forest classes in the manual interpretation results (see discussion in section 6.4.1). The manual results tended to have generally a higher landscape diversity than the digital results. Higher diversity means less dominance of one or several LCM classes. They tended to be most similar with the digital wavelet-driven functional upscaling method for both the images. The manual results generally showed also a higher landscape diversity for the p1996 image. This is exactly the opposite of the digital results.

Finally, all four patch-mosaic segmentation methods affected the perimeter-to-area ratio for both images. The LSI was generally lowest for the radiometry-based segmentation methods with large break-off values, and specifically for the more fragmented p1996 image. A low LSI means that patches become increasingly aggregated, thus spatial heterogeneity decreases. Overall, the spatial heterogeneity of both images showed a similar trend for the four patch-mosaic segmentation methods. Including a wavelet transform in radiometry-based segmentation seemed to balance landscape heterogeneity, but its impact was less distinct compared to landscape diversity.

6.5 Conclusions

6.5.1 Spatial object modeling

Both spatial modeling approaches (digital and manual) showed variations in LCM classification results. Most digital results were significantly different for both images, while most manual results were not significantly different. The *KHAT* metric showed the reduction in fragmentation of the eight LCM classes in the digital modeling approach, but did not show the major confusion between assigning shrub vegetation and agriculture in the manual modeling approach. The two modeling approaches agreed on the proportional abundance of forest vegetation, but specifically disagreed on shrub vegetation. The four digital methods showed highest agreement for the spatially more homogeneous p1990 image (absence of spatial heterogeneity). The three tropical forestry experts showed highest agreement for the spatially more heterogeneous p1996 image (absence of large entities). Both modeling approaches agreed on the underlying change process of deforestation revealing the abandoning of agricultural areas, leading to a striking increase of shrub vegetation and the burning of heavily logged forest vegetation for (maintaining) agricultural production.

Radiometry-based segmentation methods with large break-off values showed a similar vegetation configuration when compared to the manual interpretation results. However, they showed a striking difference in vegetation composition, specifically for the fragmented shrub vegetation. Only wavelet-driven patch-mosaic segmentation *d160* was not significantly different in comparison to the manual interpretation results for both the images. Unfortunately, small (linear) features disappeared during this patch-mosaic segmentation method. The KHAT depicted both the reduction in fragmentation of the LCM classes (configuration) as well as the semantic mismatch of extent and content of composite objects (composition). These findings indicated again that in a spatially heterogeneous environment the *KHAT* metric seems to address differences in spatial aggregation levels (see also the conclusions in Chapter 4, section 4.7.1).

6.5.2 Patch-mosaic segmentation methods

Both Landsat TM images of the Pelangkaraya study area showed almost similar trends towards the four patch-mosaic segmentation methods: a decreasing KHAT moving from taxonomy-based segmentation towards radiometry-based segmentation, specifically when increasing the break-off value during segmentation. As such, the geometric extent of the composite objects became larger. The spatially more heterogeneous p1996 image and the spatially fragmented shrub vegetation were most sensitive for the four patch-mosaic segmentation methods. Heterogeneous environments and fragmented vegetation contain more elementary objects. This results in a larger variety when grouping them into a LCM class at composite level.

The two taxonomy-based segmentation methods showed similar vegetation composition, but vegetation configuration of the *lcm*-driven method was generally lower. The two radiometry-based segmentation methods with similar break-off values generally did not show much differences in vegetation configuration for both images. They showed, however, striking differences in vegetation composition for the more fragmented p1996 image when using large break-off values. In such cases, a disconnection occurred between the geometric extent of composite objects and their thematic content. Therefore, break-off values cannot be freely selected, specifically not in the data-driven patch-mosaic segmentation method.

Applying a wavelet transform before a patch-mosaic segmentation improved the LCM results for spatially fragmented vegetation. It showed a striking impact on vegetation composition reducing the dominance of shrub vegetation. This means that vegetation composition is more constant if a wavelet transform is included in radiometry-based segmentation methods, specifically when using large break-off values. The wavelet transform guided a balance between the geometric extent of composite objects and their thematic content. This means that localized scales can help to digitally create composite objects similarly to human interpreters, but on one condition only.

Geometric extents cannot be unlimitedly expanded. There is a point where such an expansion led to a dramatic change in composition. At this point the majority rule could not be used to select the final land cover mosaic class, because there is no semantic match between the composite object and the LCM class. As such, knowledge on semantics is necessary when functional upscaling elementary objects into composite objects (i.e., defined in spatial aggregation classes; Chapter 3, section 3.3).

References

Abkar, A.A., (1999). Likelihood-based segmentation and classification of remotely sensed images: a Bayesian optimization approach for combining RS and GIS. PhD Thesis, University of Twente, Enschede / ITC, Enschede, 132p.

Acerbi, F.J. Jr., Wachowicz M., Carvalho, L.M.T. & Clevers, J.G.P.W. (2004). "Are we using the right quality measures in multi-resolution data fusion?" Proceedings of the 24th EARSeL Symposium New Strategies for European Remote Sensing, May, Dubrovnik, Croatia.

Bregt, A. & Bulens, J. (1996). Application-oriented generalization of area objects. In: Molenaar, M. (ed), Methods for the generalization of geo-databases, Delft: Netherlands Geodetic Commission, New Series 43:57-64.

Chui, C. K. (1992). Wavelets: A tutorial in theory and applications. Wavelet analysis and its applications, Vol. 2. Academic Press, San Diego, CA.

Daubechies, I. (1989). Orthonormal bases of wavelets with finite support: Connection with discrete filters. In: Combes, J.M., Grossman, A. & Tchamitchian, P. (eds.), Wavelets: Time-frequency methods and phase space, Springer-Verlag, Berlin, 38-65.

Daubechies, I. (1992). Ten lectures on wavelets. Cbms-Nsf Regional Conference Series in Applied Mathematics, No 61. Society for Industrial and Applied Mathematics (SIAM), Philadelphia.

FAO (2000). Global Forest Resources Assessment 2000. Main Report. FAO Forestry Paper 140. Food and Agriculture Organization of the United Nations, Rome. At www.fao.org/forestry/site/7949/en, accessed November 5, 2003.

Foufoula-Georgiou, E. & Kumar, P. (eds) (1994). Wavelets in geophysics. Wavelet analysis and its applications, Vol 4. Academic Press, San Diego, CA.

João, E.M. (1998). Causes and consequences of map generalisation. London School of Economics. Taylor & Francis, London.

Kenk, E., Sondheim, M. & Yee, B. (1988). Methods for improving accuracy of thematic mapper ground cover classifications. Canadian Journal of Remote Sensing 14(1):17-31.

Mallat, S. (1989). A theory for multiresolution signal decomposition: The wavelet representation. IEEE Transactions on Pattern Analysis and Machine Intelligence 11:674-693.

Mallat, S. (1998). A wavelet tour on signal processing. Academic Press, San Diego, CA.

Mas, J.-F. & Ramirez, I. (1996). Comparison of land use classifications obtained by visual interpretation and digital processing. ITC Journal (3/4):278-283.

MITRE (2000). IQM approach: Obtain quality from image power spectrum. At http://www.mitre.org/tech/mtf/poster.pdf, accessed July 11, 2003.

Muhammad, S., Wachowicz, M. & Carvalho, M.T. (2002a). Evaluation of wavelet transform algorithms for multi-resolution image fusion. Proceedings Fusion 2002 Conference, July, Maryland, USA.

Muhammad, S., Wachowicz, M. & Carvalho, M.T. (2002b). Extraction of Urban and rural features by using image fusion techniques and neural networks. Proceedings 3rd International Symposium Remote Sensing of Urban Areas, June, Istanbul, Turkey.

Nill, N.B. & Bouzas, B.H. (1992). Objective Image quality measure derived from digital image power spectra. Optical. Engineering 31(4):813-825.

Nill, N.B. (2003). MITRE image quality measure (IQM) Computer Program v6.5.2. At http://www.mitre.org/tech/mtf/, accessed July 12, 2005.

Richards, J.A & Xiuping Jia. (1999). Remote Sensing Digital Image Analysis: An introduction. Springer, Berlin.

Richardson, D.E. (1993). Automated spatial and thematic generalization using a context transformation model. R & B Publications, Ottawa.

Srinivasan, R. (1992). Operations manual for satellite data processing. National Forest Inventory, UTF/INS/066/INS, Working Document No. 5. Directorate General of Forest Inventory and Land Use Planning, Ministry of Forestry, Government of Indonesia, and Food and Agricultural Organization of the United Nations.

Yee, B., Kenk, E., Turpin, D. & Sondheim, M. (1986). A context based technique for smoothing of digital thematic maps. Proceedings of Graphics/Vision Interface ’86, Vancouver, British Columbia, 26-30 May, 279-283.

CHAPTER 7

SYNTHESIS

"We zien geen dingen zoals ze zijn, we zien dingen zoals wij zijn"

"We do not see things as they are, we see things as we are"

Talmudic saying

7.1 LCM classifier

This thesis presents a new theory for remote sensing data analysis called *Aggregate-Mosaic Theory* (Chapter 3). With this theory spatially heterogeneous vegetation, abundant in tropical environments, can be quantitatively modeled at different spatial aggregation levels. The latter is necessary to tailor geo-information to end-users' need with respect to decision-making (Chapter 1). The novelty of this theory is the use of spatial heterogeneity to characterize tropical vegetation types. Basically, the theory describes the implementation of patch-mosaics (Chapter 2, section 2.2.2) in digital image analysis. It uses a functional generalization framework to digitally classify remote sensing data into *Land Cover Mosaics* (LCMs). Functional generalization is an upscaling strategy based on functional relationships between landscape entities at different spatial aggregation levels. The Aggregate-Mosaic Theory distinguishes two different spatial aggregation levels: elementary objects containing land cover classes and composite objects containing LCM classes. The LCM classes represent management units (i.e., functional spatial entities) at decisive level. LCM classification is, therefore, a hierarchical process to functionally classify remote sensing data into management units at each defined spatial aggregation level (i.e., at elementary level and at composite level).

A new multi-scaled classification method at composite level (i.e., patch-mosaic classification) was developed to thematically represent the LCMs. This method requires an aggregation hierarchy besides the commonly used classification hierarchy. Advanced techniques like multi-scale segmentation and wavelet transformation were used to geometrically represent the LCMs.

The LCM classifier can be regarded as an *aggregation classifier*. It marks a new stage in the evolution of digital classifiers, which started with simple classifiers focusing on the use of only the spectral dimension of remote sensing imagery. These spectral classifiers have been extensively described since the early 1970s. After that, advanced classifiers were introduced such as those using texture (e.g., Gong et al., 1992) and segmentation approaches (e.g., Kartikeyan et al., 1998). Such spatial classifiers have been developed during the 1990s to involve also the spatial dimension of remote sensing imagery (Cihlar, 2000). Both types of classifiers, however, assume spatial homogeneity of vegetation types. This assumption is required for all traditional image analysis methods being either a spectral classifier or a spatial classifier. For many landscapes, however, this assumption is not valid. Vegetation types show heterogeneity in vegetation structure (i.e., spatial heterogeneity), besides heterogeneity in vegetation composition (i.e., spectral heterogeneity). Aggregation classifiers functionally deal with both heterogeneities, and therefore fully use the spatial dimension of remote sensing imagery besides the spectral dimension. The steps from spectral classifiers to spatial classifiers and then to aggregation classifiers are necessary to deal with the increasing spatial complexity of our living planet. These steps go along with evolutionary steps in the perception of landscapes in landscape ecology (Figure 7.1).

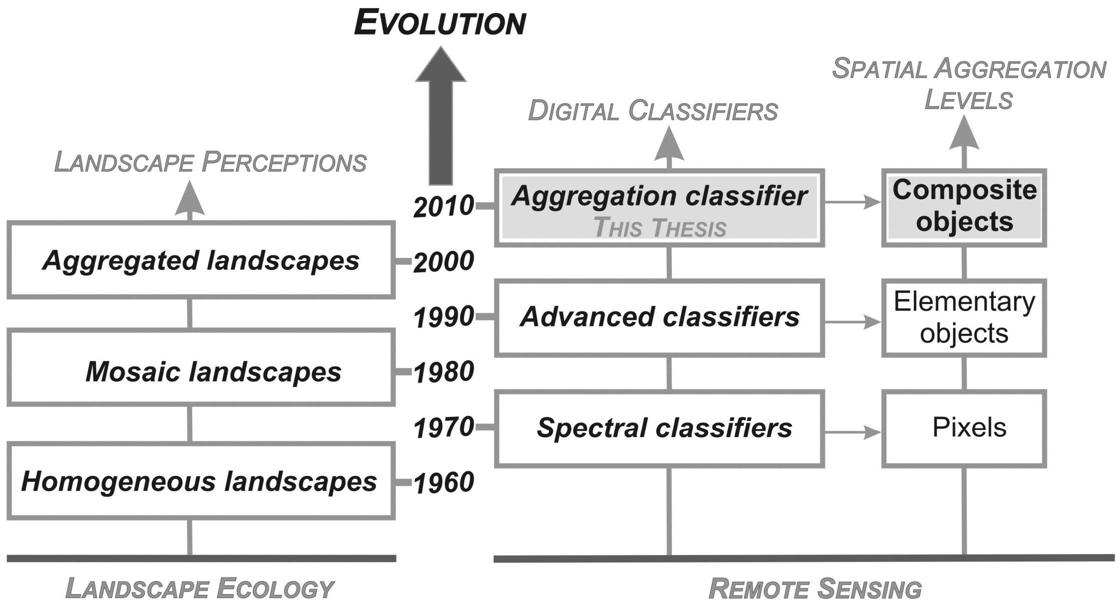


Figure 7.1: Evolutionary steps in the development of digital classifiers in remote sensing along with evolutionary steps in the development of landscape perception in landscape ecology.

With LCM classification, forest cover information can be supplied to governments and civil organizations at different spatial aggregation levels. This is a critical requirement for international policy instruments, from local to global (Cihlar, 2000). The LCM classification provides a transparent methodology to generate such information in a timely and cost-effective way. Consistency of forest cover information between administrative levels (and time-span) is of utmost importance to solve the emergence of global environmental issues as addressed in, for example, the

Framework Convention for Climate Change, the Kyoto Protocol, and the Biodiversity Convention. Applying LCM classification, remote sensing becomes more operational usable (Chapter 1). This suits decision-makers and those who are committed to preserve the rainforest for future generations.

LCM classification was tested for a study area featuring a highly heterogeneous vegetation pattern in a peatswamp forest near Pelangkaraya city, Central Kalimantan, Indonesia. This area is part of a larger area known as the Ex-Mega Rice Project (EMRP) area. Since 2006, the Dutch government financially supports the rehabilitation and revitalization of this area because of the enormous destruction that has taken place to environment and inhabitants. The developed theory and methods, however, are generic. They can be used in other applications dealing with spatial heterogeneity, such as biodiversity studies, habitat mapping, and upscaling issues in geographical information systems.

This chapter presents the major achievements related to the four thesis objectives (the remainder of this section), the two main research questions (section 7.2), the paradigm shift required in remote sensing (section 7.3), and recommendations for future research aimed at tailoring geo-information to end-users (section 7.4).

7.1.1 Effective information units

Originating from the field of landscape ecology, Land Cover Mosaics (LCMs) were found to be effective information units to monitor deforestation processes. LCMs functionally deal with both key components of vegetation heterogeneity: vegetation composition *and* vegetation structure (Chapter 2). Consequently, both forest cover *and* forest cover pattern can be described at different spatial aggregation levels (i.e., at different levels of spatial detail). When both key components can be addressed, spatial context is incorporated in the defined forest cover classes. This flexibility in defining relevant forest cover classes (i.e., functional management units), both thematically and spatially, is of significant advantage when monitoring deforestation processes.

For decision-making, moving to LCMs offer three advantages:

- LCMs do not arbitrarily characterize deforestation processes by assuming vegetation types to be spatially homogeneous. Instead, their spatial heterogeneity is used to characterize them.
- With LCMs, the level of information detail can be controlled per spatial aggregation class (i.e., by specifying the spatial size of its sub-entities). Resulting maps are truly multi-scaled (Chapter 2).
- The conceptual move from land cover classes to land cover mosaic (LCM) classes does not lead to uncontrolled thematic complexity. Tests have shown that the number of spatial aggregation classes does not necessarily increase when moving from land cover classes to LCM classes (Chapter 3).

7.1.2 New remote sensing theory

The field of landscape ecology, from which the functional spatial entity LCM originates, subscribes the need for hierarchical upscaling to reduce the abundant diversity of species into a diversity of functions at distinct levels of spatial heterogeneity (i.e., patches and patch-mosaics; Chapter 2, section 2.2.6). The Aggregate-Mosaic Theory reduces, in a likewise fashion, the abundant spectral and spatial diversity of remote sensing data into a diversity of *functional* spatial objects (management units) at *distinct* levels of information detail (i.e., elementary objects with land cover classes and composite objects with LCM classes). The terms functional and distinct, however, require a direct link between the spatial modeling *task* of remote sensing scientists and the intended end-users' *use* of the spatial modeling results. To implement such a link, it was necessary to introduce three new terms that were not yet available in the remote sensing domain. These are *land cover mosaics (LCMs* – mentioned before*)*, *spatial aggregation classes* and *analysis resolution* (Chapter 3). These new terms are necessary to move from data-driven modeling to semantic-driven modeling. Such a move, however, requires the involvement of end-users to specifically define what level of information detail they need and which spatial objects are functional to them. Consequently, the Aggregate-Mosaic Theory provides a mechanism for both remote sensing scientists and end-users to unite and mutually advance each other's field of expertise.

For remote sensing, the Aggregate-Mosaic Theory offers five major advantages:

- The Aggregate-Mosaic Theory does not only exploit the spectral information of remote sensing data through *thematic* generalization (classification), it also exploits the spatial information through *spatial* generalization (aggregation). Digital analysis, therefore, consists of a classification process and a segmentation process at both the elementary level and the composite level (i.e., patch-classification, patch segmentation; patch-mosaic classification, patch-mosaic segmentation). For this, the synoptic overview provided by remote sensing data is essential.
- The Aggregate-Mosaic Theory requires only a minimum of two additional spatial aggregation levels when analyzing remote sensing data (i.e., the elementary level and the composite level). These two levels provide already the necessary flexibility to map spatial entities at the required information detail (Chapter 5 and Chapter 6).
- The Aggregate-Mosaic Theory supports the modeling of spatial objects with fuzzy extents (i.e., thematically complex landscapes, Chapter 2, Figure 2.9b) at supra-pixel level. Such spatial objects are abundant in, for example, tropical rainforest areas. They often relate to important land use management units and therefore should be detected and monitored using remote sensing data. This thesis modeled the spatial objects with fuzzy extents using functional relationships based on both class topology (i.e., mixture of land cover classes) and class geometry (i.e., area of land cover classes; Chapter 3). The underlying assumption is that spatial objects at any level are aggregated (Chapter 5).
- The Aggregate-Mosaic Theory allows implementation of proven techniques in remote sensing, like image enhancements (radiometric, geometric), spectral and spatial transformations (NDVI, LAI, Principal Components, Fourier, wavelets), and spectral classifiers (hard-soft, supervised-unsupervised). It allows also any common remote sensing data source like radar, optical, multi-spectral, hyper-spectral and lidar, besides any geo-referenced GIS data layer. As such, it supports the adoption of expert systems also called knowledge-based image analysis systems (Richards, 1993).
- The Aggregate-Mosaic Theory provides a clear link to end-users of the analyzed remote sensing data. With the overwhelming technical possibilities,

remote sensing should not only focus on its technical aspects (data-driven), but should always be focused on the users of the geo-information (semantic-driven). As Comber et al. (2005) said: '...the remote sensing community has concentrated too much on the technical issues *(how do we produce something?)* and not enough on the semantic and ontological issues *(what are we trying to produce?)*..'. Spatial aggregation classes are a means to guarantee that those conceptualization issues will be included and addressed (Chapter 3, section 3.3).

A limitation of the Aggregate-Mosaic Theory is the required interactive approach for defining the analysis resolution of the spatial aggregation classes. The analysis resolution defines the spatial size of the elementary objects prior to functional generalization. Wang et al. (2004) proposed the Bhattacharya Distance to determine the optimal spatial size at which spatial objects achieve the highest classification accuracy. The Bhattacharya Distance could be useful once the spatial range of the analysis resolution has been specified to prevent the analysis resolution to remain purely data-driven.

7.1.3 New digital analysis methods

Based on the Aggregate-Mosaic Theory, a new multi-scaled classification method at composite level (i.e., patch-mosaic classification) and four possible segmentation methods at composite level (i.e., patch-mosaic segmentation) were developed to digitally classify remote sensing data into LCMs. Patch-mosaic classification was developed to thematically represent LCMs (Chapter 5). Patch-mosaic segmentation was developed to geometrically represent LCMs (Chapter 6). Making use of both the geometric aspects of spatial objects besides the thematic aspects results in digital analysis methods that are *spatial* generalization operations and not *thematic* generalization operations (Chapter 2). The four patch-mosaic segmentation methods were called *lc*-driven, *lcm*-driven, *data*-driven and *wavelet*-driven (Chapter 6). The lc-driven and lcm-driven methods are taxonomy-based. The data-driven and wavelet-driven methods are radiometry-based.

Concerning patch-mosaic classification the following remarks can be made:

- Patch-mosaic classification requires an aggregation hierarchy besides a classification hierarchy. The classification hierarchy was used for *thematic-specialization*, whereas the aggregation hierarchy was used for *spatial-generalization*. This thesis introduced the terms thematic-generalization and spatial-generalization for definition transparency. Thematic-generalization is acknowledged as classification in conceptual generalization, whereas spatial-generalization is acknowledged as aggregation (Chapter 2).
- Spatial-generalization requires an optimization algorithm for which simulated annealing was used. Simulated annealing is increasingly applied in remote sensing (e.g., Penn, 2002; Kasetkasem et al., 2005).

Concerning patch-mosaic segmentation the following remarks can be made:

- The spatial extents of composite objects in *radiometry-based* patch-mosaic segmentation (data-driven, wavelet-driven) are modeled independently of the patch-mosaic classification results. Possible errors produced in patch-mosaic classification will not be propagated. Such functional upscaling methods include some sort of self-correction when moving from land cover classes to LCM classes. This is not the case in *taxonomy-based* patch-mosaic segmentation (lc-driven, lcm-driven). For such functional upscaling methods, (patch / patch-mosaic) classification results drive the modeling of the spatial extents. Consequently, possible errors will be propagated.
- The lc-driven method is usually applied in cartography, while the lcm-driven method reflects the definition of functional generalization conform Molenaar (1998). The data-driven method follows the *FNEA* (Fractal Net Evolution Approach; Chapter 4, section 4.2; Baatz & Schäpe, 2000; Hay et al., 2003), while the wavelet-driven method is an extension of the *FNEA* approach.

When developing patch-mosaic classification and patch-mosaic segmentation, the use and impact of fuzzy sets in classification processes, of the simple majority rule (to link thematic content and geometric extent in radiometry-based patch-mosaic segmentation) and of MITRE's IQ measure (to quantitatively select the wavelet-transformed images containing the optimal spatial and spectral information per spectral band) were not addressed.

7.1.4 Usability of new digital analysis methods

A *forest/non-forest* map for a decision-maker at national level was used as case study to assess the use of LCM classification compared to a conventional land cover classification (Chapter 3). Additionally, five evaluation metrics were used to also assess the LCM classification (Chapter 4, 5 and 6). These were the *KHAT* coefficient and four landscape pattern metrics: Percentage of Landscape *(PLAND)*, Number of Patches (*NP)*, Simpson's Diversity Index (*SIDI)*, and Landscape Shape Index *(LSI)*. Moreover, *manual* interpretation results were used to provide a direction to what extent spatial objects need to be functionally upscaled according to three tropical forestry experts (Chapter 6).

Concerning the case study on the use of LCM classification (Chapter 3, Fig 3.9), three major conclusions are:

- LCM classification provides a clearer forest/non-forest map as compared to a conventional land cover classification.
- Sharp edges remain sharp and de-clouding of small clouds is easy when applying the quantitative rules of LCM classification.
- The number of spatial objects decreased exponentially from thousands to hundreds when moving from elementary objects to composite objects in LCM classification (i.e., reduction of complexity and more spatial context).

Concerning the patch-classification results at elementary level (Chapter 4) and the LCM classification results at composite level (Chapter 5 and 6), four major conclusions are:

- LCM classification is superior to land cover classification in modeling spatial heterogeneity for two reasons. (see Table 7.1). First, compared to the conventional land cover classifications, LCM classification can provide spatially more aggregated results (i.e., a significant *LSI* drop) *without* thematically loosing information (i.e., a similar SIDI). Spatial heterogeneity can be digitally mapped at different spatial aggregation levels. Second, LCM classification provides almost similar results for differently fragmented images (i.e., a similar LSI (5-15) for both the p1990 image and the spatially more heterogeneous p1996 image). Semantic-driven modeling proved to be a real option using remote sensing data.

- A semantic relation exists between the thematic content and the geometric extent of spatial objects. This is demonstrated by a dramatic dip of the SIDI in data-driven patch-mosaic segmentation and to a lesser extent in wavelet-driven patch-mosaic segmentation (Chapter 6, Figure 6.13). This dramatic dip is a result of increasing the geometric extent while maintaining the same thematic content. In fact, the geometric extent already moved up in the aggregation hierarchy to a composite level at a higher spatial aggregation level (i.e., CO+ level), whereas the thematic content remained at composite level (i.e., CO level). This means that the geometric extent of spatial objects cannot be unlimitedly extended in radiometry-based patch-mosaic segmentation methods (i.e., the break-off value $v2_{scale}$ cannot be unlimitedly increased; Chapter 6, section 6.2.3).
- Roughly, both the two taxonomy-based patch-mosaic segmentation methods and the two radiometry-based patch-mosaic segmentation methods (when applying low break-off values) provide functional upscaling results at a similar spatial aggregation level. However, the spatial objects at composite level become increasingly aggregated when increasing the break-off value in radiometry-based methods. For fine spatial aggregation levels, functional upscaling with the lcm-driven method is the most straightforward one to implement. Its geometric extent is not dependent on the land cover classification results obtained at elementary level (i.e., patch-classification), and its segmentation process lacks complexity (i.e., specifying the break-off value and the additional thematic decision rule). For broad spatial aggregation levels, functional upscaling with the wavelet-driven method outperformed functional upscaling with the *FNEA*-related data-driven method (Chapter 6, Figure 6.13).
- Functional upscaling with the wavelet-driven method best fits the manual interpretation results though it needs refinement to obtain results at a spatial aggregation level similar to the one chosen by forestry experts.

Table 7.1: Summarized LSI and SIDI figures for the elementary objects versus the composite objects.

Spatial object type	Classification classes	p1990 image LSI	p1996 image LSI	p1990 image SIDI	p1996 image SIDI	Source
Elementary	LC	15-25	20-35	0.75-0.8	0.75-0.8	Figure 4.13
Composite	LCM	15-20	10-30	0.75-0.8	0.75-0.8	Figure 5.10 Figure 5.11
Composite	LCM	5-15	5-15	0.75-0.8	0.74-0.8	Figure 6.13

The assessment of the use of LCM classification was limited to reference data collected at a conventional spatial aggregation level (i.e., homogeneous land cover classes). In addition, the manual interpretation results were limited to three tropical forestry experts. Such a number does not allow any statistical analysis on the manual interpretation results. It was, however, a means to obtain an expert's view on classification results at composite level for the Pelangkaraya study area.

7.2 LCM hierarchical framework

7.2.1 Effectiveness

According to Cihlar (2000) classification algorithms should ideally satisfy the following six criteria: accuracy, reproducibility by others (given the same input data), robustness (not sensitive to small changes in the input data), ability to fully exploit the information content of the data, uniform applicability over the whole domain of interest, and objectiveness (not dependent on the analyst's judgment). He mentioned, however, that many present digital image classification methods do not meet these criteria, and none meets them completely although they are fundamental to a scientifically based methodology. The LCM classification framework almost meets all six criteria as Table 7.2 shows. For the two criteria partly met, improvement and refinement can be obtained with additional research.

Concerning the criterion *accuracy*, current requirements on collecting reference data do not take into account the spatial aggregation level of land cover classes, whether the reference data are derived from the field (ground truth) or using finer resolution data. Yang et al. (2000) addressed this problem as a consequence of the 'definition of label agreement' between the map and ground data. For the southeast region of the United States (using Landsat TM data), he found that the overall accuracy improved from 55.9% in a pixel-to-pixel comparison to 66.8% in a pixel-to-dominant class within a 3x3 pixel block comparison, to 79% in a pixel-to-any pixel within this 3x3 pixel block comparison. Such an increase in accuracy could have major impacts for operational applications; specifically as land cover maps derived from remote sensing data are often judged to be of insufficient quality (Foody, 2002). For homogeneous landscapes, changing this 'definition of label agreement' would not affect accuracy. For heterogeneous landscapes, however, accuracy did change. In Yang's example above, it even changed with 23.1%. Therefore, reference data should be restricted to spatial aggregation classes, otherwise apples and oranges are compared to derive accuracy. Confusion matrices can be filled with spatial aggregation classes at similar spatial aggregation levels for both the map and ground data labels. Such accuracy figures are useful for end-users, because those end-users were involved when defining the spatial aggregation classes. Restricting reference data to spatial aggregation classes will suit the operational use of remote sensing data; application will be assured. Concerning the criterion *applicability*, an anomaly was introduced for landscapes composed of similarly sized spatial objects when using the two selected upscaling parameters minimum-area *MA* and shared-border *BN* (see Chapter 6, Figure 6.8; functional upscaling method d80, p1990 image).

Table 7.2: Fulfillment of LCM classification framework to criteria of Cihlar (2000).

Criteria	*Fulfillment*	*Comments*
Accuracy	+	*Maintains a semantic relation between thematic and geometry.*
	+/-	*Reference data require restriction to spatial aggregation classes due to extension of remote sensing domain. Additional research required.*
Reproducibility	+	*Minimized role of the analyst to specific parts of the digital process.*
Robustness	+	*Sensitivity analysis showed no abrupt changes for small changes in the input data.*
Exploiting content	+	*Exploits both spectral and spatial content of remote sensing data.*
Applicability	+	*Similar outcome for two temporal Landsat TM images with different forest fragmentation in Kalimantan, Indonesia.*
	+/-	*Refinement of upscaling parameters to solve anomaly. Additional research required.*
Objectiveness	+	*Quantitative parameterization of vegetation composition and vegetation structure.*

Currently, upscaling (in terms of spatial generalization, Chapter 2) becomes increasingly important in various disciplines. Therefore, it should not be surprising that such upscaling also becomes increasingly important in remote sensing, specifically regarding the increasing spatial and spectral resolution of sensors. The results in Chapter 4, 5 and 6 show that without spatial generalization, digital methods cannot match the knowledge of manual interpreters on spatial context in land cover definitions (i.e., compare the LSI of Figure 4.13, Figure 5.11 and Figure 6.13). The LCM classification framework, therefore, marks a new step towards a fully digital operational generation of geo-information. Crucial in this development is the LCM parameterization because it is based on quantitative input.

7.2.2 Implementation constraints

Implementing the LCM classification framework went along with extensive sensitivity analysis. This was necessary to reveal the robustness of the patch-mosaic classification process and the applied segmentation processes (patch / patch-mosaic), and to demonstrate the flexibility of hierarchical upscaling.

Implementing the LCM classification framework requires at each spatial aggregation level both a classification process and a segmentation process. Classification and segmentation are in no way simple processes. Especially, patch-mosaic classification being a multi-scaled classification process (Chapter 5), requires significant physical, mathematical and statistical knowledge. Complexity increases by changing from single-scaled to true multi-scaled geo-information. The sensitivity analysis revealed that small changes in the settings of the two upscaling parameters did not cause unexpected differences in output results.

The modular structure of the LCM classification framework provides the necessary flexibility to include specific image processing techniques, classification algorithms, or other significant analysis methods at each spatial aggregation level. An example of this flexibility is the use of wavelets (new technique) in the context of segmenting the spatial extent of LCMs (new application of wavelets). Its use was compared to a radiometry-based patch-mosaic segmentation method that, within this context, did not use this new technique (Chapter 6). The sensitivity analysis demonstrated that implementing such a new technique and new application did not produce unexpected or weird results. An important issue for any implementation is, however, its possibility to be expressed in quantifiable parameters. For example, a quantitative image quality measure (MITRE's IQM) was needed to select the scale level offering the highest image quality (IQ) for each wavelet-transformed Landsat TM band (Chapter 6).

Implementing the LCM classification framework requires selection of seven factors: level of decision-making, spatial aggregation classes, analysis resolution, upscaling parameters, spatial aggregation levels, segmentation algorithm and remote sensing data source. Each of these seven factors will be briefly discussed hereafter.

1. Level of decision-making

The demonstrated application of the LCM classification framework focused on decision-making at national level (e.g., the ministry of forestry of Indonesia). Decision-making at national level is often most powerful, but providing geo-information for that level is most difficult. Generalized information is needed, suitable at policy and verification level (i.e.., strategic decisions). Through selecting appropriate spatial aggregation classes, however, geo-information can be tailored to any decision-making level other than the national level; either to a lower level (e.g., provincial or district) or to a higher level (e.g., global).

2. Spatial aggregation classes

For demonstration purposes, a same spatial aggregation class was used for all eight generally defined LCM classes. Spatial aggregation classes specify the settings of the upscaling parameters (Chapter 5). For the Pelangkaraya study area, this means that similar settings for minimum-area *MA* and shared-border *BN* were used for, for example, the LCM class 'mainly logged forest' and for the LCM class 'mainly agriculture' (e.g., *MA*=150 ha, *BN*=0.55%). Similar settings for minimum-area *MA* assume similarity in vegetation structure, and for shared-border *BN* in vegetation composition. Such similarity does not always occur. For example, the agriculture part of the Pelangkaraya study area shows a finer spatial structure than the forestry part. If it is necessary from a decision-making point, it could be useful to apply lower minimum-area *MA* settings for the LCM classes related to agriculture. In a study on detecting wildlife habitats in Botswana, three different minimum-area *MA* settings were used in the specification of nine LCM classes (Dröge, 2005).

3. Analysis resolution

The implementation of the LCM classification framework was limited to a single analysis resolution, i.e. one spatial aggregation level of the elementary objects. The influence of the analysis resolution on upscaling results (i.e., LCM classification results at composite level) was not investigated. However, because of semantic constraints, the spatial aggregation range of the elementary objects requires specification prior to spatial generalization into composite objects. For example, individual trees cannot be directly spatially generalized into a biome although they are part of it (Chapter 2, Figure 2.14). The analysis resolution should be specified once the spatial aggregation classes are defined. Thereafter, additional measures can be used to determine the optimal spatial aggregation level of the elementary objects such as the Bhattacharya Distance (Wang et al., 2004 – see also section 7.1.2) or wavelet energy (Murwira, 2003).

4. Upscaling parameters

The two selected upscaling parameters minimum-area *MA* and shared-border *BN* proved to be useful in functionally upscaling the Pelangkaraya study area into the eight general LCM classes (Chapter 5). Shared-border *BN* is used to quantify class topology (mixture), and minimum-area *MA* to quantify class geometry (area). The assumption inherently involved in generally defined LCM classes is that each LCM class consists of a mixture of small and large spatial objects, the latter being the dominant land cover type. This spatial mixture can be effectively parameterized with the two selected upscaling parameters. However, LCM classes can be defined as specific as necessary. They can consist of two or even three dominant land cover classes (comparable to grated sweets on ice-creams). In such cases, landscapes are often composed of similarly sized spatial objects and the assumption on spatial dominance of one land cover class cannot hold. Consequently, besides minimum-area *MA* and shared-border *BN*, additional upscaling parameters are necessary to effectively parameterize those landscapes.

5. Spatial aggregation levels

For demonstration purposes, the implementation of the LCM classification framework was limited to two spatial aggregation levels, one level consisting of elementary objects and one level consisting of composite objects. The LCM classification framework provides, however, a further upscaling mechanism to recursively aggregate the composite objects (CO) into higher-level composite objects (CO+). In fact, such an upscaling mechanism is unlimitedly. Moving from CO to CO+ (or further to CO++) could be very useful for global-level research, like for instance, pan-Asiatic, pan-African, or pan-European land cover classifications. This type of upscaling requires cooperation between involved parties on how to define spatial aggregation classes when three or more levels are involved. Defining spatial aggregation classes of CO+ could also affect the definition of spatial aggregation classes at CO. Consequently, global-level research could even support the development of *national standards* on defining spatial aggregation classes. Lack of national standards is, for example, a problem for the FAO when combining forest data from different countries. National standards often differ in their definitions and assumptions on spatial context. Additional cooperation between involved parties is needed to set standards on spatial context at national level. As a start, global-level research can use the demonstrated two-layered LCM classification framework. Specifically, the elementary objects are the land cover classes currently used at national level, whereas the composite objects are the LCM classes at global level.

6. Segmentation algorithm

The eCognition segmentation algorithm has been used because of its underlying region-based method, its ability to show the least under-segmentation compared to five other segmentation algorithms, and its use in ecological applications (Chapter 4). However, any segmentation algorithm can be implemented in the LCM classification framework. If desired, it is even possible to implement different segmentation algorithms at different spatial aggregation levels. Whatever is implemented, transparency and functionality should be the main focus. Concerning segmentation algorithms, it is useful that leading methods integrated in traditional software like ERDAS Imagine and ENVI face technological advanced methods integrated in booming software like eCognition. The underlying concepts vary between traditional methods and newcomers. Both ERDAS and ENVI are founded in the late 1970s. Their applications rely mainly on basic image processing concepts developed in that era, i.e., per-pixel classification (including homogeneity assumption) in a multi-dimensional feature space (Blaschke & Strobl, 2001). Meanwhile, both remote sensing and its application fields made an enormous progress over the last years due to improved resolution and data availability. Currently, problems have to be solved, ranging from local to global level, with increasing complexity of land resources. The need for spatial concepts that can solve these recent problems requires these spatial concepts to be integrated in the analysis of remote sensing data. The underlying concepts of newcomers like eCognition rely on such integration. Although software should never be a limit nor be a focus, sound research requires software with completely described algorithms. Therefore, a major shortcoming of eCognition is the lacking description of the segmentation algorithm. Nevertheless, analysis strategies should be evaluated on the basis of the validity of underlying spatial concepts, rather than evaluating spatial concepts on the basis of a particular analysis strategy (Woodcock & Strahler, 1987).

7. Remote sensing data source

The LCM classification framework was implemented using optical multi-spectral remote sensing data (i.e., two Landsat TM images). Generally, many operational remote sensing programmes are using optical multi-spectral remote sensing data because of its availability and ease of interpretation. In addition to Landsat data, the LCM classification framework can also suit other remote sensing sources. A recent study on iron content investigated the use of the LCM classification framework using hyperspectral data (Muller, 2006). The LCM classification framework proved also to be useful for detecting wildlife habitats in the Okavango Delta, Botswana. The latter used IKONOS data besides Landsat TM data (Dröge, 2005).

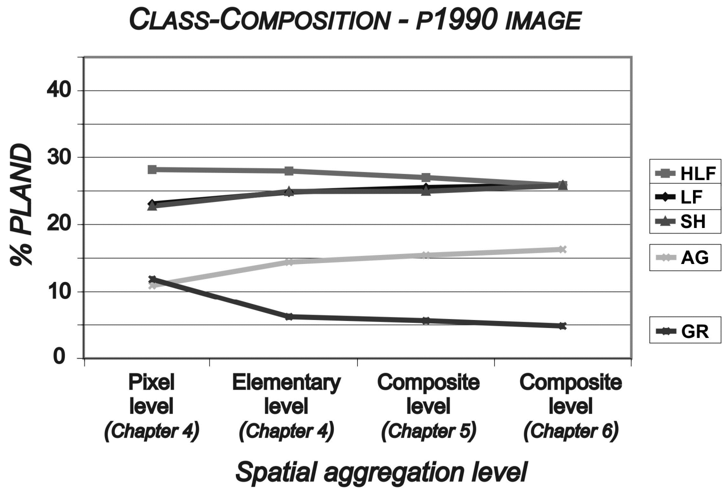
7.3 Paradigm shift

Improving consistency on forest cover information requires an explicit understanding of the classifier's assumption on spatial heterogeneity. The dominance of spectral classifiers, however, has led to a limited view of spatial heterogeneity occurring in landscapes (Woodcock & Strahler, 1987). This dominance nourished the idea that increasing the spatial resolution of remote sensing data would automatically reduce spatial heterogeneity (i.e., vegetation structure) in the image, and thus would automatically improve classification accuracy. This misunderstanding, however, was already revealed when comparing Landsat TM data with Landsat MSS data far back in the 1980s. In fact, the increase of the spatial resolution from 80m to 30m even decreased classification accuracy, despite the spectral advantages of the TM sensor (e.g., Acevedo et al., 1984; Irons et al., 1985). Prior to that, analysis of airborne scanner data also revealed that refinement of spatial resolution did not automatically improve classification accuracies even though the advantages of a higher-resolution sensor appeared visually obvious (Markham & Townshend, 1981). Consequently, with current sensors offering better than 1m ground resolution in combination with an increasing focus on monitoring global processes, spatial heterogeneity can no longer be neglected when analyzing remote sensing data. Neither can hyperspectral data neutralize the spatial modeling problem inherently related to spatial heterogeneity, because the additional spectral bands can only improve results with respect to vegetation composition, not vegetation structure.

7.3.1 Spatial context

With increasing spatial heterogeneity, spatial context in forest definitions becomes more important, as illustrated in Figure 7.2, which summarizes cover percentages (PLAND mean) of spatial classes in the Pelangkaraya study area at three spatial aggregation levels. Though all extremes are included in the figure, it clearly shows that the more fragmented p1996 image shows larger differences in cover percentages of the various spatial aggregation classes than the less fragmented p1990 image. In addition, the largest differences in cover percentages are found for the two spatially most fragmented classes: shrub (SH) and heavily logged forest (HLF). Consequently, figures for forest cover will increasingly vary when assuming spatial homogeneity for spatial entities that are spatially heterogeneous.

Concerning decision-making, the inclusion of spatial context in forest cover definitions when classifying remote sensing data offers a significant advantage (Chapter 1, Figure 1.14). In fact, that figure provides a first impression on the use of the Aggregate-Mosaic Theory in change assessment studies with remote sensing data. To explain this, two assumptions are necessary to be made. First, assume that from a nature conservation point of view certain management activities are needed to minimize future changes. Second, assume that a limited budget is allocated to execute this conservation plan. Next, the question arises where in the area should this money be spent to execute desired management activities?



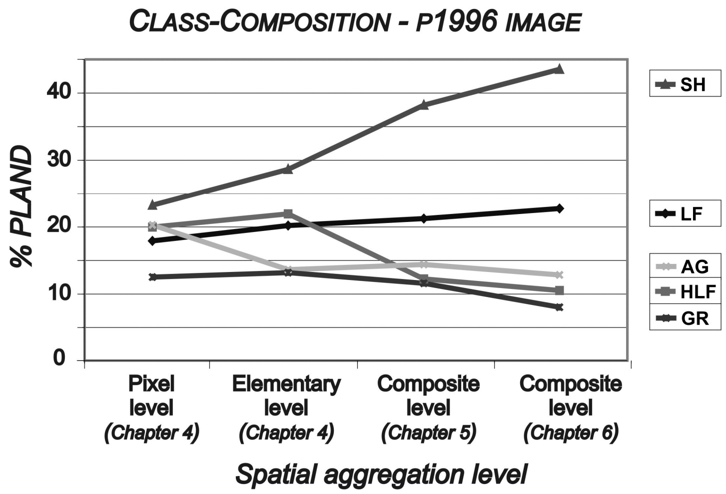


Figure 7.2: Cover percentages (PLAND mean) of spatial aggregation classes at three spatial aggregation levels in the Pelangkaraya study area. The figure is derived from Chapters 4, 5 and 6, specifically Tables 4.5, 5.7 and 6.2 (figure displayed in line graphs for visual clarity).

At pixel level, an extensive but *diffuse* portion of the area shows a major change. At elementary and composite level, still an extensive but much more *specific* portion of the area shows a major change. Moving to composite level, the change areas become even more specific. The latter are related to important management units as defined in the spatial aggregation classes. Spending the money to such *semantic-driven* change areas will probably have more effect on conservation issues than spending the money to the *data-driven* change areas derived at the pixel level. In words of Green et al. (1994): "...the knowledge that a change has occurred is relatively uninformative unless the change can be linked to an impact on resources or on benefits and costs on those resources ...". Semantic definitions are scale related, therefore only forest cover definitions that include spatial context can link changes to impact. Currently, spectral and advanced classifiers are related to land cover classes; they do not include spatial context in their definitions (on the contrary, they assume spatial homogeneity). Providing spatial context by defining spatial aggregation classes can eliminate differences in cover percentages that occur due to neglecting differences in spatial context (Chapter 3, Figure 3.3). In addition, Foody (2002) argued that land cover modifications in which the land cover type may have been altered but not changed (e.g., degradation, thinning, etc.) are inappropriately represented by conventional post-classification comparison methods of change detection. Environmentally, such land cover modifications may be as significant as land cover conversions (Lambin, 1997; Foody 2002). The ability to monitor land cover modifications would, for example, help inform environmental policy and decision-making to underpin the use of sustainable resources (Foody, 2001). Defining spatial aggregation classes can support such monitoring, because spatial context is made functionally explicit.

7.3.2 Semantic-driven monitoring

From the beginning, technological advances have been, and still are, the driving forces of remote sensing and its application fields. In many cases, the major focus has been to increase the spectral and spatial resolution of the sensors. This, however, has not automatically led to more useful geo-information for decision-making. With a global tendency to *decentralize* decision-making towards global thinking and towards more local operations, various actors invariably take decisions at different administrative or organizational levels. These differences in levels require geo-information at different levels of spatial detail or at different spatial aggregation levels. In fact, the question should not be *how* to provide a massive amount of geo-information, but *what* kind of geo-information is needed in the decision-making process of the end-users, and how to find it. Therefore, defining specific requirements on spatial aggregation levels (and spatial aggregation classes) of *supplied* geo-information should also be a central question in any remote sensing study. Surprisingly, almost no remote sensing research focuses on this issue.

Supplying geo-information at the necessary spatial aggregation levels and their classes requires a change in attitude of remote sensing experts. For over 30 years remote sensing experts answered questions like '...which remote sensing data *y* is most accurate to determine land cover or species *z* in area *k*...'. Instead of only addressing the technological possibilities of equipment, remote sensing experts should also critically investigate the geo-information need of end-users. What are the exact needs of end-users? Have their needs been properly identified? What kinds of decisions do they have to make (e.g, international commitments)? Do remote sensing results appropriately define their management units? Are those definitions related to spatial context? Concerning deforestation, is total deforested area of prime importance, or the spatial pattern of the deforestation process? Answering such questions requires different digital analysis approaches. Instead of defining general land cover classes (pinpointing on exact boundaries), revealing spatial patterns of key processes are of importance (functionally modeling spatial heterogeneity).

This change in attitude requires interdisciplinary remote sensing experts who are able to bridge the gap in expertise between remote sensing technology and the application field. Bridging this gap is necessary regarding the increasing specialization in knowledge along with an increasing complexity in the management of our planet's resources. World population is still growing and economic activities increase. In fact, our environment is rapidly changing from "oceans" of homogeneous landscapes with single functions to "oceans" of heterogeneous landscapes with multiple functions. This transition goes along with many cross-border influences. Managing such a complexity and controlling environmental processes calls for tailored geo-information to predict scenarios (see also Chapter 4, section 4.6.3; Chapter 5, section 5.6.2; Chapter 6, section 6.4.2), and to monitor and evaluate the outcomes of crucial decisions at local, national and global level.

Given the broad diversity of, for example, forest environments worldwide, the challenge is highly complex and demands effective monitoring systems (ESA, 2005). This thesis provides a theory and the methods to implement such monitoring systems. It proved the usefulness of LCM classification for the digital analysis of spatially heterogeneous vegetation at different spatial aggregation levels. The implementation 'only' requires a paradigm shift from *homogeneous* land cover thinking to *heterogeneous* LCM thinking.

7.4 Recommendations

When digitally classifying remote sensing data, human expertise cannot be caught in just one set of functional upscaling rules, specifically not when modeling spatial heterogeneity. The LCM classification framework shows, however, a direction to proceed because the heterogeneous LCMs are directly linked to the traditionally used homogeneous land cover classes. Furthermore, additional research can refine the LCM classification framework. In contrast to the LCM classification framework, no further progress, refinements or improvements are to be expected in manual image classifications, although currently operational projects still rely on them. Even highly skilled interpreters show varying interpretation results. Future research should be directed towards:

I

Studying the impact of the analysis resolution on functional upscaling results at composite level. This will provide knowledge about the extent to which spatial aggregation levels of elementary objects affect composite objects. This knowledge can guide the procedure for defining *spatial aggregation classes*. Obviously, individual trees cannot directly be upscaled into a biome, although they are part of it (Chapter 2, Figure 2.14). It is yet unknown, however, at which spatial range vegetation types can be functionally upscaled into a biome. Subsequently, improving knowledge on defining spatial aggregation classes will support the decision-making of end-users. A related recommendation is to move from a global analysis resolution to a local one. This thesis similarly implemented the analysis resolution for all LCM classes. This could be regarded as a *global* analysis resolution. An interesting development would be to go for a *class-dependent* or *local* analysis resolution. This means that each LCM class has its own analysis resolution at the elementary level. This can be achieved by applying additional segmentation after creating the elementary objects (i.e., split or merge, even moving to sub-pixel level). Major advantages of such a local analysis resolution are a lesser dependency on the resolution of the remote sensing data, and a further move towards multi-scaled geo-information.

II

Studying the upscaling mechanism of the LCM classification framework for modeling global level processes from composite objects (CO level) to higher-level composite objects (CO+ level) will not only provide additional knowledge on the *analysis resolution*, but will also support global level research. Specifically, a detailed research on further upscaling the functional upscaling strategy with the lcm-driven method could be useful to finally fit the manual interpretation results.

III

Studying the two criteria accuracy and applicability that were partly met according to Cihlar (2000). This research is needed to provide guidelines how to restrict reference data to spatial aggregation classes. Preliminary research on using stratified randomly sampled *grids* with sizes of 540 x 540 meters (18 x 18 Landsat TM pixels) proved to be sufficient to identify the seven main LCMs in detecting wildlife habitats in the Okavango Delta, Botswana (Dröge, 2004 & 2005). Studying the *criterion applicability*, research is needed to refine the parameterization of landscapes consisting of similarly sized elementary objects. One could think about an additional upscaling parameter describing the shortest-distance between elementary objects that are functionally related. Delaunay triangulation was successfully used to obtain such spatial relationships between elementary objects in a study on urban land-use classification (Zhan et al., 2002; Zhan, 2003). A related recommendation is to expand the domain of the upscaling parameter that quantifies the LCM parameter *area* from area to morphology. This means that not only the spatial size of an elementary object is of importance, but also its shape. This would not only suit the classification of linear spatial objects, but could also solve obvious misclassifications between spatial classes (e.g., river and clouds).

IV

Studying the impact of using fuzzy sets in patch-classification and patch-mosaic classification this requires additional settings of the dispersion value of the applied membership functions. Also settings should be included to obtain a conventional Boolean logic rule for assessing the use of fuzzy sets in such classifications.

V

Studying the use of the additional thematic rule (i.e., simple majority) in the functional upscaling strategy with radiometry-based patch-mosaic segmentation methods requires additional classification rules. He et al. (2002), for example, proposed random assignment in geometry-driven generalization (Chapter 2, section 2.3.6).

VI

Studying the use of the quantitative measure (i.e., Mitre's IQM)when selecting the optimum wavelet-transformed image(s) requires other quantitative measures. A related recommendation is to use with care the *FNEA* approach as currently described in literature, because a semantic relation between geometric extent and thematic content is not formalized.

VII

Last but not least, studying the use of aggregation classifiers to ultimately control environmental processes at global level requires a paradigm shift from the *homogeneous* land cover concept to the *heterogeneous* LCM concept. The *heterogeneous* LCM concept represents (spatial) complexity as specific as possible at different spatial aggregation levels. Ultimately, geo-information is tailored to the need of end-users. Therefore, an urgent recommendation to the remote sensing community is to go for aggregation classifiers in order to understand and control environmental processes at a global level. Only then sustainable development of tropical rainforest areas will be enhanced for future generations.

References

Acevedo, W., Buis, J.S. & Wrigley, R.C. (1984). Changes in classification accuracy due to varying Thematic Mapper and Multispectral Scanner spatial, spectral, and radiometric resolution. Proceedings of the 18th International Symposium on Remote Sensing of Environment 1:27-44, Ann Arbor, Michigan, October 1-5.

Baatz M. & Schäpe A. (2000). Multiresolution segmentation, an optimisation approach for high quality multi-scale image segmentation. In: Strobl J, Blaschke T., & Griesebner, G. (eds). Angewandte Geographische Informationsverarbeitung XII, Wichmann Verlag, Heidelberg, 12-23.

Blaschke, T. & Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. Geoinformation Systems 6:12-17.

Cihlar, J. (2000). Land cover mapping of large areas from satellites: status and research priorities. International Journal of Remote Sensing 21(6&7):1093-1114.

Comber, A., Fisher, P. & Wadsworth, R. (2005). You know what land cover is but does anyone else?...an investigation into semantic and ontological confusion. International Journal of Remote Sensing 26(1):223-228.

Dröge, E.D. (2004). Field survey in the Okavango Delta to collect sample data on vegetation mosaics. Internship report, Resource Ecology Group / Laboratory of Geo-Information Science and Remote Sensing, Wageningen University.

Dröge, E.D. (2005). Detecting wildlife habitats of large herbivore species at supra-pixel level in the Okavango Delta, Botswana. MSc. Thesis, Thesis Report GIRS-2005-22, Wageningen University.

ESA (2005). GMES: The living planet programme. Global Monitoring for Environment and Security (GMES), European Space Agency, Paris. At http://www.esa.int/esaLP/LPgmes.html, accessed September 26, 2005.

Foody, G.M. (2001). Monitoring the magnitude of land-cover change around the southern limits of the Sahara. Photogrammetric Engineering and Remote Sensing 67(7):841-847.

Foody, G.M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment 80(1):185-201.

Gong, P., Marceau, D.J. & Howard, P.J. (1992). A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data. Remote Sensing of Environment 40(2):137-151.

Green, K. Kempka, D. & Lackey, L. (1994). Using remote sensing to detect and monitor land-cover and land-use change. Photogrammetric Engineering & Remote Sensing 60(3):331-337.

Hay, G., Blaschke, T., Marceau, D. & Bouchard, A. (2003). A comparison of three image-object methods for the multiscale analysis of landscape structure. ISPRS Journal of Photogrammetry & Remote Sensing 57:327-345.

He, H.S., Ventura, S.J. & Mladenoff, D.J. (2002). Effects of spatial aggregation approaches on classified satellite imagery. International Journal of Geographical Information Science 16(1):93-109.

Irons, J.R., Markham, B.L, Nelson, R.F., Toll, D.L. & Wiliams, D.L. (1985). The effects of spatial resolution on the classification of Thematic Mapper data. International Journal of Remote Sensing 6(8):1385-1403.

Kartikeyan, B. Sarkar, A., Majumder, K.L.(1998). A segmentation approach to classification of remote sensing imagery. International Journal of Remote Sensing 19(9):1695-1709.

Kasetkasem, T., Arora, M.K. & Varshney, P.K. (2005). Super-resolution land cover mapping using a Markov random field based approach. Remote Sensing of Environment 96:302 – 314

Lambin, E.F. (1997). Modelling and monitoring land-cover change processes in tropical regions. Progress in Physical Geography 21(3):375-393.

Markham, B.L., Townshend, J.R.G. (1981). Land cover classification accuracy as a function of sensor spatial resolution. Proceedings of the 15th International Symposium on Remote Sensing of Environment 3:1075-1090, Ann Arbor, Michigan, May 11-15.

Molenaar, M. (1998). An introduction to the theory of spatial object modelling for GIS. Taylor & Francis, London.

Muller, E. (2006). Validation of an object based and contextual post classification for soil iron determination by means of Hyperspectral DAIS 7915 data. Validating an object based (post) classification based on the Aggregate-Mosaic Theory for soil iron classification by means of Hyperspectral DAIS 7915 data. MSc. Thesis, Thesis Report GIRS-2006-31, Wageningen University.

Murwira, A. (2003). Scale matters! A new approach to quantify spatial heterogeneity for predicting the distribution of wildlife. PhD Thesis, Wageningen University, ITC Dissertation number 106.

Penn, B.S. (2002). Using simulated annealing to obtain optimal linear end-member mixtures of hyperspectral data. Computers & Geosciences Volume 28(7):809-817.

Richards, J.A. (1993). Remote sensing digital image analysis: An introduction. Springer-Verlag, Berlin.

Wang, L., Sousa, W.P. & Gong, P. (2004). Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. International Journal of Remote Sensing 25(24):5655-5668.

Woodcock, C.E. & Strahler, A.H. (1987). The factor of scale in remote sensing. Remote Sensing of Environment 21:311-332.

Yang, L., Stehman, S.V., Wickham, J., Jonathan, S. & VanDriel, N.J. (2000). Thematic validation of land cover data of the eastern United States using aerial photography: Feasibility and challenges (2000). In Heuvelink, G.B.M. & Lemmens, M.J.P.M. (Eds.): Proceedings of the 4th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, Delft University Press, Delft:747-754.

Zhan, Q., Molenaar, M., Tempfli, K. (2002). Finding spatial units for land use classifcation based on hierarchical image objects. The International Archives of Photogrammetry and Remote Sensing 34, Part 4:263-268.

Zhan, Q. (2003). A hierarchical object-based approach for urban land-sue classification from remote sensing data. ITC Dissertation no. 103. CIP-DATA Koninklijke Bibiotheek, Den Haag.

SUMMARY

Technological advances have been, and still are, the driving forces of satellite remote sensing and its application fields. In many cases, the major focus has been to increase the spectral and spatial resolution of the satellite sensors. As a result, current remote sensing theories, methods and processing techniques treat the spatial heterogeneity of tropical vegetation only as a technical (remote sensing) problem dealing with autocorrelation and spectral overlap. Despite huge efforts, such a 'product-thinking' approach did not yet lead to better information on forest cover, nor on its underlying change processes when monitoring deforestation in tropical rainforest areas. The rate of deforestation of these areas is alarmingly high and affects both local and global economy and society. This necessitates a method of forest monitoring that is tailored to decision-making. This thesis presents, therefore, a 'customer-thinking' approach to look at the spatial heterogeneity by using the information content of vegetation patterns that show footprints of deforestation processes. This new way of looking at spatial heterogeneity can provide information on forest cover that meets the needs of different decision levels.

Chapter 1 outlines three fundamental bottlenecks when moving to a 'customer-thinking' treatment of spatial heterogeneity in digital image analysis. These are understanding spatial heterogeneity in tropical environments, understanding spatial aggregation levels in decision-making, and understanding the underlying spatial homogeneity assumption in digital classification methods. Typically, tropical vegetation shows vegetation patterns and border transitions that remain spatially heterogeneous at a spatially more detailed level. Such characteristics demand for vegetation typologies that can register these patterns and borders. Today, decision making is increasingly taking place at local to global levels for both administrative and organizational matters. This means that each decision-level needs its own (significant) information on forest cover. Such needs demand for specification on required spatial aggregation levels of forest cover at each decision-level in order to relate the spatial heterogeneity of vegetation patterns to functional management units. Many digital classification methods inherently maintain an underlying spatial *homogeneity* assumption that neglects the spatial *heterogeneity* of vegetation patterns at decision levels. In fact, current spatial aggregation levels at which forest cover is being digitally classified do not match the needs of different levels in decision making. Such shortcomings require two major responsibilities of remote sensing scientists. These two responsibilities are introduced as the definition task and the monitoring task. To solve the above mentioned three fundamental bottlenecks, it is therefore necessary to quantify spatial heterogeneity. This topic is discussed in Chapter 2. This first chapter also gives the research objectives, gives details on the 'Pelangkaraya' study area (Kalimantan, Indonesia) and gives information on the outline of this PhD thesis.

Chapter 2 presents the quantification of spatial heterogeneity. Landscape ecology with its specific focus on spatiality in relation to functionality provided the backbone of this quantification: the *patch-mosaic* ecosystem functional type. This biotic component is part of a bottom-up hierarchical approach that relates spatial heterogeneity to *functional heterogeneity*. As such, the diversity of species is reduced to a diversity of functions and structures based on a context-dependent (functional) generalization of the real world. Considering landscapes as ordered and interrelated multi-scale composites of local *patches* (structure) and *patch-mosaics* (function), then the patch-mosaics address both of the two key components of vegetation. These two vegetation components are composition (seen as spectral heterogeneity on satellite images) and configuration (seen as spatial heterogeneity on satellite images). It is indispensable to involve both vegetation components in the digital classification of spatially heterogeneous environments like tropical rainforest areas. Why that is needed is explained on the basis of a discussion of the underlying structural models and functional relationships of patch-mosaics. One aspect that is related, is the investigation of the so-called 'modifiable areal unit problem' (MAUP). After all, choosing non-overlapping areal units (patches) constitute both the scale and the aggregation problem when structure and function of spatially heterogeneous environments are linked. The remote sensing literature recognizes the importance of proper modeling of both vegetation components. This has led to a range of innovative digital analysis techniques such as hybrid approaches of fields and objects, contextual classifiers, Markov random fields, co-occurrencies, fractals, semi-variograms, cover

frequencies, multi-scale segmentations, and wavelet transformations. This chapter therefore also presents a review on the implementation of the patch-mosaic ecosystem functional type within these digital analysis techniques. It was found that underlying assumptions hamper such an implementation in applying these techniques. They either neglect that the thematic content of spatial entities are often *spatially* not distinct, limiting the modeling of vegetation composition, or they neglect that the organization of spatial entities has a *functional* hierarchical structure limiting the modeling of vegetation configuration. Therefore, this thesis recommends reconsidering remote sensing in its broadest sense of spatial object modelling and selecting functional generalization. This strategy of spatial generalization enables a conceptually move from patches to patch-mosaics. Remote sensing, however, lacks theory on the quantification of functional relationships that take into account *both* the composition *and* the configuration of spatial entities in order to implement the patch-mosaic ecosystem functional type in digital image analysis.

Therefore, **Chapter 3** introduces a new theoretical approach called *Aggregate-Mosaic Theory*. This theory describes the implementation of the patch-mosaic ecosystem functional type in digital image analysis considering both the composition (thematic aspects) and the configuration (geometric aspects) of spatial entities in the quantification of functional relationships. Conceptually, this theory incorporates a functional heterogeneity approach of landscape ecology and a functional generalization strategy of spatial object modeling for facilitating a *Land Cover Mosaics* (*LCM)* classification. This LCM classification quantitatively models the spatial heterogeneity at two different levels of spatial aggregation: *homogeneous* land cover classes at elementary level (the patches) and *heterogeneous* land cover mosaic (LCM) classes at composite level (the patch-mosaics). Essential for this quantitative modeling is that the functional LCM classes at composite level are created based on the *'mixture'* (thematic aspects) and the *'area'* (geometric aspects) of the structural land cover classes at elementary level. 'Mixture' and 'area' are called the two LCM parameters in the Aggregate Mosaic Theory. Topologic rules define the 'mixture' and geometric rules define the 'area'. The two spatial aggregation levels require their own digital analysis processes. From pixel level to elementary level these processes are called patch-segmentation and patch-classification. From elementary level to composite level they are called patch-mosaic classification and patch-mosaic segmentation. Aggregation hierarchies and classification hierarchies are used to structure these classification and segmentation processes: aggregation hierarchies for structuring the *spatial* generalization of remote sensing data and classification hierarchies for structuring their *thematic* generalization. Moving to LCM classification requires two additional new terms: *spatial aggregation classes* and *analysis resolution*. The spatial aggregation classes explicitly address the spatial aggregation levels of functional management units. Defining these classes requires an *interactive* information flow between remote sensing specialists and end-users. The analysis resolution specifies the spatial resolution from which a functional generalization starts. It is a third component of spatial scale and it is introduced to bound spatial aggregation classes to geometric restrictions. As such, the Aggregate-Mosaic Theory allows a semantic-driven digital classification of spatially heterogeneous environments. This chapter shows an example of a forest/non-forest map based on the Aggregate-Mosaic Theory. This map looks like a map that is manually interpreted (to handle spatial heterogeneity), though it is actually the result of a digital LCM classification based on quantitative parameters.

Chapter 4 studies the impact of parameter settings in patch-segmentation on functional generalization results at elementary level related to forest cover and forest cover pattern (using the segmentation algorithm of eCognition). A total of six evaluation metrics were used for this study: two discrepancy metrics (*RUMA* and *KHAT*) and four landscape pattern metrics (*PLAND, NP, SIDI, LSI*). It was found that the spatially more heterogeneous image and the spatially most fragmented land cover class showed most sensitivity for differences in parameter settings. However, the parameter settings mainly affected image configuration; they hardly affected image composition. This means that spatial heterogeneity can be segmented using different parameter settings *without* thematically loosing information at elementary level. Generally, the two studied images showed similar trends when changing the parameter settings. Given that the practice of agriculture in peatswamp forests is problematic, interpreting the figures of proportional abundance (coverage of land cover classes) at elementary level results in a change scenario that is more likely than if these figures are obtained at the pixel level. This underlines the need to define meaningful spatial objects (Chapter 3). The standard *KHAT* metric was unable to measure under-segmentation of the spatially more homogeneous image. It seemed that the *KHAT* metric in this study only addressed differences in spatial aggregation levels applying the standard approach that uses per-pixel classified images (a per-pixel spatial model) to assess classification accuracy of segmented images (a patch spatial model). It can therefore be appropriate to reconsider the application of this standard approach for spatially heterogeneous environments; these environments require measures that address both the composition and the configuration. The applied majority filtering did not shift the spatial aggregation level from per-pixel level to elementary level. A small 'break-off' value, a high 'color' weighting, and a high 'smoothness' weighting were chosen as input for continuing the study on LCM classification at composite level (Chapter 5). These parameter settings reduced under-segmentation, fine-tuned the distinction between the two forest cover classes, and met the requirements of the analysis resolution.

Chapter 5 introduces patch-mosaic classification for thematically upscaling elementary objects into composite objects. This newly developed classification is a true multi-scaled process and consists of six steps: (1) defining LCM classes, (2) defining upscaling parameters for quantifying the two LCM parameters 'mixture' and 'area', (3) defining threshold values of the upscaling parameters, (4) defining classification hierarchy for estimating 'area', (5) defining aggregation hierarchy for estimating 'mixture', and (6) estimating the final LCM class for each elementary object. This chapter further studies the impact of threshold values of two upscaling parameters in patch-mosaic classification on functional generalization results at composite level related to forest cover and forest cover pattern. These two upscaling parameters are called *minimum-area MA* and *shared-border BN*. Minimum-area *MA* calculates 'area' and estimates the spatial size of each elementary object. Shared-border *BN* calculates 'mixture' and estimates the relative border of each elementary object to the LCM classes of its neighboring elementary objects. Five evaluation metrics (*KHAT, PLAND, NP, SIDI and LSI*) were used for this study. It was found that the spatially more heterogeneous image and the spatially most fragmented vegetation (i.e., shrub) showed most sensitivity for threshold differences. Remarkably, when the upscaling thresholds mainly affected image configuration, image composition was hardly affected for both the images. This means that spatial heterogeneity can be functionally generalized using different upscaling thresholds *without* thematically loosing information at composite level. This is a major improvement compared with commonly used geometry-driven generalizations that either cause distortion of cover type proportions or cause disaggregation of spatial patterns. Generally, the two studied images showed similar trends for the image configuration. The LCM classes were less fragmented by increasing the threshold for minimum-area *MA* or decreasing the threshold for shared-border *BN*. The KHAT (addressing differences in spatial aggregation levels) depicted this trend. The two spatial aggregation levels (i.e., elementary and composite) gave a similar change scenario interpreting their figures on proportional abundance (coverage of land cover classes and LCM classes). The problem of practicing agriculture in peatswamp forests, deforestation and its underlying change processes, however, were more severe (and thus best highlighted) at composite level. A minimum-area *MA* of 150 ha and a shared-border *BN* of 0.55 were chosen as input for continuing the study on LCM classification at composite level (Chapter 6). These upscaling thresholds gave a similar effect on image configuration and were closest to the required minimum area of 100 ha as defined in forest definitions for tropical countries.

Chapter 6 introduces patch-mosaic segmentation for geometrically upscaling elementary objects into composite objects. This newly developed segmentation consists out of four methods that are based on two general segmentation approaches. The so-called *lc*-driven and *lcm*-driven methods are based on taxonomy (class-similarity), while the so-called *data*-driven and *wavelet*-driven methods are based on radiometry (radiometric-similarity). This chapter further studies the impact of these four methods on functional generalization results at composite level related to forest cover and forest cover pattern. Three different manual interpretation results are added to this study to obtain an expert's view on LCM classification at composite level. Again, five evaluation metrics (*KHAT, PLAND, NP, SIDI and LSI*) were used for evaluating both the digital results and the manual results. It was found that the spatially most fragmented vegetation (i.e., shrub) showed most sensitivity for the four patch-mosaic segmentation methods; this was particularly true for shrub vegetation of the more heterogeneous image. This shrub vegetation also caused most confusion for the three manual experts, but now for the homogeneous image. In addition, the proportional abundance (coverage) of shrub vegetation was substantially lower in the manual results for both the images. These findings necessitate quantifying spatial heterogeneity in order to relate shrub vegetation to a change process (i.e., logging or abandoning agriculture). Generally, both the images of the Pelangkaraya study area showed almost similar configuration trends applying the four methods. The fragmentation of LCM classes decreased when changing from taxonomy-based methods to radiometry-based methods; this fragmentation specifically decreased for the radiometry-based methods when the geometric extent of composite objects was enlarged. However, striking differences in image composition occurred between the two images when explicitly increasing geometric extents in *data*-driven segmentation. Apparently, a disconnection occurred between the geometric extent of composite objects and their thematic content for the spatially more heterogeneous image. This finding indicates the existence of a relation between extent and content of composite objects (i.e., semantics). Remarkably, wavelet-driven segmentation seemed to guide such a relation into a direction comparable to an expert's view. This means that localized scales can help to digitally create composite objects. The KHAT depicted both the reduction in fragmentation of the LCM classes (image configuration) as well as the semantic mismatch of the extent and content of composite objects (image composition). This underlines the statement in Chapter 4 that in a spatially heterogeneous environment the KHAT metric seems to address differences in spatial aggregation levels. In addition, most manual results were not significantly different for both the images. This means that experts create composite objects at a similar spatial aggregation level (clearly shown by KHAT). Both the digital and the manual results agreed on the underlying change processes of deforestation; agricultural areas were abandoned leading to a striking increase of shrub vegetation and areas with heavily-logged forest were burned for maintaining agricultural production.

Chapter 7 provides the synthesis of this thesis that recommends a paradigm shift from *homogeneous* land cover thinking to *heterogeneous* LCM thinking. This thesis proved that such a shift is possible and introduced LCM classification for digitally classifying spatially heterogeneous environments like tropical rainforest areas. Results showed that LCM classification is superior to land cover classification in modeling

spatial heterogeneity at user-defined spatial aggregation levels. It almost met the six criteria of Cihlar (2000) (i.e., accuracy, reproducibility, robustness, exploiting content, applicability and objectiveness). Related advantages of LCM classification are the parameterization of expert knowledge on semantic relations, the restriction of reference data to spatial aggregation classes to ensure operational use of remote sensing data, the possibility of monitoring land cover modifications that reveal spatial patterns of key processes in addition to land cover conversions, and the flexibility of including specific image processing techniques or other significant analysis methods (like wavelets) at each spatial aggregation level. It was also found that LCM classification can be regarded as an '*aggregation classifier*' marking a new stage in the evolution of digital classifiers. Aggregation classifiers are necessary regarding the increasing specialization in knowledge along with an increasing complexity in the management of our planet's resources. Therefore, implementation of LCM classification requires interdisciplinary remote sensing experts who are able to bridge the gap in expertise between remote sensing technology and application fields. These experts require knowledge on introduced factors like level of decision-making, spatial aggregation classes, analysis resolution, upscaling parameters and spatial aggregation levels, besides knowledge on common factors like segmentation algorithms, classification algorithms and remote sensing data sources. Limitations and recommendations of these introduced factors are given to encourage further research on LCM classification and to provide a direction in digitally classifying spatial complexity as specific as necessary. Finally, an explicit understanding of spatial heterogeneity will improve consistency of information on forest cover and forest cover pattern. Ultimately, this will lead to understanding and controlling environmental processes at a global level. Only then sustainable development of tropical rainforest areas will be enhanced for the benefit of future generations.

SAMENVATTING

Technologische vooruitgang is tot op de dag van vandaag altijd een drijvende kracht geweest achter satelliet remote sensing en haar toepassingsgebieden. Vaak was het belangrijkste aandachtspunt de spectrale en ruimtelijke resolutie van de satelliet sensoren te vergroten. Als gevolg hiervan benaderen de huidige remote sensing theorieën, methoden en verwerkingstechnieken de ruimtelijke heterogeniteit van tropische vegetatie alleen als een technisch (remote sensing) probleem, zoals autocorrelatie of spectrale overlap. Ondanks enorme inspanningen heeft deze 'productgerichte' benadering niet tot betere informatie over bosbedekking geleid, noch inzicht gegeven in onderliggende veranderingsprocessen bij het monitoren van ontbossing in tropisch regenwoudgebieden. Het tempo van de ontbossing van deze gebieden is alarmerend hoog en raakt zowel de lokale als mondiale economie en samenleving. Dit vraagt om een methode van bostoezicht die toegesneden is op besluitvorming. In dit proefschrift wordt daarom een 'klantgerichte' benadering gepresenteerd om naar de ruimtelijke heterogeniteit te kijken, waarbij gebruik wordt gemaakt van de informatie-inhoud van vegetatiepatronen die sporen van ontbossingsprocessen laten zien. Deze nieuwe manier van kijken naar ruimtelijke heterogeniteit kan informatie over bosbedekking opleveren die aansluit op de behoeften van de verschillende beslissingsniveaus.

Hoofdstuk 1 bespreekt drie fundamentele knelpunten die ontstaan als bij digitale beeldanalyse ruimtelijke heterogeniteit vanuit het perspectief van de klant wordt benaderd. De knelpunten betreffen inzicht in ruimtelijke heterogeniteit in tropische omgevingen, inzicht in ruimtelijke aggregatieniveaus in besluitvorming en inzicht in de onderliggende aanname van ruimtelijke homogeniteit in digitale classificatiemethoden. Karakteristiek voor tropische vegetatie zijn de vegetatiepatronen en grensovergangen die ook op een meer gedetailleerd niveau ruimtelijk heterogeen blijven. Dergelijke kenmerken vragen om vegetatietypologieën die deze patronen en grenzen kunnen registreren. Hedendaagse besluitvorming wordt in toenemende mate op lokaal tot mondiaal niveau genomen voor zowel administratieve als organisatorische zaken. Dit betekent dat elk beslissingsniveau zijn

eigen (significante) informatie over bosbedekking nodig heeft. Dergelijke behoeften vragen om specificatie van de vereiste ruimtelijke aggregatieniveaus van de bosbedekking op elk beslissingsniveau. Dit om de ruimtelijke heterogeniteit van vegetatiepatronen te relateren aan functionele beheerseenheden. Tal van digitale classificatiemethoden gaan standaard uit van een onderliggende aanname van ruimtelijke *homogeniteit*, waardoor de ruimtelijke *heterogeniteit* van vegetatiepatronen op beslissingsniveaus wordt genegeerd. In feite komen de huidige ruimtelijke aggregatieniveaus, waarop bosbedekking momenteel digitaal wordt geclassificeerd, niet overeen met de behoeften van de verschillende niveaus van besluitvorming. Dergelijke tekortkomingen vragen om twee belangrijke verantwoordelijkheden van remote sensing wetenschappers. Deze twee verantwoordelijkheden zijn hier geïntroduceerd als de definitietaak en de toezichthoudende taak. Voor het oplossen van bovengenoemde drie fundamentele knelpunten, is het daarom noodzakelijk om ruimtelijke heterogeniteit te kwantificeren. Dit onderwerp wordt behandeld in Hoofdstuk 2. Dit eerste hoofdstuk geeft bovendien de doelstellingen van het onderzoek, geeft details over het 'Pelangkaraya' onderzoeksgebied (Kalimantan, Indonesië) en geeft informatie over de opzet van dit proefschrift.

Hoofdstuk 2 behandelt de kwantificering van ruimtelijke heterogeniteit. Landschapsecologie met haar specifieke focus op ruimtelijkheid in relatie tot de functionaliteit leverde de ruggengraat voor deze kwantificering: het patch-mozaïek ecosysteem functionele type. Deze biotische component is onderdeel van een bottom-up hiërarchische benadering waarbij ruimtelijke heterogeniteit wordt gerelateerd aan *functionele heterogeniteit*. Hiermee wordt de diversiteit van soorten teruggebracht tot een diversiteit van functies en structuren, gebaseerd op een contextafhankelijke (functionele) generalisatie van de echte wereld. Wanneer landschappen worden beschouwd als geordende en onderling gerelateerde multi-schaal composieten van lokale *patches* (structuur) en *patch-mozaïeken* (functie), dan omvatten de patch-mozaïeken beide hoofdcomponenten van vegetatie. Deze twee vegetatiecomponenten zijn compositie (op satellietbeelden te zien als spectrale heterogeniteit) en configuratie (op satellietbeelden te zien als ruimtelijke heterogeniteit). Om ruimtelijk heterogene omgevingen zoals tropisch regenwoud-gebieden digitaal te classificeren, is het onontbeerlijk beide vegetatie componenten bij de classificatie te betrekken. Waarom dat nodig is, wordt uitgelegd aan de hand van een bespreking van de onderliggende structurele modellen en functionele relaties van patch-mozaïeken. Een aspect dat hiermee samenhangt, is het onderzoek van het zogeheten 'modifiable areal unit problem' (MAUP). Immers, als wordt gekozen voor niet-overlappende oppervlakte-eenheden ('patches'), ontstaat er zowel een schaalprobleem (keuze basiseenheden) als een aggregatieprobleem (keuze aggregatiestrategie) wanneer structuur en functie van ruimtelijk heterogene omgevingen worden gekoppeld. Het belang van goede modellering van beide vegetatiecomponenten wordt onderkend in de remote sensing literatuur. Dit heeft geleid tot een scala aan innovatieve digitale analysetechnieken zoals hybride benaderingen van velden en objecten, contextuele classificaties, Markov random fields, co-occurrenties, fractalen, semivariogrammen, bedekkingsfrequenties, multischaalsegmentaties en wavelet-transformaties. Dit hoofdstuk bevat daarom ook een bespreking over de implementatie van het patch-mozaïek ecosysteem functionele type binnen deze digitale analyse technieken. Gebleken is dat een dergelijke implementatie wordt bemoeilijkt door onderliggende aannames bij het toepassen van deze technieken. Er wordt ofwel genegeerd dat de thematische inhoud van ruimtelijke entiteiten vaak *ruimtelijk* gezien niet onderscheidend zijn, wat de modellering van de vegetatiecompositie beperkt, of er wordt genegeerd dat de ordening van ruimtelijke entiteiten een *functioneel* hiërarchische structuur heeft, wat de modellering van de vegetatieconfiguratie beperkt. Daarom wordt in dit proefschrift voorgesteld om de remote sensing zo breed mogelijk vanuit de ruimtelijke objectmodellering te benaderen en te kiezen voor functionele generalisatie. Deze ruimtelijke generalisatiestrategie maakt een conceptuele stap van patches naar patch-mozaïeken mogelijk. Het ontbreekt de remote sensing echter aan theorieën met betrekking tot de kwantificering van functionele relaties die rekening houden met *zowel* de compositie *als* de configuratie van ruimtelijke entiteiten om het patch-mozaïek ecosysteem functionele type te implementeren in de digitale beeldanalyse.

Daarom wordt in **Hoofdstuk 3** een nieuwe theoretische benadering geïntroduceerd, namelijk de *Aggregaat-Mozaïek Theorie*. Deze theorie beschrijft de implementatie van het patch-mozaïek ecosysteem functionele type in de digitale beeldanalyse en richt zich bij de kwantificering van functionele relaties zowel op de compositie (thematische aspecten) als op de configuratie (geografische aspecten) van ruimtelijke entiteiten. Deze theorie integreert een functionele heterogeniteitsbenadering uit de landschapsecologie en een functionele generalisatiestrategie uit de ruimtelijke objectmodellering om een *landbedekkingsmozaïeken (LCM)* classificatie mogelijk te maken. Deze LCM classificatie modelleert kwantitatief de ruimtelijke heterogeniteit op twee verschillende ruimtelijke aggregatieniveaus: *homogene* landbedekkingsklassen op elementair niveau (de patches) en *heterogene* landbedekkingsmozaïek (LCM) klassen op composiet niveau (de patch-mozaïeken). Van essentieel belang in deze kwantitatieve modellering is dat de functionele LCM klassen op composiet niveau worden gemaakt op basis van *'mix'* (thematische aspecten) en *'gebiedsgrootte'* (geometrische aspecten) van de structurele landbedekkingsklassen op elementair niveau. 'Mix' en 'gebiedsgrootte' worden de twee LCM parameters genoemd in de Aggregaat-Mozaïek Theorie. Topologische regels definiëren de 'mix' en geometrische regels definiëren de 'gebiedsgrootte'. De twee ruimtelijke aggregatieniveaus vereisen hun eigen digitale analyseprocessen. Van pixel niveau naar elementair niveau worden deze processen patch-segmentatie en patch-classificatie genoemd. Van elementair niveau naar composiet niveau worden deze processen patch-mozaïek classificatie en patch-mozaïek segmentatie genoemd. Om deze classificatie en segmentatie processen te structureren, worden aggregatiehiërarchieën en classificatiehiërarchieën gebruikt: aggregatiehiërarchieën voor het structureren van de *ruimtelijke* generalisatie van remote sensing gegevens, en classificatiehiërarchieën voor het structureren van hun *thematische* generalisatie. Nog twee nieuwe, voor LCM classificatie relevante termen worden hier geïntroduceerd: *ruimtelijke aggregatieklassen* en *analyseresolutie*. Ruimtelijke aggregatieklassen betreffen expliciet de ruimtelijke aggregatieniveaus van functionele beheerseenheden. Om deze klassen te definiëren, is een *interactieve* informatiestroom vereist tussen specialisten op het gebied van remote sensing en eindgebruikers. De analyseresolutie geeft de ruimtelijke resolutie aan die het beginpunt is van een functionele generalisatie. Het is een derde component van de ruimtelijke schaal en het is geïntroduceerd om ruimtelijke aggregatieklassen te koppelen aan geometrische restricties. De Aggregaat-Mozaïek Theorie biedt dus de mogelijkheid voor een semantisch gestuurde digitale classificatie van ruimtelijk heterogene omgevingen. Dit hoofdstuk geeft een voorbeeld van een bos/niet-bos kaart, die gebaseerd is op de Aggregaat-Mozaïek Theorie. Deze kaart lijkt op een kaart die handmatig geïnterpreteerd is (om ruimtelijke heterogeniteit aan te pakken); in werkelijkheid is de kaart het resultaat van een digitale LCM classificatie op basis van kwantitatieve parameters.

Hoofdstuk 4 bevat een onderzoek naar het effect van parameterinstellingen in patch-segmentatie op de resultaten van functionele generalisatie op elementair niveau, gerelateerd aan bosbedekking en het patroon van bosbedekking. Hierbij wordt gebruik gemaakt van het segmentatiealgoritme van eCognition. In totaal zijn voor dit onderzoek zes evaluatiemetrieken gebruikt: twee discrepantiemetrieken (RUMA en KHAT) en vier landschapspatroonmetrieken (PLAND, NP, SIDI en LSI). Gebleken is dat het ruimtelijk meer heterogene beeld en de ruimtelijk sterkst gefragmenteerde landbedekkingsklasse het gevoeligst waren voor verschillen in parameterinstellingen. De parameterinstellingen beïnvloedden echter hoofdzakelijk de beeldconfiguratie en nauwelijks de beeldcompositie. Dit betekent dat ruimtelijke heterogeniteit kan worden gesegmenteerd met behulp van verschillende parameterinstellingen, *zonder* verlies van informatie op thematisch elementair niveau. In het algemeen lieten de twee bestudeerde beelden overeenkomstige trends zien bij het wijziging van de parameterinstellingen. Gezien het feit dat het beoefenen van landbouw in veenmoerasbossen problematisch is, geven de cijfers van de proportionele hoeveelheid (bedekkingsgraad van landbedekkingsklassen) op elementair niveau na interpretatie een waarschijnlijker veranderingsscenario aan dan wanneer deze cijfers afkomstig zijn van het pixel niveau. Dit onderstreept de noodzaak om zinvolle ruimtelijke objecten te definiëren (Hoofdstuk 3). Het was niet mogelijk met de standaard KHAT metriek de ondersegmentatie van het ruimtelijk homogenere beeld te meten. Het leek of de KHAT metriek in dit onderzoek zich alleen richtte op verschillen in ruimtelijke aggregatieniveaus. De standaardbenadering werd namelijk aangehouden: hierbij wordt gebruik gemaakt van per pixel geclassificeerde beelden (een ruimtelijk model op pixel-basis) om de nauwkeurigheid van de classificatie van gesegmenteerde beelden te bepalen (een ruimtelijk model op patch-basis). Het kan daarom voor ruimtelijk heterogene omgevingen dan ook zinvol zijn om de toepassing van deze standaardbenadering te heroverwegen; deze omgevingen behoeven meetmethoden die zich zowel op de compositie als de configuratie richten. De toegepaste 'majority' filtering heeft het ruimtelijke aggregatieniveau niet verlegd van pixel niveau naar elementair niveau. Als input voor het vervolg van het onderzoek naar LCM classificatie op composiet niveau (Hoofdstuk 5) is gekozen voor een lage 'break-off' waarde, een hoge wegingsfactor voor 'kleur' en een hoge wegingsfactor voor 'smoothness'. Met deze parameterinstellingen daalde de ondersegmentatie, verfijnde het onderscheid tussen de twee bosbedekkingsklassen, en werd aan de vereisten van de analyseresolutie voldaan.

In **Hoofdstuk 5** wordt de patch-mozaïek classificatie geïntroduceerd voor het thematisch opschalen van elementaire objecten in composiet objecten. Deze classificatie is nieuw. Het is een echt multischaal proces dat uit zes stappen bestaat: (1) LCM klassen definiëren, (2) opschalingsparameters definiëren voor het kwantificeren van de twee LCM parameters 'mix' en 'gebiedsgrootte', (3) drempelwaarden definiëren voor de opschalingsparameters, (4) een classificatiehiërarchie definiëren voor het bepalen van 'gebiedsgrootte', (5) een aggregatie-hiërarchie definiëren voor het bepalen van 'mix' en (6) de definitieve LCM klasse bepalen voor elk elementair object. Dit hoofdstuk bevat verder een nader onderzoek naar het effect van drempelwaarden van twee opschalingsparameters in patch-mozaïek classificatie op de resultaten van functionele generalisatie op composiet niveau, gerelateerd aan bosbedekking en het patroon van bosbedekking. Deze twee opschalingsparameters worden genoemd 'minimum-area *MA'* en 'shared-border *BN'*. 'Minimum-area *MA'* kwantificeert 'gebiedsgrootte' en berekent de oppervlakte van elk elementair object. 'Shared-border *BN'* kwantificeert 'mix' en berekent de relatieve grens van elk elementair object met de LCM klassen van zijn naastgelegen elementaire objecten. Voor dit onderzoek zijn vijf evaluatiemetrieken gebruikt (*KHAT, PLAND, NP, SIDI en LSI*). Gebleken is dat het ruimtelijk meer heterogene beeld en de ruimtelijk sterkst gefragmenteerde vegetatie (i.e. struikvegetatie) het gevoeligst waren voor verschillen in drempelwaarden. Opmerkelijk was dat de drempelwaarden van de opschalingsparameters hoofdzakelijk de beeldconfiguratie beïnvloedde en nauwelijks de beeldcompositie. Dit gold voor beide beelden. Dit betekent dat ruimtelijke heterogeniteit functioneel kan worden gegeneraliseerd met behulp van verschillende opschalingsdrempels, *zonder* dat informatie in thematisch opzicht op composiet niveau verloren gaat. Dit is een grote verbetering ten opzichte van de reguliere, geometrisch-gestuurde generalisaties die leiden tot vervorming van de verhoudingen van bedekkingstypen, of tot het uiteenvallen van ruimtelijke patronen. In het algemeen lieten de twee bestudeerde beelden overeenkomstige trends zien voor de beeldconfiguratie. De LCM klassen waren minder gefragmenteerd na het verhogen van de drempel voor 'minimum-area *MA'* of het verlagen van de drempel voor 'shared-border *BN'*. De KHAT (gericht op verschillen in ruimtelijke aggregatieniveaus) gaf deze trend weer. De twee ruimtelijke aggregatieniveaus (i.e., elementair en composiet) gaven een soortgelijk veranderingsscenario aan bij de interpretatie van de cijfers met betrekking tot de proportionele hoeveelheid (bedekkingsgraad van landbedekkingsklassen en landbedekkingsmozaïek LCM klassen). Het probleem van het uitoefenen van landbouw in veenmoerasbossen, de ontbossing en de bijbehorende, onderliggende veranderingsprocessen waren echter ernstiger (en dus het duidelijkst zichtbaar) op composiet niveau. Als input voor het vervolg van het onderzoek naar LCM classificatie op composiet niveau (Hoofdstuk 6) is gekozen voor een 'minimum-area *MA'* van 150 ha en een 'shared-border *BN'* van 0,55. Deze opschalingsdrempels lieten een overeenkomstig effect zien op de beeldconfiguratie en lagen het dichtst bij het vereiste minimumgebied van 100 ha zoals dat gedefinieerd is in bosdefinities voor tropische landen.

In **Hoofdstuk 6** wordt patch-mozaïek segmentatie geïntroduceerd voor het geometrisch opschalen van elementaire objecten in composiet objecten. Deze segmentatie is nieuw. Het omvat vier methoden die gebaseerd zijn op twee algemene segmentatiebenaderingen. De zogeheten *lc*-gestuurde en *lcm*-gestuurde methoden zijn gebaseerd op taxonomie (gelijkenis van klasse), en de zogeheten *gegevens*-gestuurde en *wavelet*-gestuurde methoden zijn gebaseerd op radiometrie (radiometrische gelijkenis). Dit hoofdstuk bevat verder een nader onderzoek naar het effect van deze vier methoden op de resultaten van functionele generalisatie op composiet niveau, gerelateerd aan bosbedekking en het patroon van bosbedekking. Drie verschillende, handmatig verkregen interpretatieresultaten zijn toegevoegd aan dit onderzoek voor een deskundig oordeel over LCM classificatie op composiet niveau. Ook voor dit onderzoek zijn vijf evaluatiemetrieken gebruikt (*KHAT, PLAND, NP, SIDI en LSI*) voor het beoordelen van zowel de digitale als de handmatig verkregen resultaten. Gebleken is dat de ruimtelijk meest gefragmenteerde vegetatie (i.e., struikvegetatie) het gevoeligst was voor de vier methoden van patch-mozaïek segmentatie; dit gold in het bijzonder voor struikvegetatie van het meer heterogene beeld. Deze struikvegetatie veroorzaakte ook voor de drie onderzoekers die handmatig te werk gingen de meeste verwarring, maar dan voor het meer homogene beeld. Bovendien gold voor beide beelden dat de proportionele hoeveelheid (de bedekkingsgraad) van struikvegetatie aanzienlijk lager was in de handmatig verkregen resultaten. Deze bevindingen geven aan dat er behoefte is aan het kwantificeren van ruimtelijke heterogeniteit om struikvegetatie te relateren aan een veranderingsproces (i.e., houtkap of het verlaten van landbouwgebieden). Beide beelden van het 'Pelangkaraya' onderzoeksgebied lieten over het algemeen vrijwel identieke beeldconfiguratie trends zien wanneer de vier methoden werden toegepast. De fragmentatie van LCM klassen nam af wanneer van taxonomische methoden werd overgestapt op radiometrische methoden; deze fragmentatie nam met name af bij de radiometrische methoden wanneer de geometrische grootte van composietobjecten werd vergroot. De verschillen in beeldcompositie tussen de twee beelden werden echter opzienbarend groot zodra de geometrische grootte van composietobjecten in de *gegevens*-gestuurde segmentatie expliciet werd vergroot. Klaarblijkelijk ontstond er voor het ruimtelijk meer heterogene beeld een ontkoppeling tussen de geometrische grootte van composietobjecten en hun thematische inhoud. Deze bevinding geeft aan dat er een relatie bestaat tussen de grootte en de inhoud van composietobjecten (i.e., semantiek). Opmerkelijk genoeg leek een wavelet-gestuurde segmentatie een richting te geven aan een dergelijke relatie die vergelijkbaar is met een deskundig oordeel. Dit betekent dat met behulp van gelokaliseerde schalen, composietobjecten digitaal kunnen worden gemaakt. De KHAT gaf zowel de fragmentatiedaling van de LCM klassen (beeldconfiguratie) aan als de semantische mismatch van grootte en inhoud van de composietobjecten (beeldcompositie). Dit onderstreept de stelling uit Hoofdstuk 4 dat in een ruimtelijk heterogene omgeving de KHAT metriek zich lijkt te richten op verschillen in ruimtelijke aggregatieniveaus. Er waren geen significante verschillen tussen de handmatig verkregen resultaten: dit gold voor beide beelden. Dit betekent dat deskundigen composietobjecten maken op een overeenkomstig ruimtelijk aggregatieniveau (zoals ook duidelijk aangegeven door de KHAT). Zowel de digitale als handmatig verkregen resultaten waren het eens over de onderliggende veranderingsprocessen van de ontbossing: landbouwgebieden werden verlaten wat leidde tot een aanzienlijke toename van de struikvegetatie, en gebieden met zwaar-gekapt bos werden afgebrand voor het in stand houden van de landbouwproductie.

Hoofdstuk 7 bevat de synthese van dit proefschrift, waarin een paradigmaverschuiving wordt aanbevolen om landbedekking niet meer vanuit *homogeen* perspectief te beschouwen, maar over te stappen op een *heterogeen* perspectief. In dit proefschrift wordt aangetoond dat een dergelijke verschuiving mogelijk is en wordt LCM classificatie geïntroduceerd voor het digitaal classificeren van ruimtelijk heterogene omgevingen zoals tropisch regenwoudgebieden. De resultaten laten zien dat bij het modelleren van ruimtelijke heterogeniteit op door de gebruiker gedefinieerde ruimtelijke aggregatieniveaus, een heterogene landbedekkingsmozaïeken (LCM) classificatie te verkiezen is boven een homogene landbedekkingsclassificatie. Er wordt bijna voldaan aan de zes criteria van Cihlar (2000), namelijk nauwkeurigheid, reproduceerbaarheid, robuustheid, exploitatie van inhoud, toepasbaarheid en objectiviteit. Gerelateerde voordelen van de LCM classificatie zijn de parameterisering van vakkennis met betrekking tot semantische relaties, de restrictie van referentie-gegevens tot ruimtelijke aggregatieklassen om het operationeel gebruik van remote sensing data te garanderen, de mogelijkheid om wijzigingen in landbedekking te monitoren die ruimtelijke patronen laten zien van sleutelprocessen naast het monitoren van gebruikelijke conversies in landbedekking, en de flexibiliteit om specifieke technieken in de beeldverwerking of andere zinvolle analysemethoden (zoals wavelets), op elk ruimtelijk aggregatieniveau op te nemen. Bovendien is gebleken dat LCM classificatie kan worden beschouwd als een *'aggregatie-classificatie'*, die een nieuw stadium in de evolutie van digitale classificaties markeert. Aggregatie-classificaties zijn noodzakelijk gezien de toenemende specialisatie in kennis samen met een toenemende complexiteit in het beheer van de hulpbronnen van onze planeet. Daarom zijn voor het implementeren van LCM classificaties interdisciplinaire (remote sensing) deskundigen nodig, die in staat zijn de kenniskloof tussen de remote sensing technologie en haar toepassingsgebieden te overbruggen. Deze deskundigen moeten beschikken over kennis van geïntroduceerde factoren zoals niveau van besluitvorming, ruimtelijke aggregatieklassen, analyseresolutie, opschalingsparameters en ruimtelijke aggregatieniveaus, naast bestaande factoren zoals segmentatiealgoritmen, classificatiealgoritmen en remote sensing databronnen. Beperkingen en aanbevelingen van deze geïntroduceerde factoren worden gegeven om verder onderzoek naar LCM classificatie te stimuleren en om richting te geven aan het digitaal classificeren van ruimtelijke complexiteit, zo specifiek als nodig is. Tot slot: een expliciet begrip van ruimtelijke heterogeniteit zal de consistentie van informatie over bosbedekking en het patroon van bosbedekking ten goede komen. Dit zal uiteindelijk leiden tot begrip en controle van milieuprocessen op mondiaal niveau. Alleen dan zal een duurzame ontwikkeling van tropisch regenwoudgebieden worden versterkt ten behoeve van toekomstige generaties.

RINGKASAN

Kemajuan teknologi di bidang penginderaan jauh dan penerapannya telah dan terus berkembang. Dalam banyak kasus, fokus utamanya adalah untuk meningkatkan resolusi spectral dan spasial dari sensor satelit. Akibatnya, teori penginderaan jauh dan metode dan teknik pengolahan yang tersedia saat ini, memperlakukan heterogenitas spasial vegetasi tropis hanya sebagai masalah teknis yang penginderaan jauh seperti autokorelasi dan tumpang tindih spektral. Meskipun upaya-upaya besar, ini '*pemikiran yang berorientasi pada produk'* belum mengarah pada informasi yang lebih baik mengenai tutupan hutan, maupun pada perubahan proses-proses yang mendasarinya ketika pemantauan deforestasi di daerah hutan hujan tropis. Tingginya angka deforestasi di daerah hutan hujan tropis, akan mempengaruhi ekonomi lokal dan global serta masyarakat, sehingga mengharuskan pemantauan hutan yang disesuaikan dengan pengambilan keputusan. Tesis ini menyajikan, oleh karena itu, pendekatan *'pemikiran yang berorientasi pada pelanggan'* untuk memandang heterogenitas spasial dengan menggunakan muatan informasi dari pola vegetasi yang menunjukkan jejak kaki *('footprints')* dari proses deforestasi. Cara baru ini dapat menyediakan informasi tentang tutupan hutan yang memenuhi kebutuhan tingkat keputusan yang berbeda.

Bab 1 menguraikan tiga hambatan mendasar ketika menuju kepada perlakuan *'pemikiran yang berorientasi pada pelanggan'* terhadap heterogenitas spasial dalam analisis citra secara digital. Hal ini adalah pemahaman heterogenitas spasial di lingkungan tropis, pemahaman tingkat agregasi spasial dalam pengambilan keputusan, dan pemahaman yang mendasari asumsi spasial homogenitas dalam metode klasifikasi digital. Biasanya, vegetasi tropis menunjukkan pola vegetasi dan batas transisi yang secara spasial tetap heterogenetis di tingkat spasial yang lebih rinci. Karakteristik-karakteristik yang demikian menuntut vegetasi tipologi yang dapat menunjukkan pola-pola dan batas-batas ini. Hari ini, pengambilan keputusan yang terus meningkat beroperasi di tingkat lokal menuju tingkat global untuk hal-hal administrasi dan organisasi. Ini memerlukan informasi tutupan hutan menjadi berarti pada setiap tingkat. Kebutuhan yang demikian menuntut spesifikasi pada tingkat

agregasi spasial mengenai tutupan hutan yang dibutuhkan untuk menghubungkan heterogenitas spasial dari pola vegetasi terhadap unit manajemen fungsional. Banyak metode klasifikasi digital secara tetap (‘*inherent’*) mendasari sebuah asumsi spasial *homogenitas* yang mengabaikan heterogenitas spasial pola vegetasi pada tingkat keputusan. Kenyataanya, tingkat agregasi spasial pada saat ini yang mana tutupan hutan sedang diklasifikasi secara digital tidak sesuai dengan tingkat keputusan. Kelemahan-kelemahan yang demikian menuntut dua pertanggung jawaban penting dari para ilmuwan pengindaraan jauh yang dikenal sebagai tugas difinisi dan tugas monitoring. Semua tuntutan ini memerlukan kuantifikasi dari heterogenitas spasial. Hal ini dibahas dalam Bab 2. Pada Bab pertama ini juga memuat tujuan penelitian, rincian daerah studi di Pelangkaraya (Kalimantan, Indonesia) dan rincian dari outline tesis PhD ini.

Bab 2 menyajikan kuantifikasi heterogenitas spasial. Lanskap ekologi dengan fokus khusus pada spasialitas dalam hubunganya dengan fungsionalitas, menyediakan tulang punggung dari quantifikasi berikut: ‘*patch-mosaic’* ekosistem yang tipe fungsional. Komponen biotik ini merupakan bagian dari hirarki pendekatan ‘*bottom-up’* yang berhubungan dengan heterogenitas spasial terhadap fungsional heterogenitas. Dengan demikian, keragaman spesies dikurangi hingga menjadi sebuah keragaman fungsi dan struktur berdasarkan konteks ketergantungan (fungsional) generalisasi dari dunia nyata. Mempertimbangkan lanskap sebagai susunan dan gabungan multi-skala yang saling berhubungan dari lokal *‘patches’* (struktur) dan ‘*patch-mosaics’* (fungsi), kemudian ‘*patch-mosaics’* menunjukkan kedua komponen kunci dari vegetasi: komposisi (dilihat sebagai heterogenitas spektral pada citra satelit) dan konfigurasi (dilihat sebagai heterogenitas spasial pada citra satelit). Melibatkan kedua komponen tersebut adalah sebuah kebutuhan secara di digital mengklasifikasikan dari lingkungan-lingkungan spasial yang heterogen seperti daerah hutan hujan tropis. Model struktural yang mendasari dan hubungan fungsional patch-mosaik dibahas untuk menjelaskan kebutuhan ini. Isu yang terkait adalah mengeksplorasi masalah ‘*areal unit’* yang termodifikasi (‘*the modifiable areal unit problem’* or *MAUP*). Ini karena memilih ‘*areal unit’* yang tidak-tumpang tindih (*patch*) merupakan baik secara skala dan masalah agregasi ketika menghubungkan struktur dan fungsi lingkungan-lingkungan spasial yang heterogen. Literatur penginderaan jauh mengakui pentingnya pemodelan yang tepat dari kedua komponen vegetasi. Hal ini mengakibatkan berbagai teknik analisis digital yang inovatif seperti pendekatan *'hybrid approaches fields and objects', 'contextual classifiers', 'Markov random fields', 'co-occurrencies', 'fractals', 'semivariograms', 'cover frequencies', 'fractals', 'semivariograms', 'cover frequencies', 'multi-scale segmentations' dan 'wavelet transformations'*. Bab ini karena itu juga mengulas terhadap suatu implementasi '*patch-mosaic'* ekosistem yang tipe fungsional dalam teknik-teknik analisis digital yang inovatif tersebut. Ditemukan bahwa asumsi yang mendasari ketika menerapkan teknik-teknik ini menghambat seperti sebuah implementasi. Teknik-teknik tersebut mengabaikan bahwa kandungan tematik dari entitas-entitas spasial seringkali secara spasial tidak jelas, yang membatasi pemodelan komposisi vegetasi, atau teknik-teknik tersebut mengabaikan bahwa organisasi dari entitas-entitas spasial mempunyai struktur hirarkis fungsional, yang membatasi pemodelan konfigurasi vegetasi. Oleh karena itu, tesis ini merekomendasikan untuk mempertimbangkan kembali penginderaan jauh dalam arti luas dari pemodelan obyek spasial. Strategi ini dari generalisasi spasial memungkinkan bergerak secara konseptual pindah dari *'patches'* ke *'patch-mosaics'*. Penginderaan jauh, bagaimanapun, tidak memiliki teori tentang kuantifikasi hubungan fungsional yang memperhitungkan baik komposisi dan konfigurasi entitas-entitas spasial untuk suatu implementasi '*patch-mosaic'* ekosistem yang tipe fungsional dalam analisis citra secara digital.

Oleh karena itu, **Bab 3** memperkenalkan pendekatan teoritis baru yang disebut *Teori Agregat-Mosaik*. Teori ini menjelaskan suatu implementasi *'patch-mosaic'* ekosistem yang tipe fungsional dalam analisis citra secara digital yang mempertimbangkan baik komposisi (aspek tematik) dan konfigurasi (aspek geometrik) dari entitas-entitas spasial dalam kuantifikasi hubungan fungsional. Secara konseptual, teori ini menggabungkan suatu pendekatan heterogenitas fungsional dari ekologi lanskap dan suatu strategi generalisasi fungsional dari pemodelan obyek spasial untuk memfasilitasi klasifikasi Tutupan Lahan Mosaik (*'Land Cover Mosaics'* atau *LCM*). Klasifikasi *LCM* ini memungkinkan pemodelan kuantitatif heterogenitas spasial di dua tingkat agregasi spasial yang berbeda: kelas-kelas tutupan lahan homogen di tingkat dasar (yaitu, *'patch'*) dan kelas-kelas tutupan lahan heterogen mosaic di tingkat komposit (yaitu, '*patch-mosaic*'). Hal yang terpenting untuk pemodelan kuantitatif adalah bahwa kelas-kelas fungsional *LCM* di tingkat komposit dibuat berdasarkan *'mixture'* (*campuran;* aspek tematik) dan *'area'* (*luas areal;* aspek geometris) dari kelas-kelas struktural tutupan lahan di tingkat dasar. *'Mixture'* dan *'area'* ini disebut dua parameter *LCM* dalam Teori Agregat-Mosaik. Aturan topologi menetapkan *'mixture'* dan aturan geometri menetapkan *'area'*. Kedua tingkat agregasi spasial membutuhkan proses-proses analisis digital secara tersendiri. Dari tingkat pixel ke tingkat dasar proses-proses ini disebut '*patch'*-segmentasi dan *'patch'*-klasifikasi. Dari tingkat dasar ke tingkat komposit proses-proses ini disebut klasifikasi *'patch-mosaic'* dan *segmentasi 'patch-mosaic'*. Hierarki agregasi dan hierarki klasifikasi digunakan untuk menstruktur proses-proses klasifikasi dan segmentasi ini: hirarki agregasi untuk penataan generalisasi data spasial penginderaan jauh dan hirarki klasifikasi untuk penataan generalisasi tematik. Pindah ke klasifikasi *LCM* membutuhkan dua tambahan persyaratan baru, yaitu: *kelas-kelas agregasi spasial ('spatial aggregation classes')* dan *resolusi analisis ('analysis resolution').* Kelas-kelas agregasi spasial secara eksplisit menunjukkan tingkat-tingkat agregasi spasial dari unit manajemen fungsional. Medifinisikan kelas-kelas ini membutuhkan arus informasi yang interaktif antara spesialis penginderaan jauh dan para pengguna-akhir. Resolusi analisis menentukan resolusi spasial dari mana sebuah generalisasi fungsional dimulai. Ini adalah komponen ketiga dari skala spasial dan digunakan untuk membatasi kelas-kelas agregasi spasial untuk pembatasan geometris. Dengan demikian, Teori Agregat-Mosaic memungkinkan klasifikasi digital semantik berbasiskan lingkungan-lingkungan spasial yang heterogen. Bab ini menunjukkan sebuah peta contoh daerah hutan/non-hutan berdasarkan Teori Agregat-Mosaic. Peta ini tampak seperti peta yang ditafsirkan secara manual (untuk menangani heterogenitas spasial), meskipun sebenarnya ini adalah hasil digital dari klasifikasi LCM berdasarkan parameter kuantitatif.

Bab 4 mempelajari dampak dari pengaturan parameter di *patch-segmentasi* pada hasil fungsionalisasi generalisasi di tingkat dasar yang terkait dengan tutupan hutan dan pola tutupan hutan (dengan menggunakan segmentasi algoritma eCognition). Sebanyak enam metrik evaluasi digunakan untuk penelitian ini: dua perbedaan metrik (*RUMA* dan *KHAT*) dan empat metrik pola lanskap (*PLAND*, *NP*, *SIDI* dan *LSI*).

Ditemukan bahwa citra spasial yang lebih heterogen dan kelas spasial tutupan lahan yang paling terfragmentasi menunjukkan paling sensitif terhadap perbedaan pengaturan parameter. Namun demikian, pengaturan parameter terutama mempengaruhi konfigurasi citra; dan hampir tidak mempengaruhi komposisi citra. Ini berarti bahwa heterogenitas spasial dapat menjadi segmentasi di menggunakan pengaturan parameter yang berbeda *tanpa* kehilangan informasi tematik di tingkat dasar. Secara umum, dua citra yang dipelajari menunjukkan kecenderungan yang sama ketika pengaturan parameternya dirubah. Mengenai kesulitan untuk pertanian di hutan rawa gambut, menafsirkan angka-angka dari kelimpahan proporsional (cakupan kelas penutupan lahan) pada hasil di tingkat dasar menyediakan skenario perubahan yang lebih mungkinkan daripada menafsirkan angka-angka di tingkat per-pixel. Hal ini menggarisbawahi kebutuhan untuk mendefinisikan obyek spasial dengan arti (Bab 3). Metrik *KHAT* yang standar tidak mampu untuk mengukur '*under-segmentation'* dari citra spasial yang lebih homogen. Tampaknya bahwa metrik *KHAT* dalam penelitian ini hanya menunjukkan perbedaan-perbedaan dalam tingkat-tingkat agregasi spasial yang mengaplikasikan pendekatan standar yang menggunakan klasifikasi citra per-pixel *('a per-pixel spatial model'*) untuk menilai akurasi klasifikasi citra tersegmentasi *('a patch spatial model*'). Oleh karena itu, lingkungan-lingkungan spasial yang heterogen membutuhkan pertimbangan kembali dalam menerapkan pendekatan standar; lingkungan-lingkungan ini membutuhkan langkah-langkah baik pada komposisi dan konfigurasi. Mayoritas penyaringan yang diterapkan tidak memperluas tingkat agregasi spasial dari tingkat per-pixel ke tingkat dasar. Sebuah nilai *'break-off'* yang kecil, bobot 'warna' yang tinggi, dan bobot 'kehalusan' yang tinggi dipilih sebagai masukan untuk melanjutkan studi pada klasifikasi *LCM* di tingkat komposit (Bab 5). Pengaturan ini untuk parameter tersebut mengurangi *'under-segmentation',* memperhalus perbedaan antara dua kelas tutupan hutan, dan memenuhi persyaratan resolusi analisis.

Bab 5 memperkenalkan klasifikasi *'patch-mosaic'* untuk *'upscaling'* secara tematis obyek spasial di tingkat dasar menjadi obyek spasial di tingkat komposit. Klasifikasi ini yang baru dikembangkan adalah proses multi-skala yang benar dan terdiri dari enam langkah: (1) mendefinisikan kelas-kelas *LCM*, (2) mendefinisikan parameter *'upscaling'* untuk mengukur dua parameter *LCM* yaitu *'mixture'* dan *'area'*, (3) menentukan nilai-nilai ambang untuk parameter *'upscaling'*, (4) mendefinisikan hirarki klasifikasi untuk menaksir *'area'*, (5) mendefinisikan hirarki agregasi untuk memperkirakan *'mixture'*, (6) dan perkiraan kelas *LCM* akhir untuk setiap obyek spasial di tingkat dasar. Bab ini mempelajari lebih lanjut dampak dari nilai-nilai ambang untuk dua parameter *'upscaling'* dalam klasifikasi *'patch-mosaic'* pada hasil generalisasi fungsional di tingkat komposit yang terkait dengan tutupan hutan dan pola tutupan hutan. Kedua parameter *'upscaling'* disebut *'minimum-area' (minimum-daerah) MA* dan *'shared-border' (bersama-perbatasan) BN*. *'Minimum-area' MA* diukur *'area'* dan diperkirakan dari ukuran spasial setiap obyek spasial di tingkat dasar. *'Shared-border' BN* diukur *'mixture'* dan diperkirakan dari perbatasan relatif setiap obyek spasial di tingkat dasar dengan kelas-kelas *LCM* dari obyek spasial tetangganya di tingkat dasar. Sebanyak lima metrik evaluasi (*KHAT, PLAND, NP, SIDI* dan *LSI*) digunakan untuk penelitian ini. Ditemukan bahwa citra spasial yang lebih heterogen dan vegetasi spasial yang paling terfragmentasi (yaitu, semak) menunjukkan paling sensitif terhadap perbedaan ambang. Hebatnya, ketika ambang *'upscaling'* terutama mempengaruhi konfigurasi citra, komposisi citra hampir tidak terpengaruh untuk kedua citra tersebut. Ini berarti bahwa heterogenitas spasial dapat menjadi generalisasi fungsional di menggunakan ambang *'upscaling'* yang berbeda *tanpa* kehilangan informasi tematik di tingkat komposit. Ini adalah peningkatan besar dibandingkan dengan generalisasi berdasarkan geometri yang salah satunya menyebabkan distorsi tipe proporsi penutup atau menyebabkan disagregasi pola spasial. Secara umum, dua citra yang dipelajari menunjukkan kecenderungan yang sama untuk konfigurasi citra. Kelas-kelas *LCM* adalah kurang terfragmentasi dengan meningkatkan ambang untuk *'minimum-area' MA* atau dengan menurunkan ambang untuk *'shared-border' BN*. Metrik *KHAT* ini (menunjukkan perbedaan dalam tingkat agregasi spasial) menggambarkan kecenderungan ini. Baik tingkat-tingkat agregasi spasial (yaitu, dasar dan komposit) memberikan skenario perubahan yang sama didalam menafsirkan angka-angka pada kelimpahan proporsional (cakupan kelas penutupan lahan dan kelas *LCM*). Masalah pelatihan pertanian di hutan rawa gambut, deforestasi dan yang mendasarinya merubah proses-proses, bagaimanapun, adalah lebih parah (lebih ditekankan) di tingkat komposit. Sebuah '*minimum-area*' *MA* seluas 150 ha dan *'shared-border' BN* senilai 0.55 dipilih sebagai masukan untuk melanjutkan studi pada klasifikasi *LCM* di tingkat komposit (Bab 6). Nilai-nilai ini untuk ambang *'upscaling'* tersebut memberikan efek yang sama pada konfigurasi citra dan merupakan yang terdekat untuk daerah minimum dari 100 ha sebagaimana yang didefinisikan dalam definisi hutan untuk negara-negara tropis.

Bab 6 memperkenalkan segmentasi *'patch-mosaic'* untuk *'upscaling'* secare geometris obyek spasial di tingkat dasar menjadi obyek spasial di tingkat komposit. Segmentasi ini yang baru dikembangkan terdiri dari empat metode yang didasarkan pada dua pendekatan segmentasi umum. Dikenal metode *'lc-driven'* dan *'lcm-driven'* adalah didasarkan pada taksonomi (kelas-kesamaan), sedangkan yang dikenal dengan metode *'data-drive'* dan *'wavelet-driven'* adalah didasarkan pada radiometri (radiometrik-kesamaan). Bab ini mempelajari lebih lanjut dampak dari keempat metode tersebut pada hasil generalisasi fungsional di tingkat komposit yang terkait dengan tutupan hutan dan pola tutupan hutan. Tiga hasil interpretasi manual yang berbeda ditambahkan ke studi ini untuk mendapatkan pandangan seorang ahli tentang klasifikasi *LCM* di tingkat komposit. Sekali lagi, sebanyak lima metrik evaluasi (*KHAT*, *PLAND*, *NP*, *SIDI* dan *LSI*) digunakan untuk mengevaluasi baik hasil digital dan hasil manual. Ditemukan bahwa vegetasi spasial yang paling terfragmentasi (yaitu, semak) menunjukkan paling sensitif terhadap keempat metode segmentasi *'patch-mosaic'*; temuan ini terutama berlaku untuk vegetasi semak dari citra yang lebih heterogen. Vegetasi semak ini juga menyebabkan paling membingungkan untuk tiga para ahli manual, namun sekarang dari citra yang lebih homogen. Selain itu, kelimpahan proporsional (cakupan) semak itu adalah substansial yang lebih rendah pada hasil manual untuk kedua citra. Temuan ini mengharuskan perlunya kuantifikasi heterogenitas spasial untuk berhubungan vegetasi semak dengan suatu proses perubahan (misalnya, penebangan hutan atau lahan pertanian terlantar). Secara umum, baik citra dari daerah studi Pelangkaraya menunjukkan kecenderungan konfigurasi yang hampir sama dalam penerapan empat metode segmentasi *'patch-mosaic'*. Fragmentasi kelas-kelas *LCM* berkurang ketika mengubah dari metode berbasis taksonomi ke metode berbasis radiometri; fragmentasi ini khusus berkurang untuk metode berbasis radiometri bila menambah luasan geometris obyek spasial di tingkat komposit. Namun, perbedaan mencolok dalam komposisi citra terjadi antara dua citra ketika meningkatnya secara eksplisit luasan geometris dalam methode segmentasi *'data-driven'*. Rupanya, pemutusan yang terjadi antara luasan geometris dari obyek spasial di tingkat komposit dan kandungan tematik dari obyek ini pada citra spasial yang lebih heterogen. Temuan ini menunjukkan adanya hubungan antara luasan dan kandungan dari obyek spasial di tingkat komposit (yaitu, semantik). Hebatnya, methode segmentasi *'wavelet-driven'* tampak seperti memandu untuk relasi ini ke arah yang sebanding dengan pandangan seorang ahli. Ini berarti bahwa skala lokal dapat membantu untuk secara digital membuat obyek spasial di tingkat komposit. Metrik *KHAT* mengambarkan pengurangan fragmentasi kelas-kelas *LCM* (konfigurasi citra), serta ketidakcocokan *'semantic'* dari luasan dan kandungan obyek spasial di tingkat komposit (komposisi citra). Ini menggarisbawahi pernyataan pada Bab 4 bahwa dalam lingkungan-lingkungan spasial yang heterogen, metrik *KHAT* tampaknya menunjukkan perbedaan dalam tingkat-tingkat agregasi spasial. Selain itu, kebanyakan hasil manual tidak berbeda nyata untuk kedua citra. Ini berarti bahwa para ahli membuat obyek spasial di tingkat komposit pada tingkat agregasi spasial yang sama (jelas ditunjukkan oleh metric *KHAT*). Baik hasil digital dan manual setuju terhadap proses perubahan yang mendasari deforestasi; meninggalkan daerah pertanian yang terlantar menyebabkan meningkatkan yang menyolok dari vegetasi semak, dan pembakaran terhadap vegetasi hutan yang ditebang secara berat untuk (menjaga) produksi pertanian.

Bab 7 menyediakan sintesis dari tesis yang merekomendasikan sebuah pergeseran paradigma dari pemikiran tutupan lahan *homogen* ke pemikiran *LCM heterogen*. Tesis ini membuktikan bahwa pergeseran yang demikian itu mungkin dan memperkenalkan klasifikasi *LCM* untuk mengklasifikasikan secara digital lingkungan-lingkungan spasial yang heterogen seperti daerah hutan hujan tropis. Hasil menunjukkan bahwa klasifikasi *LCM* lebih unggul dari klasifikasi tutupan lahan dalam pemodelan heterogenitas spasial di tingkat agregasi spasial yang para pengguna-akhir. Ini hampir memenuhi sebanyak enam kriteria dari Cihlar (2000) (yaitu, akurasi, reproduktifitas, kekokohan, pemanfaatan kandungan, penerapan dan obyektivitas). Keuntungan yang berhubungan dari klasifikasi *LCM* adalah parameterisasi pengetahuan dari para ahli terhadap keterkaitan *'semantic'*, pembatasan data referensi untuk kelas-kelas agregasi spasial guna memastikan penggunaan operasional data penginderaan jauh, kemungkinan pemantauan modifikasi tutupan lahan yang mengungkapkan proses kunci pola spasial di samping tutupan lahan konversi, dan fleksibilitas yang termasuk teknik pengolahan citra tertentu atau metode analisis lain yang signifikan (seperti *'wavelet'*) pada setiap tingkat agregasi spasial. Hal ini juga menunjukkan bahwa klasifikasi *LCM* dapat dianggap sebagai *'penggolong agregasi'* ditandai tahap baru dalam evolusi pengklasifikasi digital. Penggolong agregasi itu diperlukan karena meningkatnya spesialisasi dalam pengetahuan bersama dengan meningkatnya kompleksitas dalam pengelolaan sumber daya alam. Oleh karena itu, penerapan klasifikasi *LCM* memerlukan ahli interdisipliner penginderaan jauh yang mampu menjembatani kesenjangan keahlian antara teknologi penginderaan jauh dan bidang aplikasi. Para ahli ini membutuhkan pengetahuan terhadap faktor-faktor yang dijelaskan tersebut seperti tingkat pengambilan keputusan, kelas-kelas agregasi spasial, resolusi analisis, parameter *'upscaling'* dan tingkat agregasi spasial, selain faktor umum seperti segmentasi algoritma, klasifikasi algoritma dan sumber data penginderaan jauh. Keterbatasan dan rekomendasi-rekomendasi dari faktor-faktor ini diberikan untuk mendorong penelitian lanjutan tentang klasifikasi *LCM* dan untuk memberikan arahan dalam mengklasifikasikan secara digital kompleksitas spasial sespesifik yang diperlukan. Akhirnya, pemahaman eksplisit tentang heterogenitas spasial akan meningkatkan konsistensi pada informasi tutupan hutan dan pola tutupan hutan. Pada akhirnya, hal ini akan mengarah pada pemahaman dan pengendalian proses-proces lingkungan di tingkat global. Hanya maka pembangunan berkelanjutan di daerah hutan hujan tropis yang akan diperkuat untuk bermanfaat generasi mendatang.

GLOSSARY

Analysis resolution: Specifies the spatial resolution from which a functional generalization starts (i.e., it provides the required minimum/maximum spatial size of elementary objects). This resolution is a spatial scale component specifically used during data analysis.

Composite objects: Groups of neighboring elementary objects that can contain different land cover classes, but represent together the same single land cover mosaic (LCM) class (i.e., patch-mosaics).

Elementary objects: Groups of neighbouring image pixels that can contain different radiometric values, but represent together the same single land cover class (i.e., patches).

Functional generalization: A spatial generalization strategy based on functional relationships between spatial objects. Both class-topology and class-geometry are used to quantitatively define these functional relationships.

LCM classification: A hierarchical upscaling framework to enable a functional classification of remote sensing data into useful management units at decisive level (i.e., from pixels to elementary objects to composite objects).

Land cover mosaic (LCM): A spatial entity (i.e., patch-mosaic) consisting of different sub-entities (i.e., patches). Those sub-entities can differ with respect to their type (i.e., addressing vegetation composition) and to their area (i.e., addressing vegetation configuration). In either case, the spatial entity is called heterogeneous.

Multi-resolution segmentation: A segmentation operation creating spatial objects at different resolution levels. These spatial objects are not specifically interrelated.

Multi-scaled systems: Systems with an ordered progression of interrelated spatial scales.

Multi-scale segmentation: A segmentation operation creating spatial objects at different spatial aggregation levels (i.e., lower level objects, focal level objects, and higher level objects). These spatial objects are interrelated.

Spatial aggregation level: A level of spatial detail at which vegetation patterns should be specified (c.q. classified) to be of significance for decision-making.

Thematic generalization: A conceptual generalization operation to obtain spatial objects at different thematic levels. Considers no geometric but only thematic aspects of spatial objects, and therefore conventionally called classification.

Spatial generalization: A conceptual generalization operation to obtain spatial objects at different spatial aggregation levels. Considers both geometric and thematic aspects of spatial objects, and therefore conventionally called aggregation.

Spatial aggregation class: A functional spatial unit (i.e., management unit) for an end-user of geo-information.

Thematically complex landscapes: Landscapes allowing different basic entities to fall within different aggregated basic entities. The geometric condition of containment is dropped; spatial extents of basic entities do not fully fall within spatial extents of aggregated basic entities.

Thematically nested landscapes: Landscapes of which spatial extents of basic entities entirely fall within spatial extents of aggregated basic entities. In geo-science, this is also called the geometric condition of containment (Droesen, 1999).

APPENDICES

Appendix 4.1 Correlation figures between landscape pattern metrics

*Spearman's rho correlation between **class-related** landscape pattern metrics (N=322).*

		CA	PLAND	NP	LPI	TE	LSI	AREA_MN	CLUMPY	PLADJ	AI
CA	Corr Coefficient	1,000	1,000	0,382	0,910	0,736	0,211	0,787	0,669	0,785	0,757
	Sig. (2-tailed)	.	.	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
PLAND	Corr Coefficient	1,000	1,000	0,382	0,910	0,736	0,211	0,787	0,669	0,785	0,757
	Sig. (2-tailed)	.	.	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
NP	Corr Coefficient	0,382	0,382	1,000	0,139	0,830	0,840	-0,117	-0,136	-0,040	-0,071
	Sig. (2-tailed)	0,000	0,000	.	0,012	0,000	0,000	0,036	0,015	0,473	0,205
LPI	Corr Coefficient	0,910	0,910	0,139	1,000	0,507	-0,083	0,906	0,850	0,918	0,903
	Sig. (2-tailed)	0,000	0,000	0,012	.	0,000	0,139	0,000	0,000	0,000	0,000
TE	Corr Coefficient	0,736	0,736	0,830	0,507	1,000	0,760	0,323	0,204	0,322	0,287
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	.	0,000	0,000	0,000	0,000	0,000
LSI	Corr Coefficient	0,211	0,211	0,840	-0,083	0,760	1,000	-0,270	-0,414	-0,310	-0,345
	Sig. (2-tailed)	0,000	0,000	0,000	0,139	0,000	.	0,000	0,000	0,000	0,000
AREA_MN	Corr Coefficient	0,787	0,787	-0,117	0,906	0,323	-0,270	1,000	0,934	0,963	0,956
	Sig. (2-tailed)	0,000	0,000	0,036	0,000	0,000	0,000	.	0,000	0,000	0,000
CLUMPY	Corr Coefficient	0,669	0,669	-0,136	0,850	0,204	-0,414	0,934	1,000	0,981	0,988
	Sig. (2-tailed)	0,000	0,000	0,015	0,000	0,000	0,000	0,000	.	0,000	0,000
PLADJ	Corr Coefficient	0,785	0,785	-0,040	0,918	0,322	-0,310	0,963	0,981	1,000	0,998
	Sig. (2-tailed)	0,000	0,000	0,473	0,000	0,000	0,000	0,000	0,000	.	0,000
AI	Corr Coefficient	0,757	0,757	-0,071	0,903	0,287	-0,345	0,956	0,988	0,998	1,000
	Sig. (2-tailed)	0,000	0,000	0,205	0,000	0,000	0,000	0,000	0,000	0,000	.

*Explanation **class related** metrics:*

CA	Total (Class) Area	LSI	Landscape Shape Index
PLAND	Percentage of Landscape	AREA_MN	Patch Area Distribution
NP	Number of Patches	CLUMPY	Clumpiness Index
LPI	Largest Patch Index	PLADJ	Percentage of Like Adjacencies
TE	Total Edge	AI	Aggregation Index

Spearman's rho correlation between ***landscape related*** *landscape pattern metrics (N=46).*

		NP	PD	LPI	TE	LSI	CONTAG	SIDI	SIEI	AI
NP	Corr Coefficient	1,000	1,000	-0,843	0,958	0,958	-0,950	0,641	0,638	-0,959
	Sig. (2-tailed)	.	.	0,000	0,000	0,000	0,000	0,000	0,000	0,000
PD	Corr Coefficient	1,000	1,000	-0,843	0,958	0,958	-0,950	0,641	0,638	-0,959
	Sig. (2-tailed)	.	.	0,000	0,000	0,000	0,000	0,000	0,000	0,000
LPI	Corr Coefficient	-0,843	-0,843	1,000	-0,841	-0,841	0,831	-0,386	-0,385	0,842
	Sig. (2-tailed)	0,000	0,000	.	0,000	0,000	0,000	0,008	0,008	0,000
TE	Corr Coefficient	0,958	0,958	-0,841	1,000	1,000	-0,984	0,705	0,702	-1,000
	Sig. (2-tailed)	0,000	0,000	0,000	.	.	0,000	0,000	0,000	0,000
LSI	Corr Coefficient	0,958	0,958	-0,841	1,000	1,000	-0,984	0,705	0,702	-1,000
	Sig. (2-tailed)	0,000	0,000	0,000	.	.	0,000	0,000	0,000	0,000
CONTAG	Corr Coefficient	-0,950	-0,950	0,831	-0,984	-0,984	1,000	-0,717	-0,715	0,984
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	.	0,000	0,000	0,000
SIDI	Corr Coefficient	0,641	0,641	-0,386	0,705	0,705	-0,717	1,000	1,000	-0,707
	Sig. (2-tailed)	0,000	0,000	0,008	0,000	0,000	0,000	.	0,000	0,000
SIEI	Corr Coefficient	0,638	0,638	-0,385	0,702	0,702	-0,715	1,000	1,000	-0,704
	Sig. (2-tailed)	0,000	0,000	0,008	0,000	0,000	0,000	0,000	.	0,000
AI	Corr Coefficient	-0,959	-0,959	0,842	-1,000	-1,000	0,984	-0,707	-0,704	1,000
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	.

Explanation ***landscape related*** *metrics:*

NP	Number of Patches	CONTAG	Contagion
PD	Patch Density	SIDI	Simpson's Diversity Index
LPI	Largest Patch Index	SIEI	Simpson's Evenness Index
TE	Total Edge	AI	Aggregation Index
LSI	Landscape Shape Index		

Appendix 4.2 Z statistics of patch-classification results at elementary level

A. p1990 image using reference 90mlk

segmentation parameters		90v10	90v15	90v20	90v25	90wcol05	90wcol06	90wcol07	90wcol08	90wcol09	90wsmo05	90wsmo07	90wsmo09	90wsmo10
	KHAT	*0.623*	*0.614*	*0.604*	*0.599*	*0.598*	*0.598*	*0.609*	*0.607*	*0.613*	*0.613*	*0.614*	*0.621*	*0.622*
	std err	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*
90v10		-	*1.06*	*2.24*	*2.83*	*2.95*	*2.95*	*1.65*	*1.89*	*1.18*	*1.18*	*1.06*	*0.24*	*0.12*
90v15		*1.06*	-	*1.18*	*1.77*	*1.89*	*1.89*	*0.59*	*0.82*	*0.12*	*0.12*	*0.00*	*0.82*	*0.94*
90v20		*2.24*	*1.18*	-	*0.59*	*0.71*	*0.71*	*0.59*	*0.35*	*1.06*	*1.06*	*1.18*	*2.00*	*2.12*
90v25		*2.83*	*1.77*	*0.59*	-	*0.12*	*0.12*	*1.18*	*0.94*	*1.65*	*1.65*	*1.77*	*2.59*	*2.71*
90wcol05		*2.95*	*1.89*	*0.71*	*0.12*	-	*0.00*	*1.30*	*1.06*	*1.77*	*1.77*	*1.89*	*2.71*	*2.83*
90wcol06		*2.95*	*1.89*	*0.71*	*0.12*	*0.00*	-	*1.30*	*1.06*	*1.77*	*1.77*	*1.89*	*2.71*	*2.83*
90wcol07		*1.65*	*0.59*	*0.59*	*1.18*	*1.30*	*1.30*	-	*0.24*	*0.47*	*0.47*	*0.59*	*1.41*	*1.53*
90wcol08		*1.89*	*0.82*	*0.35*	*0.94*	*1.06*	*1.06*	*0.24*	-	*0.71*	*0.71*	*0.82*	*1.65*	*1.77*
90wcol09		*1.18*	*0.12*	*1.06*	*1.65*	*1.77*	*1.77*	*0.47*	*0.71*	-	*0.00*	*0.12*	*0.94*	*1.06*
90wsmo05		*1.18*	*0.12*	*1.06*	*1.65*	*1.77*	*1.77*	*0.47*	*0.71*	*0.00*	-	*0.12*	*0.94*	*1.06*
90wsmo07		*1.06*	*0.00*	*1.18*	*1.77*	*1.89*	*1.89*	*0.59*	*0.82*	*0.12*	*0.12*	-	*0.82*	*0.94*
90wsmo09		*0.24*	*0.82*	*2.00*	*2.59*	*2.71*	*2.71*	*1.41*	*1.65*	*0.94*	*0.94*	*0.82*	-	*0.12*
90wsmo10		*0.12*	*0.94*	*2.12*	*2.71*	*2.83*	*2.83*	*1.53*	*1.77*	*1.06*	*1.06*	*0.94*	*0.12*	-

Explanation abbreviations *v = break-off value v_{scale}, wcol = color weighting w_{color} , wsmo = smoothness weighting w_{smooth}*

B. p1990 image using reference 90mlk5x5

segmentation parameters		*90v10*	*90v15*	*90v20*	*90v25*	*90wcol05*	*90wcol06*	*90wcol07*	*90wcol08*	*90wcol09*	*90wsmo05*	*90wsmo07*	*90wsmo09*	*90wsmo10*
	KHAT	*0.650*	*0.643*	*0.638*	*0.630*	*0.632*	*0.635*	*0.639*	*0.640*	*0.645*	*0.645*	*0.643*	*0.650*	*0.657*
	std err	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*
90v10		-	*0.82*	*1.41*	*2.36*	*2.12*	*1.77*	*1.30*	*1.18*	*0.59*	*0.59*	*0.82*	*0.00*	*0.82*
90v15		*0.82*	-	*0.59*	*1.53*	*1.30*	*0.94*	*0.47*	*0.35*	*0.24*	*0.24*	*0.00*	*0.82*	*1.65*
90v20		*1.41*	*0.59*	-	*0.94*	*0.71*	*0.35*	*0.12*	*0.24*	*0.82*	*0.82*	*0.59*	*1.41*	*2.24*
90v25		*2.36*	*1.53*	*0.94*	-	*0.24*	*0.59*	*1.06*	*1.18*	*1.77*	*1.77*	*1.53*	*2.36*	*3.18*
90wcol05		*2.12*	*1.30*	*0.71*	*0.24*	-	*0.35*	*0.82*	*0.94*	*1.53*	*1.53*	*1.30*	*2.12*	*2.95*
90wcol06		*1.77*	*0.94*	*0.35*	*0.59*	*0.35*	-	*0.47*	*0.59*	*1.18*	*1.18*	*0.94*	*1.77*	*2.59*
90wcol07		*1.30*	*0.47*	*0.12*	*1.06*	*0.82*	*0.47*	-	*0.12*	*0.71*	*0.71*	*0.47*	*1.30*	*2.12*
90wcol08		*1.18*	*0.35*	*0.24*	*1.18*	*0.94*	*0.59*	*0.12*	-	*0.59*	*0.59*	*0.35*	*1.18*	*2.00*
90wcol09		*0.59*	*0.24*	*0.82*	*1.77*	*1.53*	*1.18*	*0.71*	*0.59*	-	*0.00*	*0.24*	*0.59*	*1.41*
90wsmo05		*0.59*	*0.24*	*0.82*	*1.77*	*1.53*	*1.18*	*0.71*	*0.59*	*0.00*	-	*0.24*	*0.59*	*1.41*
90wsmo07		*0.82*	*0.00*	*0.59*	*1.53*	*1.30*	*0.94*	*0.47*	*0.35*	*0.24*	*0.24*	-	*0.82*	*1.65*
90wsmo09		*0.00*	*0.82*	*1.41*	*2.36*	*2.12*	*1.77*	*1.30*	*1.18*	*0.59*	*0.59*	*0.82*	-	*0.82*
90wsmo10		*0.82*	*1.65*	*2.24*	*3.18*	*2.95*	*2.59*	*2.12*	*2.00*	*1.41*	*1.41*	*1.65*	*0.82*	-

Explanation abbreviations *v = break-off value v_{scale}, wcol = color weighting w_{color} , wsmo = smoothness weighting w_{smooth}*

C. p1996 image using reference 96mlk

segmentation parameters		*96v1 0*	*96v1 5*	*96v2 0*	*96v2 5*	*96wc ol05*	*96wc ol06*	*96wc ol07*	*96wc ol08*	*96wc ol09*	*96ws mo05*	*96ws mo07*	*96ws mo09*	*96ws mo10*
	KHAT	*0.603*	*0.609*	*0.558*	*0.468*	*0.52*	*0.576*	*0.56*	*0.594*	*0.592*	*0.592*	*0.609*	*0.594*	*0.596*
	Std err	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*
96v10		*-*	*0.71*	*5.30*	*15.91*	*9.78*	*3.18*	*5.07*	*1.06*	*1.30*	*1.30*	*0.71*	*1.06*	*0.82*
96v15		*0.71*	*-*	*6.01*	*16.62*	*10.49*	*3.89*	*5.77*	*1.77*	*2.00*	*2.00*	*0.00*	*1.77*	*1.53*
96v20		*5.30*	*6.01*	*-*	*10.61*	*4.48*	*2.12*	*0.24*	*4.24*	*4.01*	*4.01*	*6.01*	*4.24*	*4.48*
96v25		*15.91*	*16.62*	*10.61*	*-*	*6.13*	*12.73*	*10.84*	*14.85*	*14.61*	*14.61*	*16.62*	*14.85*	*15.08*
96wcol05		*9.78*	*10.49*	*4.48*	*6.13*	*-*	*6.60*	*4.71*	*8.72*	*8.49*	*8.49*	*10.49*	*8.72*	*8.96*
96wcol06		*3.18*	*3.89*	*2.12*	*12.73*	*6.60*	*-*	*1.89*	*2.12*	*1.89*	*1.89*	*3.89*	*2.12*	*2.36*
96wcol07		*5.07*	*5.77*	*0.24*	*10.84*	*4.71*	*1.89*	*-*	*4.01*	*3.77*	*3.77*	*5.77*	*4.01*	*4.24*
96wcol08		*1.06*	*1.77*	*4.24*	*14.85*	*8.72*	*2.12*	*4.01*	*-*	*0.24*	*0.24*	*1.77*	*0.00*	*0.24*
96wcol09		*1.30*	*2.00*	*4.01*	*14.61*	*8.49*	*1.89*	*3.77*	*0.24*	*-*	*0.00*	*2.00*	*0.24*	*0.47*
96wsmo05		*1.30*	*2.00*	*4.01*	*14.61*	*8.49*	*1.89*	*3.77*	*0.24*	*0.00*	*-*	*2.00*	*0.24*	*0.47*
96wsmo07		*0.71*	*0.00*	*6.01*	*16.62*	*10.49*	*3.89*	*5.77*	*1.77*	*2.00*	*2.00*	*-*	*1.77*	*1.53*
96wsmo09		*1.06*	*1.77*	*4.24*	*14.85*	*8.72*	*2.12*	*4.01*	*0.00*	*0.24*	*0.24*	*1.77*	*-*	*0.24*
96wsmo10		*0.82*	*1.53*	*4.48*	*15.08*	*8.96*	*2.36*	*4.24*	*0.24*	*0.47*	*0.47*	*1.53*	*0.24*	*-*

Explanation abbreviations *v = break-off value v_{scale}, wcol = color weighting w_{color} , wsmo = smoothness weighting w_{smooth}*

D. p1996 image using reference 96mlk5x5

segmentation parameters		*96v1 0*	*96v1 5*	*96v2 0*	*96v2 5*	*96wc ol05*	*96wc ol06*	*96wc ol07*	*96wc ol08*	*96wc ol09*	*96ws mo05*	*96ws mo07*	*96ws mo09*	*96ws mo10*
	kappa	*0.643*	*0.656*	*0.599*	*0.508*	*0.563*	*0.619*	*0.601*	*0.634*	*0.632*	*0.632*	*0.656*	*0.638*	*0.632*
	std err	*0.006*	*0.005*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.006*	*0.005*	*0.006*	*0.006*
96v10		*-*	*1.66*	*5.19*	*15.91*	*9.43*	*2.83*	*4.95*	*1.06*	*1.30*	*1.30*	*1.66*	*0.59*	*1.30*
96v15		*1.66*	*-*	*7.30*	*18.95*	*11.91*	*4.74*	*7.04*	*2.82*	*3.07*	*3.07*	*0.00*	*2.30*	*3.07*
96v20		*5.19*	*7.30*	*-*	*10.72*	*4.24*	*2.36*	*0.24*	*4.12*	*3.89*	*3.89*	*7.30*	*4.60*	*3.89*
96v25		*15.91*	*18.95*	*10.72*	*-*	*6.48*	*13.08*	*10.96*	*14.85*	*14.61*	*14.61*	*18.95*	*15.32*	*14.61*
96wcol05		*9.43*	*11.91*	*4.24*	*6.48*	*-*	*6.60*	*4.48*	*8.37*	*8.13*	*8.13*	*11.91*	*8.84*	*8.13*
96wcol06		*2.83*	*4.74*	*2.36*	*13.08*	*6.60*	*-*	*2.12*	*1.77*	*1.53*	*1.53*	*4.74*	*2.24*	*1.53*
96wcol07		*4.95*	*7.04*	*0.24*	*10.96*	*4.48*	*2.12*	*-*	*3.89*	*3.65*	*3.65*	*7.04*	*4.36*	*3.65*
96wcol08		*1.06*	*2.82*	*4.12*	*14.85*	*8.37*	*1.77*	*3.89*	*-*	*0.24*	*0.24*	*2.82*	*0.47*	*0.24*
96wcol09		*1.30*	*3.07*	*3.89*	*14.61*	*8.13*	*1.53*	*3.65*	*0.24*	*-*	*-*	*3.07*	*0.71*	*0.00*
96wsmo05		*1.30*	*3.07*	*3.89*	*14.61*	*8.13*	*1.53*	*3.65*	*0.24*	*-*	*-*	*3.07*	*0.71*	*0.00*
96wsmo07		*1.66*	*0.00*	*7.30*	*18.95*	*11.91*	*4.74*	*7.04*	*2.82*	*3.07*	*3.07*	*-*	*2.30*	*3.07*
96wsmo09		*0.59*	*2.30*	*4.60*	*15.32*	*8.84*	*2.24*	*4.36*	*0.47*	*0.71*	*0.71*	*2.30*	*-*	*0.71*
96wsmo10		*1.30*	*3.07*	*3.89*	*14.61*	*8.13*	*1.53*	*3.65*	*0.24*	*0.00*	*0.00*	*3.07*	*0.71*	*-*

Explanation abbreviations *v = break-off value v_{scale}, wcol = color weighting w_{color} , wsmo = smoothness weighting w_{smooth}*

Appendix 5.1 Details of the LCM classification method and simulated annealing

The LCM classification method as described in section 5.2.1 was incorporated in eCognition software. This means that both the classification hierarchy and aggregation hierarchy of the LCM classification method were incorporated. The eCognition software contains three class hierarchies: the inheritance hierarchy, the groups hierarchy and the structure hierarchy. The LCM classification hierarchy was incorporated in both the inheritance hierarchy and structure hierarchy. The aggregation hierarchy was incorporated in both the groups hierarchy and structure hierarchy. In addition, although the LCM classification method consists of only two aggregation levels, in eCognition additional 'levels' were needed to run the LCM classification method.
Simulated annealing is available in the eCognition software. Simulated annealing was used to randomly change the computed membership of the elementary objects to a subclass, taking into account the membership values of all subclasses. To apply simulated annealing, three user-defined parameter settings are needed, they are called temperature, cooling-speed and number-of-cycles (Baatz et al., 2002). The temperature defines the extent to which random change takes place and can have a percentage value between [0;100]. The higher the temperature chosen, the more decisions are done stochastically. A stochastic decision allows a spatial object to be assigned to a class other than the one with the highest membership value. The cooling-speed defines the decrease of the temperature to zero in order to end with a totally deterministic classification decision. A deterministic decision assigns an image object to the class with the highest membership value. The larger the cooling-speed chosen, the faster the temperature is cooled down, reducing the number of stochastic decisions. The number of cycles defines the classification transitions, before the annealing can proceed, and the temperature can take its next value.
A preliminary study was executed to indicate for which settings the LCM classification became unstable (see also section 5.2.1). A stable classification result means that there is no single difference between the LCM classifications results for different simulated annealing settings. First, the number of cycles was investigated for two temperature values (0%, and 90%) and two cooling speed values (0.0, and 0.6). The values for the number of cycles ranged between 1 and 7 cycles. It was found that was that classification results below 4 cycles became unstable. Second, the relation between temperature and cooling-speed was examined. Five temperature values ranging between 0% and 100% are tested against eight cooling speed values ranging between 0.0 and 5.0, all with 5 cycles. The results of this investigation are given in Figure A. This figure shows a so-called 'border of stability'. The area under this border indicates stable LCM classification results; the area above this border indicates unstable LCM classification results. As such, high temperature values (> 60%) need low cooling-speed values (< 0.9) to remain stable. Low temperature values (< 40%) can have higher cooling values (< 4.5) to remain stable. Based on these findings and to favor the optimization process, the sensitivity of the two classification parameters MA and BN were investigated using the following simulated annealing settings: number of cycles 5; temperature 90%, cooling-speed 0.6.

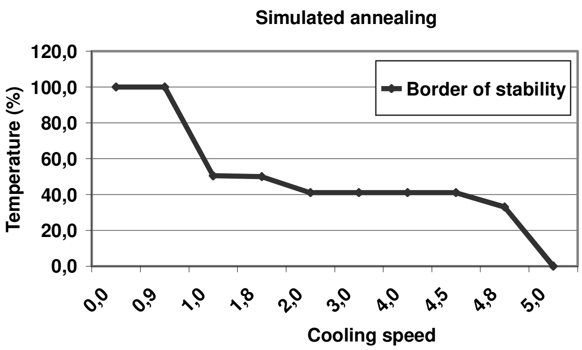


Figure A: Border of stability using simulated annealing in the LCM classification method.

Appendix 5.2 Number of elementary objects per minimum-area MA threshold per land cover class

P1990

MA	*agriculture*	*clouds*	*grass*	*heavilly logged forest*	*logged forest*	*river*	*shrub*	*water*	*Σ*
<5	*334*	*84*	*83*	*14*	*5*	*87*	*64*	*26*	
5.5	*27*	*5*	*11*	*5*	*2*	*1*	*14*	*4*	
15	*447*	*31*	*145*	*105*	*21*	*10*	*348*	*20*	
25	*248*	*2*	*97*	*144*	*41*	*5*	*321*	*9*	
50	*156*	*0*	*72*	*274*	*133*	*9*	*347*	*2*	
100	*16*	*0*	*7*	*165*	*155*	*6*	*87*	*0*	
150	*0*	*0*	*0*	*29*	*42*	*2*	*12*	*0*	
200	*0*	*0*	*0*	*7*	*27*	*1*	*1*	*0*	
250	*0*	*0*	*0*	*0*	*7*	*0*	*0*	*0*	
300	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	
350	*0*	*0*	*0*	*1*	*1*	*0*	*0*	*0*	
400	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	
15000	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
18800	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
>18800	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
Σ	*1228*	*122*	*415*	*744*	*436*	*121*	*1194*	*61*	*4321*

P1996

MA	*agriculture*	*cloud*	*grass*	*heavilly logged forest*	*logged forest*	*river*	*shrub*	*water*	*Σ*
<5	*128*	*283*	*71*	*40*	*30*	*29*	*157*	*27*	
5.5	*23*	*13*	*18*	*8*	*3*	*1*	*26*	*5*	
15	*342*	*54*	*287*	*191*	*32*	*12*	*555*	*55*	
25	*266*	*4*	*215*	*192*	*46*	*1*	*449*	*22*	
50	*184*	*0*	*144*	*224*	*126*	*5*	*363*	*17*	
100	*23*	*0*	*16*	*108*	*128*	*4*	*80*	*4*	
150	*1*	*0*	*0*	*18*	*41*	*0*	*4*	*0*	
200	*0*	*0*	*0*	*2*	*15*	*2*	*0*	*0*	
250	*0*	*0*	*0*	*1*	*4*	*1*	*0*	*0*	
300	*0*	*0*	*0*	*0*	*0*	*1*	*0*	*0*	
350	*0*	*0*	*0*	*0*	*1*	*0*	*0*	*0*	
400	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
15000	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
18800	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
>18800	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
Σ	*967*	*354*	*751*	*784*	*426*	*56*	*1634*	*130*	*5102*

Appendix 5.3 Z-statistics of LCM classification results at composite level for different threshold combinations of the two upscaling parameters minimum-area MA and shared-border BN in patch-mosaic classification

A. p1990 image using reference elementary objects (v_{scale} 10, w_{color} 0.9, w_{smooth} 0.9)

MA			5	5,5	15	15	15	25	50	100	150	150	150	150	150	150	200	250	300	350	400	15000	15000	15000	18800
	BN		0,55	0,55	0,45	0,55	0,65	0,55	0,55	0,55	0,35	0,45	0,55	0,65	0,75	0,85	0,55	0,55	0,55	0,55	0,55	0,45	0,55	0,65	0,55
		KHAT	0,946	0,947	0,918	0,919	0,925	0,905	0,884	0,855	0,827	0,836	0,848	0,870	0,890	0,904	0,831	0,826	0,814	0,814	0,800	0,510	0,658	0,800	0,658
		std error	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0,004	0,004	0,004	0,004	0,004	0,004	0.003	0,004	0,004	0,004	0,004	0,005	0,006	0,006	0,005	0,006
5	0,55		-	0,24	6,60	6,36	4,95	9,66	12,40	18,20	22,45	22,00	19,60	15,20	11,20	9,90	23,00	24,00	26,40	26,40	25,04	65,00	42,93	25,04	42,93
5,5	0,55		0,24	-	6,84	6,60	5,19	9,90	12,60	18,40	22,64	22,20	19,80	15,40	11,40	10,14	23,20	24,20	26,60	26,60	25,21	65,14	43,08	25,21	43,08
15	0,45		6,60	6,84	-	0,24	1,65	3,06	6,80	12,60	17,16	16,40	14,00	9,60	5,60	3,30	17,40	18,40	20,80	20,80	20,24	60,82	38,76	20,24	38,76
15	0,55		6,36	6,60	0,24	-	1,41	3,30	7,00	12,80	17,35	16,60	14,20	9,80	5,80	3,54	17,60	18,60	21,00	21,00	20,41	60,97	38,91	20,41	38,91
15	0,65		4,95	5,19	1,65	1,41	-	4,71	8,20	14,00	18,49	17,80	15,40	11,00	7,00	4,95	18,80	19,80	22,20	22,20	21,44	61,86	39,80	21,44	39,80
25	0,55		9,66	9,90	3,06	3,30	4,71	-	4,20	10,00	14,71	13,80	11,40	7,00	3,00	0,24	14,80	15,80	18,20	18,20	18,01	58,88	36,82	18,01	36,82
50	0,55		12,40	12,60	6,80	7,00	8,20	4,20	-	5,13	9,61	8,49	6,36	2,47	1,06	4,00	9,37	10,25	12,37	12,37	13,12	51,86	31,34	13,12	31,34
100	0,55		18,20	18,40	12,60	12,80	14,00	10,00	5,13	-	4,71	3,36	1,24	2,65	6,19	9,80	4,24	5,13	7,25	7,25	8,59	47,84	27,32	8,59	27,32
150	0,35		22,45	22,64	17,16	17,35	18,49	14,71	9,61	4,71	-	1,50	3,52	7,24	10,62	14,52	0,65	0,19	2,22	2,22	4,09	42,76	22,80	4,09	22,80
150	0,45		22,00	22,20	16,40	16,60	17,80	13,80	8,49	3,36	1,50	-	2,12	6,01	9,55	13,60	0,88	1,77	3,89	3,89	5,62	45,21	24,68	5,62	24,68
150	0,55		19,60	19,80	14,00	14,20	15,40	11,40	6,36	1,24	3,52	2,12	-	3,89	7,42	11,20	3,01	3,89	6,01	6,01	7,50	46,87	26,35	7,50	26,35
150	0,65		15,20	15,40	9,60	9,80	11,00	7,00	2,47	2,65	7,24	6,01	3,89	-	3,54	6,80	6,89	7,78	9,90	9,90	10,93	49,92	29,40	10,93	29,40
150	0,75		11,20	11,40	5,60	5,80	7,00	3,00	1,06	6,19	10,62	9,55	7,42	3,54	-	2,80	10,43	11,31	13,44	13,44	14,06	52,70	32,17	14,06	32,17
150	0,85		9,90	10,14	3,30	3,54	4,95	0,24	4,00	9,80	14,52	13,60	11,20	6,80	2,80	-	14,60	15,60	18,00	18,00	17,84	58,73	36,67	17,84	36,67
200	0,55		23,00	23,20	17,40	17,60	18,80	14,80	9,37	4,24	0,65	0,88	3,01	6,89	10,43	14,60	-	0,88	3,01	3,01	4,84	44,51	23,99	4,84	23,99
250	0,55		24,00	24,20	18,40	18,60	19,80	15,80	10,25	5,13	0,19	1,77	3,89	7,78	11,31	15,60	0,88	-	2,12	2,12	4,06	43,82	23,30	4,06	23,30
300	0,55		26,40	26,60	20,80	21,00	22,20	18,20	12,37	7,25	2,22	3,89	6,01	9,90	13,44	18,00	3,01	2,12	-	0.00	2,19	42,16	21,63	2,19	21,63
350	0,55		26,40	26,60	20,80	21,00	22,20	18,20	12,37	7,25	2,22	3,89	6,01	9,90	13,44	18,00	3,01	2,12	0.00	-	2,19	42,16	21,63	2,19	21,63
400	0,55		25,04	25,21	20,24	20,41	21,44	18,01	13,12	8,59	4,09	5,62	7,50	10,93	14,06	17,84	4,84	4,06	2,19	2,19	-	37,13	18,18	0.00	18,18
15000	0,45		65,00	65,14	60,82	60,97	61,86	58,88	51,86	47,84	42,76	45,21	46,87	49,92	52,70	58,73	44,51	43,82	42,16	42,16	37,13	-	17,44	37,13	17,44
15000	0,55		42,93	43,08	38,76	38,91	39,80	36,82	31,34	27,32	22,80	24,68	26,35	29,40	32,17	36,67	23,99	23,30	21,63	21,63	18,18	17,44	-	18,18	0.00
15000	0,65		25,04	25,21	20,24	20,41	21,44	18,01	13,12	8,59	4,09	5,62	7,50	10,93	14,06	17,84	4,84	4,06	2,19	2,19	0.00	37,13	18,18	-	18,18
18800	0,55		42,93	43,08	38,76	38,91	39,80	36,82	31,34	27,32	22,80	24,68	26,35	29,40	32,17	36,67	23,99	23,30	21,63	21,63	18,18	17,44	0.00	18,18	-

B. p1996 image using reference elementary objects (v_{scale} 10, w_{color} 0.9, w_{smooth} 0.9)

MA			5	5,5	15	15	15	25	50	100	150	150	150	150	150	150	200	250	300	350	400	15000	15000	15000	18800
	BN		0,55	0,55	0,45	0,55	0,65	0,55	0,55	0,55	0,35	0,45	0,55	0,65	0,75	0,85	0,55	0,55	0,55	0,55	0,55	0,45	0,55	0,65	0,55
		KHAT	0,940	0,940	0,903	0,908	0,915	0,881	0,846	0,802	0,736	0,749	0,783	0,833	0,860	0,890	0,773	0,754	0,752	0,745	0,736	0,539	0,618	0,796	0,618
		std error	0,003	0,003	0,003	0,003	0,003	0,004	0,004	0,005	0,005	0,005	0,005	0,004	0,004	0,004	0,005	0,005	0,005	0,005	0,005	0,006	0,006	0,005	0,006
5	0,55		-	0.00	8,72	7,54	5,89	11,80	18,80	23,67	34,99	32,76	26,93	21,40	16,00	10,00	28,64	31,90	32,24	33,44	34,99	59,78	48,00	24,70	48,00
5,5	0,55		0.00	-	8,72	7,54	5,89	11,80	18,80	23,67	34,99	32,76	26,93	21,40	16,00	10,00	28,64	31,90	32,24	33,44	34,99	59,78	48,00	24,70	48,00
15	0,45		8,72	8,72	-	1,18	2,83	4,40	11,40	17,32	28,64	26,41	20,58	14,00	8,60	2,60	22,29	25,55	25,90	27,10	28,64	54,26	42,49	18,35	42,49
15	0,55		7,54	7,54	1,18	-	1,65	5,40	12,40	18,18	29,50	27,27	21,44	15,00	9,60	3,60	23,15	26,41	26,75	27,95	29,50	55,01	43,23	19,21	43,23
15	0,65		5,89	5,89	2,83	1,65	-	6,80	13,80	19,38	30,70	28,47	22,64	16,40	11,00	5,00	24,35	27,61	27,95	29,15	30,70	56,05	44,27	20,41	44,27
25	0,55		11,80	11,80	4,40	5,40	6,80	-	6,19	12,34	22,65	20,61	15,31	8,49	3,71	1,59	16,87	19,83	20,15	21,24	22,65	47,43	36,47	13,27	36,47
50	0,55		18,80	18,80	11,40	12,40	13,80	6,19	-	6,87	17,18	15,15	9,84	2,30	2,47	7,78	11,40	14,37	14,68	15,77	17,18	42,57	31,62	7,81	31,62
100	0,55		23,67	23,67	17,32	18,18	19,38	12,34	6,87	-	9,33	7,50	2,69	4,84	9,06	13,74	4,10	6,79	7,07	8,06	9,33	33,67	23,56	0,85	23,56
150	0,35		34,99	34,99	28,64	29,50	30,70	22,65	17,18	9,33	-	1,84	6,65	15,15	19,37	24,05	5,23	2,55	2,26	1,27	0.00	25,22	15,11	8,49	15,11
150	0,45		32,76	32,76	26,41	27,27	28,47	20,61	15,15	7,50	1,84	-	4,81	13,12	17,34	22,02	3,39	0,71	0,42	0,57	1,84	26,89	16,77	6,65	16,77
150	0,55		26,93	26,93	20,58	21,44	22,64	15,31	9,84	2,69	6,65	4,81	-	7,81	12,03	16,71	1,41	4,10	4,38	5,37	6,65	31,24	21,13	1,84	21,13
150	0,65		21,40	21,40	14,00	15,00	16,40	8,49	2,30	4,84	15,15	13,12	7,81	-	4,77	10,08	9,37	12,34	12,65	13,74	15,15	40,77	29,82	5,78	29,82
150	0,75		16,00	16,00	8,60	9,60	11,00	3,71	2,47	9,06	19,37	17,34	12,03	4,77	-	5,30	13,59	16,55	16,87	17,96	19,37	44,51	33,56	10,00	33,56
150	0,85		10,00	10,00	2,60	3,60	5,00	1,59	7,78	13,74	24,05	22,02	16,71	10,08	5,30	-	18,27	21,24	21,55	22,65	24,05	48,67	37,72	14,68	37,72
200	0,55		28,64	28,64	22,29	23,15	24,35	16,87	11,40	4,10	5,23	3,39	1,41	9,37	13,59	18,27	-	2,69	2,97	3,96	5,23	29,96	19,85	3,25	19,85
250	0,55		31,90	31,90	25,55	26,41	27,61	19,83	14,37	6,79	2,55	0,71	4,10	12,34	16,55	21,24	2,69	-	0,28	1,27	2,55	27,53	17,41	5,94	17,41
300	0,55		32,24	32,24	25,90	26,75	27,95	20,15	14,68	7,07	2,26	0,42	4,38	12,65	16,87	21,55	2,97	0,28	-	0,99	2,26	27,27	17,16	6,22	17,16
350	0,55		33,44	33,44	27,10	27,95	29,15	21,24	15,77	8,06	1,27	0,57	5,37	13,74	17,96	22,65	3,96	1,27	0,99	-	1,27	26,38	16,26	7,21	16,26
400	0,55		34,99	34,99	28,64	29,50	30,70	22,65	17,18	9,33	0.00	1,84	6,65	15,15	19,37	24,05	5,23	2,55	2,26	1,27	-	25,22	15,11	8,49	15,11
15000	0,45		59,78	59,78	54,26	55,01	56,05	47,43	42,57	33,67	25,22	26,89	31,24	40,77	44,51	48,67	29,96	27,53	27,27	26,38	25,22	-	9,31	32,91	9,31
15000	0,55		48,00	48,00	42,49	43,23	44,27	36,47	31,62	23,56	15,11	16,77	21,13	29,82	33,56	37,72	19,85	17,41	17,16	16,26	15,11	9,31	-	22,79	-
15000	0,65		24,70	24,70	18,35	19,21	20,41	13,27	7,81	0,85	8,49	6,65	1,84	5,78	10,00	14,68	3,25	5,94	6,22	7,21	8,49	32,91	22,79	-	22,79
18800	0,55		48,00	48,00	42,49	43,23	44,27	36,47	31,62	23,56	15,11	16,77	21,13	29,82	33,56	37,72	19,85	17,41	17,16	16,26	15,11	9,31	-	22,79	-

Appendix 6.1 IQM - PrefDataFile

```
iqmname = IQM_OUTPUT          Output filename
iqmnametype = 1         = 1 to append to existing output file,
#                       = 0 to write over existing output file
psntype = DC            power spectrum normalization options:
#                         DC: IQ value highly dependent on image contrast (normal case)
#                         TC: IQ value dependent on image contrast
#                         AC: IQ value not dependent on image contrast
spot = 0.6              spot & viewdist are used to fix spatial frequency location of
viewdist = 351.3288     peak of Human Visual System (HVS) response curve on power spectrum
#                       292.774*spot/viewdist = peak location in cycles per pixelwidth
minsize = 256           min width subimage program will find; but smaller Square images can be input
maxsquare = 8192        max width image processed whole, in single FFT pass;
                        but larger images can be input
peakavg = A             A = avgIQ, P = peakIQ, PA = avg&peakIQ (computed if subimages exist)
SubImageInfo = N        Y = each subimage info to outputfile;  N = only average info output
beginfreq = 0.10        lowest frequency used for wedge power
wedgewidth = 4.0        angular width of one wedge;   <=180 degrees
slopecut = 999.         image blur if computed avg slope (0.05-0.25 frequency) > slopecut,
#                       then IQ sum switches (if NIIRS sensor) to: adjfreq to freqmax,
#                       slopecut=999. disables test, real working value is about 12.8
adjfreq = 0.10          see slopecut
freqmin = 0.01          0.010 is normal min frequency for IQ power summation
freqmax = 0.707107      0.707107 is normal max frequency for IQ power summation
highblur = 80.          severe blur if highblur < computed lowfreqslope
highsmear = 40.         smear if highsmear < computed wedgeratio (dir.& mag. computed)
highhaze = 0.02         heavy haze if contrast < highhaze
#                       highhaze = -99. switches on paired image processing option
sighaze = 0.07          highhaze < contrast < sighaze implies some haze present
ccdband = 3.            pixel banding if: power(0.5cy/pixwdth) > power(ccdband*0.45cy/pixwdth),
#                       then NoiseRatio & NoiseVar computed from frequency < Nyquist
dcM = 1.6092            NIIRS = dcM * Log10(IQ) + dcB,  DC normalization
dcB = 8.6849
acM = 2.2923            NIIRS = acM * Log10(IQ) + acB,  AC normalization
acB = 8.0
tcM = 1.650             NIIRS = tcM * Log10(IQ) + tcB,  TC normalization
tcB = 8.8745
highdcM = 1.6092        NIIRS = highdcM * log10(IQ) + highdcB, blur&DC normalization
highdcB = 8.6849
highacM = 2.2923        NIIRS = highacM * Log10(IQ) + highacB, blur&AC normalization
highacB = 8.0
hightcM = 0.            NIIRS = hightcM * Log10(IQ) + hightcB, blur&TC normalization
hightcB = 0.
RedW = .21              for color image: R,G,B weights for color IQ,niirs,contrast
GreenW = .72            the 3 weights must sum to 1.000
BlueW = .07
noiseflag = 0           = 0 for IQM Wiener noise filter
#                       = 1 for user-supplied noise filter (6 parms: sigmaG2,...Kappa2)
detectlevel = 5.        some noise if noiseratio < detectlevel  (noise filter applied)
highnoise = 1.1         severe noise if noiseratio < highnoise  (noise filter applied)
#                       always set:  highnoise < detectlevel
sigmaG2 = .078          definition of 6 noise filter parms (sigmaG2,...Kappa2) is in
rapw = .9268            see Opt.Eng.J.:"Objective Image Quality.." 4/92,Table1,pg.820
sigmaS2 = 6400.
DenomExp = 1.5          exponent in denominator of eq. 10, which = 1.5 in paper
Kappa1 = 19.2
Kappa2 = 1.5
```

Appendix 6.2 IQM – Part of auxDataFile

This is an example of the auxDataFile for Lansat TM band 1 with image data of original band *(i.e., tm90k__1.tif)* and wavelet transformed image bands (*j=7*). Note that the smooths are labelled as *t*_images *(e.g., tm90k__1_t1.tif)* and the details are labelled as *d*_images *(e.g., tm90k__1_d1.tif)*.

```
#
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d1.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d2.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d3.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d4.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d5.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag
 tm90k__1_d6.tif       GRAY
  1448  874  8  8 L   0  0.000000  100.000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
0.000000  0.000000  0.000000  0.000000  0.000000  1  1  1.00000
 #
Wdth_Hght_Hdr_Bpp_Ord_Cpix_FL_GSD_Alt_Pxl_Az_Lok_Fwd_Side_Gam_Ep_Ptch_Rol_Yw_Snsr_
Mod_Mag etc.
```

Appendix 6.3 IQM output for the original and wavelet transformed Landsat TM data. This list provides the IQM results for the p1990 and p1996 images of the Pelangkaraya study area

aux data file: aux_p2_1990k

normalization = DC
NIIRS = 1.60920 *log(IQ) + 8.68490
prefs data file: DefaultPref

mdy: 9/20/2003 hms: 13:46:49 IQM v6.5.2 Windows
....IQ........NIIRS...Codes.....Contrast......Width....Col...Row..Sensr.bpp.......pixel1

0.132064E-03	2.44	avg:	2	0.563564E+00	1	8	GRAY	76	tm90k__1.tif
0.475200E-05	0.12	avg:	2	0.297294E+00	1	8	GRAY	153	tm90k__1_d1.tif
0.235592E-04	1.24	avg:	2	0.267369E+00	1	8	GRAY	170	tm90k__1_d2.tif
0.221779E-04	1.19	avg:	2	0.215283E+00	1	8	GRAY	170	tm90k__1_d3.tif
0.276464E-04	1.35	avg:	2	0.206934E+00	1	8	GRAY	170	tm90k__1_d4.tif
0.349019E-04	1.51	avg:	2	0.218729E+00	1	8	GRAY	170	tm90k__1_d5.tif
0.410849E-04	1.61	avg:	2	0.211381E+00	1	8	GRAY	170	tm90k__1_d6.tif
0.456410E-04	1.67	avg:	2	0.195818E+00	1	8	GRAY	170	tm90k__1_d7.tif
0.513193E-03	3.39	avg:	2	0.505208E+00	1	8	GRAY	76	tm90k__1_t1.tif
0.521273E-03	3.40	avg:	2	0.488679E+00	1	8	GRAY	76	tm90k__1_t2.tif
0.805636E-03	3.70	avg:	2	0.625320E+00	1	8	GRAY	68	tm90k__1_t3.tif
0.828125E-03	3.72	avg:	2	0.607639E+00	1	8	GRAY	68	tm90k__1_t4.tif
0.804384E-03	3.70	avg:	2	0.582728E+00	1	8	GRAY	68	tm90k__1_t5.tif
0.758382E-03	3.65	avg:	2	0.565424E+00	1	8	GRAY	76	tm90k__1_t6.tif
0.692658E-03	3.58	avg:	2	0.530414E+00	1	8	GRAY	76	tm90k__1_t7.tif
0.100761E-02	3.86	avg:	2	0.893271E+00	1	8	GRAY	0	tm90k__3.tif
0.324980E-05	-0.15	avg:	2	0.273135E+00	1	8	GRAY	102	tm90k__3_d1.tif
0.605585E-04	1.90	avg:	2	0.309742E+00	1	8	GRAY	127	tm90k__3_d2.tif
0.689589E-04	1.99	avg:	2	0.304233E+00	1	8	GRAY	127	tm90k__3_d3.tif
0.930911E-04	2.19	avg:	2	0.312701E+00	1	8	GRAY	127	tm90k__3_d4.tif
0.118623E-03	2.36	avg:	2	0.331760E+00	1	8	GRAY	127	tm90k__3_d5.tif
0.128566E-03	2.41	avg:	2	0.322599E+00	1	8	GRAY	127	tm90k__3_d6.tif
0.790493E-04	2.05	avg:	2	0.268972E+00	1	8	GRAY	170	tm90k__3_d7.tif
0.206004E-02	4.36	avg:	2	0.862152E+00	1	8	GRAY	17	tm90k__3_t1.tif
0.166068E-02	4.21	avg:	2	0.767181E+00	1	8	GRAY	17	tm90k__3_t2.tif
0.178653E-02	4.26	avg:	2	0.777226E+00	1	8	GRAY	17	tm90k__3_t3.tif
0.139996E-02	4.09	avg:	2	0.681904E+00	1	8	GRAY	17	tm90k__3_t4.tif
0.136533E-02	4.07	avg:	2	0.663611E+00	1	8	GRAY	25	tm90k__3_t5.tif
0.201030E-02	4.34	avg:	2	0.827489E+00	1	8	GRAY	0	tm90k__3_t6.tif
0.147087E-02	4.11	avg:	2	0.710200E+00	1	8	GRAY	0	tm90k__3_t7.tif
0.168599E-03	2.61	avg:	2	0.267698E+00	1	8	GRAY	127	tm90k__4.tif
0.159306E-04	0.96	avg:	2	0.322107E+00	1	8	GRAY	136	tm90k__4_d1.tif
0.106918E-03	2.29	avg:	2	0.273077E+00	1	8	GRAY	119	tm90k__4_d2.tif
0.108658E-03	2.30	avg:	2	0.236373E+00	1	8	GRAY	127	tm90k__4_d3.tif
0.102451E-03	2.26	avg:	2	0.203362E+00	1	8	GRAY	153	tm90k__4_d4.tif
0.941682E-04	2.20	avg:	2	0.191673E+00	1	8	GRAY	170	tm90k__4_d5.tif
0.156583E-03	2.56	avg:	2	0.245217E+00	1	8	GRAY	136	tm90k__4_d6.tif
0.309390E-03	3.04	avg:	2	0.344154E+00	1	8	GRAY	136	tm90k__4_d7.tif
0.240527E-03	2.86	avg:	2	0.281743E+00	1	8	GRAY	119	tm90k__4_t1.tif
0.349094E-03	3.12	avg:	2	0.331580E+00	1	8	GRAY	110	tm90k__4_t2.tif
0.467259E-03	3.33	avg:	2	0.377575E+00	1	8	GRAY	102	tm90k__4_t3.tif

0.812619E-03	3.71	avg:	2	0.497480E+00	1	8	GRAY	76	tm90k__4_t4.tif
0.197203E-02	4.33	avg:	2	0.776754E+00	1	8	GRAY	34	tm90k__4_t5.tif
0.235133E-02	4.45	avg:	2	0.847990E+00	1	8	GRAY	34	tm90k__4_t6.tif
0.215993E-02	4.39	avg:	2	0.814731E+00	1	8	GRAY	34	tm90k__4_t7.tif
0.376709E-03	3.17	avg:	2	0.377962E+00	1	8	GRAY	85	tm90k__5.tif
0.171734E-04	1.02	avg:	2	0.333656E+00	1	8	GRAY	127	tm90k__5_d1.tif
0.114055E-03	2.34	avg:	2	0.271765E+00	1	8	GRAY	127	tm90k__5_d2.tif
0.141864E-03	2.49	avg:	2	0.267935E+00	1	8	GRAY	127	tm90k__5_d3.tif
0.161589E-03	2.58	avg:	2	0.259403E+00	1	8	GRAY	136	tm90k__5_d4.tif
0.162156E-03	2.58	avg:	2	0.245627E+00	1	8	GRAY	144	tm90k__5_d5.tif
0.181752E-03	2.62	avg:	2	0.256353E+00	1	8	GRAY	144	tm90k__5_d6.tif
0.402304E-03	3.16	avg:	2	0.364278E+00	1	8	GRAY	119	tm90k__5_d7.tif
0.565579E-03	3.46	avg:	2	0.422525E+00	1	8	GRAY	76	tm90k__5_t1.tif
0.904112E-03	3.79	avg:	2	0.521619E+00	1	8	GRAY	59	tm90k__5_t2.tif
0.135505E-02	4.07	avg:	2	0.626678E+00	1	8	GRAY	51	tm90k__5_t3.tif
0.273101E-02	4.56	avg:	2	0.890476E+00	1	8	GRAY	25	tm90k__5_t4.tif
0.406324E-02	4.84	avg:	2	0.109188E+01	1	8	GRAY	8	tm90k__5_t5.tif
0.336641E-02	4.71	avg:	2	0.995714E+00	1	8	GRAY	8	tm90k__5_t6.tif
0.327615E-02	4.69	avg:	2	0.101140E+01	1	8	GRAY	0	tm90k__5_t7.tif

aux data file: aux_p2_1996k

mdy: 9/20/2003   hms: 14: 3:40   IQM v6.5.2   Windows

....IQ........NIIRS...Codes.....Contrast......Width....Col...Row..Sensr.bpp.......pixel1

0.168785E-03	2.61	avg:	2	0.516247E+00	1	8	GRAY	85	tm96k__1.tif
0.649272E-05	0.34	avg:	2	0.332592E+00	1	8	GRAY	153	tm96k__1_d1.tif
0.281264E-04	1.36	avg:	2	0.351704E+00	1	8	GRAY	170	tm96k__1_d2.tif
0.358231E-04	1.52	avg:	2	0.343085E+00	1	8	GRAY	170	tm96k__1_d3.tif
0.121132E-03	2.36	avg:	2	0.384854E+00	1	8	GRAY	127	tm96k__1_d4.tif
0.159616E-03	2.56	avg:	2	0.400935E+00	1	8	GRAY	68	tm96k__1_d5.tif
0.676988E-04	1.96	avg:	2	0.306032E+00	1	8	GRAY	170	tm96k__1_d6.tif
0.623263E-04	1.91	avg:	2	0.275736E+00	1	8	GRAY	170	tm96k__1_d7.tif
0.634812E-03	3.54	avg:	2	0.576042E+00	1	8	GRAY	76	tm96k__1_t1.tif
0.675394E-03	3.58	avg:	2	0.552364E+00	1	8	GRAY	76	tm96k__1_t2.tif
0.701505E-03	3.61	avg:	2	0.532722E+00	1	8	GRAY	76	tm96k__1_t3.tif
0.614935E-03	3.52	avg:	2	0.487316E+00	1	8	GRAY	85	tm96k__1_t4.tif
0.527596E-03	3.41	avg:	2	0.433566E+00	1	8	GRAY	127	tm96k__1_t5.tif
0.705967E-03	3.61	avg:	2	0.520293E+00	1	8	GRAY	127	tm96k__1_t6.tif
0.697137E-03	3.60	avg:	2	0.492120E+00	1	8	GRAY	127	tm96k__1_t7.tif
0.495071E-03	3.37	avg:	2	0.657991E+00	1	8	GRAY	51	tm96k__3.tif
0.601440E-05	0.28	avg:	2	0.291235E+00	1	8	GRAY	153	tm96k__3_d1.tif
0.492669E-04	1.75	avg:	2	0.255969E+00	1	8	GRAY	153	tm96k__3_d2.tif
0.609638E-04	1.89	avg:	2	0.262136E+00	1	8	GRAY	153	tm96k__3_d3.tif
0.888684E-04	2.15	avg:	2	0.278656E+00	1	8	GRAY	153	tm96k__3_d4.tif
0.158845E-03	2.56	avg:	2	0.414218E+00	1	8	GRAY	127	tm96k__3_d5.tif
0.148260E-03	2.51	avg:	2	0.363029E+00	1	8	GRAY	127	tm96k__3_d6.tif
0.796844E-04	2.08	avg:	2	0.311733E+00	1	8	GRAY	170	tm96k__3_d7.tif
0.986313E-03	3.85	avg:	2	0.638505E+00	1	8	GRAY	51	tm96k__3_t1.tif
0.138099E-02	4.08	avg:	2	0.757509E+00	1	8	GRAY	42	tm96k__3_t2.tif
0.142579E-02	4.11	avg:	2	0.741296E+00	1	8	GRAY	42	tm96k__3_t3.tif
0.133170E-02	4.06	avg:	2	0.685913E+00	1	8	GRAY	42	tm96k__3_t4.tif
0.112264E-02	3.93	avg:	2	0.621368E+00	1	8	GRAY	51	tm96k__3_t5.tif
0.971780E-03	3.83	avg:	2	0.576456E+00	1	8	GRAY	59	tm96k__3_t6.tif
0.825935E-03	3.71	avg:	2	0.515572E+00	1	8	GRAY	68	tm96k__3_t7.tif
0.130091E-03	2.43	avg:	2	0.243706E+00	1	8	GRAY	136	tm96k__4.tif

0.191214E-03	2.70	avg:	2	0.335756E+00	1	8 GRAY	136	tm96k__4_d1.tif
0.111275E-03	2.32	avg:	2	0.287739E+00	1	8 GRAY	127	tm96k__4_d2.tif
0.118201E-03	2.36	avg:	2	0.249743E+00	1	8 GRAY	136	tm96k__4_d3.tif
0.124680E-03	2.40	avg:	2	0.225757E+00	1	8 GRAY	153	tm96k__4_d4.tif
0.118644E-03	2.36	avg:	2	0.208987E+00	1	8 GRAY	170	tm96k__4_d5.tif
0.154086E-03	2.55	avg:	2	0.237919E+00	1	8 GRAY	153	tm96k__4_d6.tif
0.205510E-03	2.73	avg:	2	0.282898E+00	1	8 GRAY	153	tm96k__4_d7.tif
0.181001E-03	2.66	avg:	2	0.256178E+00	1	8 GRAY	136	tm96k__4_t1.tif
0.234505E-03	2.83	avg:	2	0.280646E+00	1	8 GRAY	127	tm96k__4_t2.tif
0.297443E-03	2.99	avg:	2	0.307403E+00	1	8 GRAY	119	tm96k__4_t3.tif
0.441690E-03	3.25	avg:	2	0.369023E+00	1	8 GRAY	102	tm96k__4_t4.tif
0.841785E-03	3.68	avg:	2	0.508108E+00	1	8 GRAY	68	tm96k__4_t5.tif
0.132712E-02	4.00	avg:	2	0.638432E+00	1	8 GRAY	42	tm96k__4_t6.tif
0.148063E-02	4.07	avg:	2	0.664848E+00	1	8 GRAY	34	tm96k__4_t7.tif
0.435259E-03	3.28	avg:	2	0.436249E+00	1	8 GRAY	85	tm96k__5.tif
0.170079E-04	1.01	avg:	2	0.331510E+00	1	8 GRAY	136	tm96k__5_d1.tif
0.110939E-03	2.32	avg:	2	0.285135E+00	1	8 GRAY	119	tm96k__5_d2.tif
0.124548E-03	2.40	avg:	2	0.268444E+00	1	8 GRAY	127	tm96k__5_d3.tif
0.158462E-03	2.56	avg:	2	0.263770E+00	1	8 GRAY	144	tm96k__5_d4.tif
0.174532E-03	2.63	avg:	2	0.260151E+00	1	8 GRAY	136	tm96k__5_d5.tif
0.148217E-03	2.52	avg:	2	0.241164E+00	1	8 GRAY	153	tm96k__5_d6.tif
0.292670E-03	2.97	avg:	2	0.327528E+00	1	8 GRAY	136	tm96k__5_d7.tif
0.552920E-03	3.44	avg:	2	0.437462E+00	1	8 GRAY	85	tm96k__5_t1.tif
0.735724E-03	3.64	avg:	2	0.489537E+00	1	8 GRAY	76	tm96k__5_t2.tif
0.119429E-02	3.98	avg:	2	0.607555E+00	1	8 GRAY	59	tm96k__5_t3.tif
0.217065E-02	4.40	avg:	2	0.818252E+00	1	8 GRAY	34	tm96k__5_t4.tif
0.309866E-02	4.65	avg:	2	0.979934E+00	1	8 GRAY	17	tm96k__5_t5.tif
0.270003E-02	4.55	avg:	2	0.907298E+00	1	8 GRAY	25	tm96k__5_t6.tif
0.279651E-02	4.57	avg:	2	0.921517E+00	1	8 GRAY	17	tm96k__5_t7.tif

Problem Codes (thresholds set in Prefs file):
blank is normal image, freqmin = 0.01000 freqmax = 0.70711
1 significant blur: adjfreq = 0.10000 midfreqslope > 999.0000
2 severe blur: lowfreqslope > 80.000
3 severe haze: contrast < 0.0200
4 1-D smear: wedgeratio > 40.00 for wedge angle = 4.000 degrees
5 severe noise, IQMstd Noise Filter Applied, noiseratio < 1.100
6 significant noise, IQMstd Noise Filter Applied, noiseratio < 5.000
8 sensor pixel banding: 0.5cy/pix power > 3.0 * 0.45cy/pix power
(problem codes not applied if image width < 33 pixels)

Sensor:
1 General Aerial/Space Digital Sensor
2 Oblique Aerial/Space Digital Sensor
3 Aerial/Space Film Camera
4 General Sensor
5 Ground-Based Digital Camera (IQ >100 implies IQ dependent on # of sensor pixels)

"avg: 3" IQ, NIIRS, contrast are averages from 3 subimages;
for subimage info, in prefsfile set: SubImageInfo = Y

"peak: 4" peak IQ & NIIRS from 4 subimages; contrast is for this subimage

Image polarity check: "pixel1" should equal true graylevel of UpperLeftCorner pixel
of entire image; if RGB image, pixel1 value is for Blue layer

Appendix 6.4: Z-statistics of LCM classification results at composite level for the four patch-mosaic segmentation processes: lc-driven (a), lcm-driven (b), data-driven (c), and wavelet-driven (d). The values 20, 40, 80 and 160 refer to the used break-off value in radiometry-based segmentation. (co means composite objects)

P1990 TM

	co_a	*co_b*	*co_c20*	*co_c40*	*co_c80*	*co_c160*	*co_d20*	*co_d40*	*co_d80*	*co_d160*	*l-1*	*l-2*	*l-3*
co_a		15,15	19,52	23,71	30,65	40,91	21,71	23,71	29,68	42,57	43,82	45,35	43,41
co_b	15,15		3,96	9,47	15,88	25,35	5,94	9,47	14,98	26,89	28,04	29,45	27,66
co_c20	19,52	3,96		5,89	12,29	21,77	1,98	5,89	11,40	23,30	24,46	25,86	24,07
co-c40	23,71	9,47	5,89		5,89	14,61	4,10	0,00	5,07	16,03	17,09	18,38	16,73
co_c80	30,65	15,88	12,29	5,89		8,72	10,50	5,89	0,82	10,14	11,20	12,49	10,84
co_c160	40,91	25,35	21,77	14,61	8,72		19,97	14,61	9,55	1,41	2,47	3,77	2,12
co_d20	21,71	5,94	1,98	4,10	10,50	19,97		4,10	9,60	21,51	22,66	24,07	22,28
co_d40	23,71	9,47	5,89	0,00	5,89	14,61	4,10		5,07	16,03	17,09	18,38	16,73
co_d80	29,68	14,98	11,40	5,07	0,82	9,55	9,60	5,07		10,96	12,02	13,32	11,67
co_d160	42,57	26,89	23,30	16,03	10,14	1,41	21,51	16,03	10,96		1,06	2,36	0,71
l-1	43,82	28,04	24,46	17,09	11,20	2,47	22,66	17,09	12,02	1,06		1,30	0,35
l-2	45,35	29,45	25,86	18,38	12,49	3,77	24,07	18,38	13,32	2,36	1,30		1,65
l-3	43,41	27,66	24,07	16,73	10,84	2,12	22,28	16,73	11,67	0,71	0,35	1,65	

P1996 TM

	co_a	*co_b*	*co_c20*	*co_c40*	*co_c80*	*co_c160*	*co_d20*	*co_d40*	*co_d80*	*co_d160*	*l-1*	*l-2*	*l-3*
co_a		4,53	10,75	15,36	26,38	51,85	12,55	18,05	25,10	40,59	35,85	42,00	41,23
co_b	4,53		6,22	11,27	22,28	47,76	8,45	13,96	21,00	36,49	31,75	37,90	37,13
co_c20	10,75	6,22		5,63	16,64	42,12	2,82	8,32	15,36	30,86	26,12	32,27	31,50
co-c40	15,36	11,27	5,63		10,14	33,59	2,59	2,47	8,96	23,22	18,86	24,51	23,81
co_c80	26,38	22,28	16,64	10,14		23,45	12,73	7,66	1,18	13,08	8,72	14,38	13,67
co_c160	51,85	47,76	42,12	33,59	23,45		36,18	31,11	24,63	10,37	14,73	9,07	9,78
co_d20	12,55	8,45	2,82	2,59	12,73	36,18		5,07	11,55	25,81	21,45	27,11	26,40
co_d40	18,05	13,96	8,32	2,47	7,66	31,11	5,07		6,48	20,74	16,38	22,04	21,33
co_d80	25,10	21,00	15,36	8,96	1,18	24,63	11,55	6,48		14,26	9,90	15,56	14,85
co_d160	40,59	36,49	30,86	23,22	13,08	10,37	25,81	20,74	14,26		4,36	1,30	0,59
l-1	35,85	31,75	26,12	18,86	8,72	14,73	21,45	16,38	9,90	4,36		5,66	4,95
l-2	42,00	37,90	32,27	24,51	14,38	9,07	27,11	22,04	15,56	1,30	5,66		0,71
l-3	41,23	37,13	31,50	23,81	13,67	9,78	26,40	21,33	14,85	0,59	4,95	0,71	

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'Wie zich wel stut, valt zelde'
'Those who do strut, rarely collapse'
(family Maris)

"I'm almost done …", how many times I have not said that! Perhaps I started to soon mentioning this loudly to others, allowing them being confused. For me this fueled my stubbornness to keep me going during the last seven years when time unexpectedly changed from an outrageous haze speed down to a lingering tortoise pace. With such a tail and "doing the PhD" even part-time, time summed up to about 15 years that I have lived this thesis. But how I have loved every second of it! For an image-thinker, I was lucky to work with satellite imagery. Being either in the field or behind the computer, the overwhelming colorful exposure of Mother Nature has continuously inspired me. For an explorer, I was lucky that the subject itself, spatial heterogeneity, was a true challenge for frontier research. For a traveler, I was lucky that Mother Nature set me amongst so many colorful, charming and creative people who liked to share their opinions, criticism and views. In a way of singing a song, I gratefully acknowledge everyone who contributed to the creation of this research work:

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for valuable comments on research results *Monica,*
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Thank you all, **Marion**

ABOUT THE AUTHOR

Marion - Martina Hendrika - Obbink was born on December 2, 1962 on her parents' farm in Aalten, Achterhoek region, the Netherlands. After she completed the Atheneum-B secondary school (former Christelijke Scholengemeenschap Aalten) in 1981, she spent one year studying Landscape Architecture at the Wageningen Agricultural University in Wageningen, The Netherlands. In 1982, she switched to (tropical) Forestry at the same University. For hands-on tropical experience, she joined in 1986 for one year the Gadjah Mada University, Yogyakarta, Indonesia, as an Assistant Researcher in the Forestry and Nature Conservation project (FONC). During a running-race in a tropical cross-country setting, she got infected with the satellite remote sensing 'virus' when a Frenchman was watching the sky for the first SPOT image sensor that was swapping over her study area. A joint cooperation was born on the development of trees on uplands in Central Java. At the Wageningen University, she also was Member of Commission for Propaedeutic Aspects, Chairman of the Forestry Students Society, Member of Court for Examination, and Assistant Lecturer for international MSc students at the Department of Forest Management and at the Department of Land Surveying and Remote Sensing. In 1988, she graduated 'cum laude' (MSc degree) majoring in Tropical Forest Management and Remote Sensing. For six months she became a Technical Management Officer at the Department of Urban Ecology and Agriculture of the Municipality Eindhoven, the Netherlands. An assignment with the Food and Agriculture Organization (FAO) of the United Nations brought her back to Indonesia where she worked for over three and a half years as an Associated Professional Officer for Forestry and Remote Sensing Application in the National Forestry Inventory (NFI) Project of the Government of Indonesia covering topics as forest cover mapping, interpretation quality and accuracy assessment for which she performed field surveys (air and ground) in Sumatra, Kalimantan, Sulawesi, Moluccas and Papua. She also participated as a Forester & Remote Sensing Specialist in the Forest Resources Assessment (FRA) 1990 Project, a global initiative of the FAO, Rome. She got involved in other inventory projects of Nepal, Australia and

New Zealand. In 1994, she accompanied her partner back to the Netherlands, gave birth to her first daughter, and became a consultant on plantation inventory for Eelerwoude Ingenieursbureau, Rijssen, the Netherlands, as part of a two years counselling work for the Teakwood Advisory Board of Flor y Fauna S.A., Costa Rica. After given birth to her second daughter in 1996, she became a Guest Researcher at the Laboratory of Geo-information Science and Remote Sensing of Wageningen University and participated in the "Onbezoldigd Promoveren voor Vrouwen" Programme. In 1999, after given birth to her third daughter, she started with her dissertation-based PhD research funded by the Netherlands Organisation for Scientific Research (NWO) and by the Netherlands Institute for Space Research (SRON) for four and a half years on a part-time basis with project title "Accuracy aspects of monitoring systems in tropical rainforest areas". She was detached at the above mentioned Laboratory in collaboration with the Faculty of (former International Institute for) Geo-Information Science and Earth Observation (ITC), University of Twente, Enschede, The Netherlands. Additional field research for the PhD thesis was performed in Indonesia in 2003 and in the Okavango Delta, Botswana, in 2004. In all her assignments she has put great emphasis on the operational use of remote sensing, digital image processing, accuracy assessment and field surveys for forestry applications. However, from September 2004 onwards, an eye disease intensely changed her life and scientific career by destroying her central vision and distorting her vision to read. In 2008 she had to leave the Laboratory. Instead of November 2005, it became November 2010 when she finalized writing this PhD dissertation that also marks the end of her workable life in science. Currently, she has become active in the Parent Council of Pantarijn Scholengemeenschap Wageningen with specific interest in high school students with reading and learning problems like dyslexia. Another field of interest is including an assertive training in the curriculum of primary school children.

PE&RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 EC (= 22 weeks of activities)

Review of literature (6 EC)
- Accuracy aspects of monitoring systems in tropical rainforest areas

Writing of Project proposal (6 EC)
- Accuracy aspects of monitoring systems in tropical rainforest areas

Post-graduate courses (4 EC)
- Spatial Statistics for Remote Sensing (ITC, 1996)
- Modelling Techniques & Systems Engineering (PE&RC, 1998)
- Landscape Analysis of Pattern and Process (Winand Staring Centre, 1999)

Laboratory training and working visits (4.5 EC)
- Monitoring issues in national forestry inventory programmes (Centre for Forestry Inventory and Mapping (BAPLAN), Ministry of Forestry, Bogor/Jakarta, Indonesia, 2003)
- Methodology verification for accuracy assessment of the land cover mosaics approach (Okavango Research Institute, Maun, Botswana, 2004)

Invited review of (unpublished) journal (1 EC)
- Remote Sensing of Environment: Monitoring of forage conditions with MODIS imagery in the Xilingol steppe, Inner Mongolia (2003)

Deficiency, refresh, brush-up courses (3 EC)
- ILWIS for Windows 2.1 (ITC, Enschede, 1998)
- HTML (PUDOC-DLO, Wageningen, 2000)
- Working with End-note (Wageningen University Library, 2004)

Competence strengthening / skills courses (4,5 EC)
- Scientific writing (CENTA, Wageningen, 2001)
- Techniques for writing and presenting a scientific paper (MGS, Wageningen, 2001)
- Presenting in English (CENTA, Wageningen, 2003)
- Competence Assessment (VSNU, 2003)
- PhD Career Perspective (Stichting Inzet, 2003)
- Scientific publishing: An introductory workshop for PhD's and young authors (WGS, 2005)

PE&RC Annual meetings, seminars and the PE&RC weekend (2.5 EC)
- Masterclass Besag (Wageningen, 2002)
- From land cover to Land Cover Mosaics (CGI, Wageningen, 2005)

Discussion groups / local seminars / other scientific meetings (4.5 EC)
- Remote Sensing for Tropical Forest Resources and Sustainable Land-use: 10 years TELSAT (OSTC, Brussel, 1998)
- Operational Remote Sensing for Sustainable Development (EARSEL & NSEOG, Enschede, 1998)
- Geoinformation for All (NSEOG, Wageningen, 1999)
- Slot Symposium 'Ruimte voor aardse informatie 1986-2000: 15 jaar Nationaal Remote Sensing Programma (BCRS, Scheveningen, 2000)
- 1st International eCognition User Meeting (Munchen, 2001)
- Remote Sensing for Agricultural and Environmental Applications (WRSLN, Wageningen, 2002)
- Spatially explicit modelling of landscape change at the humid forest margin in Cameroon (Wageningen University, 2003)
- De ketenbenadering in Aardobservatie; een overzicht van 35 jaar Aardobservatie in Nederland (GIN & Wageningen University, 2004)

International symposia, workshops and conferences (8 EC)
- XIXth Congress of the International Society for Photogrammetry and Remote Sensing (ISPRS) 'Geoinformation for All' (Amsterdam, 2000)
- ForestSAT Symposium 'Operational Tools in Forestry using Remote Sensing Techniques' (Edingburgh, 2002)
- The Open Science Meeting 'Back to the Future', Scientific Co-operation between Indonesia and The Netherlands (Jakarta, 2003)

Supervision of 3 MSc students (3 EC)
- The application of object-based methods for modelling land cover mosaics in tropical forest areas using Landsat TM data (2002)
- Assessing sensitivity of two post classification parameters for a Land Cover Mosaic method (2003)
- Detecting wildlife habitats of large herbivore species at supra-pixel level in the Okavango Delta, Botswana (2005)

Key words: Functional generalization, spatial heterogeneity, pattern heterogeneity, decision-making, spatial object modeling, remote sensing, digital image analysis, multi-scale segmentation, wavelets, land cover mosaic classification, patch-mosaic classification, spatial aggregation classes, tropical rainforest, peatswamp forest, Indonesia

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