PROPOSITIONS

1. In order to improve the reliability of environmental assessments with GIS and remote sensing, one should take into account the multiscale nature of observational data.
   (This thesis)

2. Long time series of high spatial resolution images should be used in order to achieve an increased mapping accuracy for the remnants of semideciduous Atlantic forest.
   (This thesis)

3. Propositions should be short, controversial, and significant suggestions that advocate changes rather than conclusive statements of facts and results.

4. Data sets shall be made available "free of charge" for non-profitable studies concerning social and environmental issues.

5. Social security should be rethought in order to stimulate motivation, tolerance and patience in the Dutch youth.

6. Environmental degradation must be considered as threatening to humankind as terrorism has been during the past three months.

Propositions belonging to the Doctoral Thesis entitled
"Mapping and monitoring forest remnants: a multiscale analysis of spatio-temporal data"
by Luis M. T. de Carvalho.

Wageningen, December 10, 2001.

MAPPING AND MONITORING FOREST REMNANTS

A multiscale analysis of spatio-temporal data

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MAPPING AND MONITORING FOREST REMNANTS

A multiscale analysis of spatio-temporal data

Luis Marcelo Tavares de Carvalho

Proefschrift
ter verkrijging van de graad van doctor
op gezag van de rector magnificus
van Wageningen Universiteit,
prof. dr. ir. L. Speelman
in het openbaar te verdedigen
op maandag 10 december 2001
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A multiscale analysis of spatio-temporal data

Luis Marcelo Tavares de Carvalho

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Dedicated to my beloved wife and kids
Simone, Alissa, Arielle and Jonas

In memory of my friend and great scientist
Dr. Ivo Pereira de Camargo (1962-2001)

CONTENTS

PREFACE

About one decade ago, world leaders met in Brazil and formalised the global concern on environmental protection. At that time, *forest ecosystems* received alarming references and a number of research initiatives on the subject were encouraged. A whole chapter of the global action plan devised in Rio de Janeiro for the 21st century (the Agenda 21) is devoted to forests and deforestation and almost every other chapter relates to the primordial role of forest ecosystems in maintaining a healthy environment for mankind. The 21st century has arrived, but deforestation is still taking place indiscriminately all over the world.

In Brasil, the strongly publicised destruction of forests took the wrong direction, giving emphases to charismatic areas in detriment of really endangered ecosystems. For example, a few scientific studies have dealt with the semideciduous variant of the Atlantic forest biome and little is known world-wide about its destruction. The semideciduous Atlantic forests of Brazil are in an advanced stage of fragmentation and are subject to eminent threats, which can generate even more unrecoverable losses.

The first large scale research project dealing with semideciduous Atlantic forest was initiated in 1998 by a cooperation among three outstanding institutes in Brazil: "*Empresa brasileira de pesquisas agropecuárias*" (EMBRAPA), "*Universidade Federal de Lavras*" (UFLA), and "*Universidade de Brasília*" (UNB). The project, entitled "*Estratégia para conservação e manejo da biodiversidade em fragmentos de florestas semidecíduas*", aims at defining a scientifically based strategy for the conservation and management of this ecosystem through the integration of knowledge derived from subprojects at the landscape, community, population, and molecular levels.

Effective tools to study forest ecosystems at the landscape level are evolving rapidly with important contributions from *remote sensing* and *geographic information* technologies. Remotely sensed images cover large areas on the ground revealing multispectral, multiresolution, and multitemporal information, and hence are regarded as the most economic and effective way of gathering environmental data from regional to global scales. They are important data sources for the development and validation of ecological models, management activities and decision making.

The aim of the present contribution was to explore new methodologies for geoinformation processing and to solve problems related to forest management and research. Moreover, considering the project mentioned before, I intended to add information to aid the definition of such strategy within the framework of the subproject that studies forest remnants at the landscape and regional levels. I hope that you will find this thesis an interesting reading matter and the concepts useful to improve our capabilities of monitoring and protecting what still remains of the world forests.

Luis Carvalho

Wageningen, October 2001.

CHAPTER ONE

Introduction

Recently, in July 2001, forests gained renewed interest at the world conference on global change in Bonn, Germany, mainly because of their role in important environmental matters such as carbon cycle, climate, and biodiversity. Even so, the definition of international goals and the creation of a common understanding, as achieved by the Vienna Convention[1], have been characterised by considerable disagreement (Vuuren and Bakkes 1997). At local scales, forests also influence soil and water dynamics affecting not only ecological relations, but also social decision (Eden 1998). One basic requirement to quantify and model environmental processes is the availability of *accurate maps* of forest cover. Data acquisition at appropriate spatial and temporal scales is the keystone to achieve the mapping accuracy needed for development and reliable use of the so-called environmental models.

In Brazil, ongoing initiatives have been producing valuable information on forest resources and especially concerning assessment and monitoring of deforestation the following are relevant references (INPE 1999, INPE 2000,

[1] The Vienna Convention and the Montreal Protocol on substances depleting the ozone layer defined an action program that is currently in implementation phase. This program has already demonstrated significant achievements concerning the production and consumption of CFCs.

SOS Mata Atlântica and INPE 1993, SOS Mata Atlântica *et al.* 1998, Souza and Barreto 2000, Alves *et al.* 1999). The Amazonian and the evergreen Atlantic forests have been the subject of regular research in many scientific fields (for exhaustive references see Goldsmith 1998, Brown and Brown 1992), whereas a few recent studies on community ecology deal with the *Semideciduous Atlantic Forest* (Oliveira-Filho and Ratter 1995, Oliveira-Filho *et al.* 1997, Carvalho *et al.* 2000, Carvalho and Oliveira-Filho 2000, Oliveira-Filho and Fontes 2000). Countries that still have natural forests left should look carefully at the sad experiences of others, which became aware too late that restoration is much more expensive than protection. The Netherlands for example, with its for long impoverished flora and fauna, has been one of the leaders on developing integrated ecological approaches for nature restoration, but they know that the long term success of these efforts is still not known.

The semideciduous Atlantic forest is eminently more threatened than the Amazonian, less studied than its evergreen counterpart, and even more degraded than both are. In fact, the Brazilian Amazon forest is almost intact. Since 1977 less than 5% of the area has changed to land cover types other than forest and more than 25% is already under conservation regimes (figure 1.1). On the other hand, because of its strongly fragmented state, the more fragile Atlantic rain forest systems would have lost about 50% of the species if we consider predictions based on island biogeographical theory (figure 1.1). Fortunately, up to now no scientific study has been able to indicate any of the threatened plants or animals as extinct. Indeed, many species considered extinct 20 years ago have recently been rediscovered (Brown 1991). It is true that rare species, which have never been described, are probably already gone and the current fragmentation of this biome is causing the elimination of local populations and erosion of genetic diversity.

This thesis was motivated by problems that usually start with practical questions:

- *What is the spatial pattern of semideciduous Atlantic forest remnants?*
- *How can one quantify this pattern?*
- *How can one quantify changes in the pattern?*

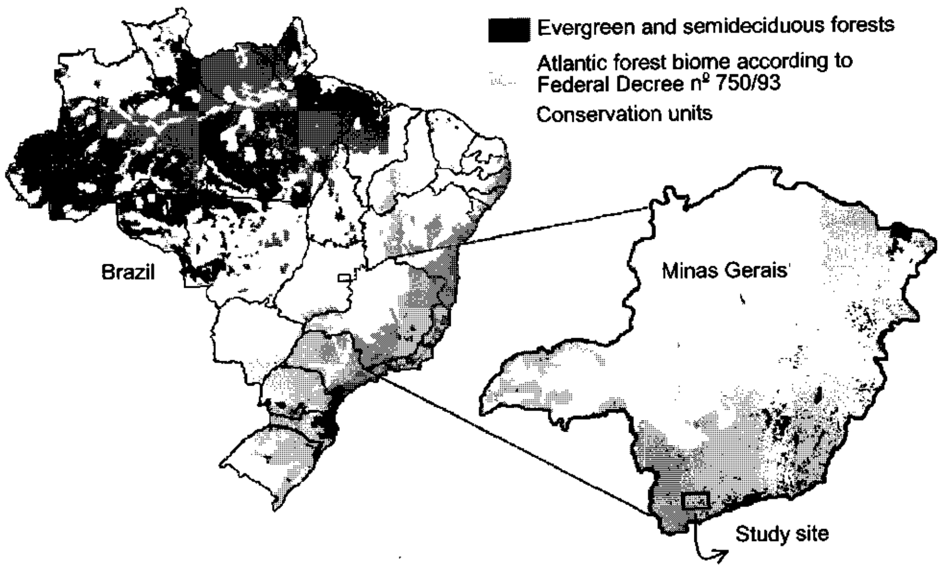

Figure 1.1 Approximate cover of forest formations in Brazil and Minas Gerais, conservation units in the Amazon region, and location of study site. Modified from INPE (2000), SOS Mata Atlântica (1998) and IBAMA (2000).

1.1 Problem definition

Advances in computer science have aided the proper extraction of relevant information from remotely sensed images as well as the effective use of geographical information systems (hereafter termed GIS) to store, analyse and present all sorts of georeferenced information. GIS allow the integration of different land attributes, including remotely sensed images, and offer new opportunities to develop and extend ecological models (Burrough and McDonnell 1998).

However, advances in remote sensing, GIS and computational resources inevitably pose additional challenges. The current and upcoming production of high resolution (spectral, spatial) data sets plus the ever increasing time series that have been collected since the Seventies must be effectively explored. Although remote sensing time series of images are promising to detect and analyse changes at the Earth's surface, many logistic and practical problems hamper the use of remote sensing for that purpose. These problems include geometric matching, calibration issues, cloud coverage, and finding effective change detection algorithms for specific purposes. This study aims to contribute to the improvement of land cover change detection and to provide practical examples.

The integration and proper analysis of high-dimensional data sets are steps of utmost importance for environmental research. New conceptual models in environmental sciences, like the perception of multiple scales, require the development of effective implementation techniques. In GIS, large databases are being generated with contributions from all over the world in various data types, structures, measurement scales, spatial scales and for different purposes, which demand more flexible analysis tools. Improvements in computational capabilities open plenty of research opportunities to tackle these challenges, where the theoretical formulation of recent approaches like artificial intelligence and multiscale transforms have been developed together with the application fields.

The study presented here is concerned, in general terms, with the investigation of adequate methods to deal with these new geoinformation analysis challenges and, more specifically, with the provision of knowledge and tools for forest related research using remote sensing and GIS.

1.2 Research questions and objectives

In order to answer the practical questions posed in the beginning of this chapter, one needs to know whether the available techniques of measurement and data analysis have the necessary capabilities. Thus, the following technical questions have to be addressed:

1) *What are the preprocessing requirements to the application of remotely sensed time series in environmental modelling? How appropriate are the existing preprocessing techniques? How appropriate are the temporal analysis tools for change detection and quantification?*

2) *What kinds of landscape features derived with remote sensing are relevant to map semideciduous Atlantic forests? Can temporal information improve traditional multispectral classification? How appropriate are the classification tools?*

3) *To what extent can geoinformation processing be automated?*

4) *Can artificial intelligence and multiscale methods improve over traditional techniques?*

Analysis of research questions

In the following paragraphs, questions will be translated into statements of what has been stressed by the scientific community (axioms) and of what will be explored in this thesis (postulates).

On time series analysis:

Axiom 1a) Cloud cover limits time series analysis with data derived from optical remote sensors (Addink and Stein 1999, Addink 2001, Wang *et al.* 1999, Guo and Moore 1993, Roerink *et al.* 2000).

Axiom 1b) Temporal analysis of remotely sensed images is sensitive to geometric registration (Dai and Knorram 1998, Townshend *et al.* 1992, Singh 1989, Gong *et al.* 1992, Stow 1999, Igbokwe 1999, Bruzzone and Prieto 2000). In order to reach subpixel accuracy, lots of ground control points must be defined in a time consuming and difficult task for most cases.

Axiom 1c) Temporal analysis is also sensitive to radiometric noise (Johnson and Kasischke 1998, Singh 1989, Schott *et al.* 1988, Hall *et al.* 1991, Elvidge *et al.* 1995). Differences in atmospheric transparency, sensor characteristics and vegetation phenology may yield misleading results.

On mapping forests:

Axiom 2a) The spectral information provided by single date remotely sensed images is often not enough to distinguish among objects with similar reflectance behaviour (Strahler 1980, Janssen and Middelkoop 1992, Hill and Foody 1994, Ma and Olson 1989, Skidmore 1988). Spectral overlap occurs mainly with coffee and exotic tree crops in the case of natural forests in general (Sayer and Whitmore 1990), and particularly, in the case of semideciduous Atlantic forests (Varona 2000, Raga 2001). Spectral confusion poses theoretical and practical challenges to the operational use of satellite remote sensing for forest mapping at regional scales (Townshend *et al.* 1997).

Axiom 2b) Classification of agricultural crops has been successfully improved with the addition of temporal data of production cycles (Clevers *et al.* 1990, Ortiz *et al.* 1997, Vieira *et al.* 2000).

Axiom 2c) In traditional probabilistic classification, a number of statistical assumptions about the data, that are not always true, must be defined (Atkinson and Tatnall 1997, Friedl and Brodley 1997). These discrepancies between analysis tools and available data might lead to poor performance and hence suboptimal results.

On automation:

Axiom 3) Large scale mapping projects demand a large degree of automation to be realised. Limitations in the available tools have prevented the operational use of remote sensing for large areas mapping (Townshend *et al.* 1997).

On alternative techniques:

Axiom 4) *Data sets derived from multiple sources are increasingly available for environmental modelling. The development of analysis tools able to handle such a data set in one framework has been recognised (Townshend et al. 1997).*

List of postulates:

Postulate 1) Temporal profiles should be modelled with nonlinear regression techniques for a more effective minimisation of cloud contamination and distortions caused by misregistration.

Postulate 2) Long time series can be used to improve the separation of spectrally similar objects on the Earth's surface. It can be particularly useful to distinguish between natural and man-made land cover types.

Postulate 3) Geographical data carry information at multiple spatial and temporal scales. Automation could be more effective if this multiscale nature is taken into account during processing.

Postulate 4) Artificial intelligence techniques and multiscale methods can handle the increasing amount of available data more effectively than the traditional techniques.

Objectives

A proper balance between practical issues and technical methods is required to investigate the usefulness of Earth observation techniques and GIS for forest mapping and monitoring. Two practical objectives are listed below, where the emphases are on solutions to problems that forest managers have to deal with:

(1) to define a mapping strategy for semideciduous Atlantic forest in the "*Vale do Alto Rio Grande*", and

(2) to develop a deforestation warning system to enable timely action to be taken.

Considering these practical objectives as a starting point, other specific objectives of a more technical nature arise. These are the problems that geoinformation scientists have to deal with:

(1) to investigate methods in order to separate spectrally similar land cover types by using other information sources and/or alternative image analysis methods,

(2) to develop a strategy to preprocess and extract information (e.g., change detection) from long time series of high spatial resolution data,

(3) to develop an automatic approach for detection and quantification of land cover changes using remotely sensed images.

1.3 Scope and organisation

Although focused on remote sensing image processing, this thesis is fundamentally concerned with new and advanced data analysis methods and most of the techniques described here can be used virtually in any application field. Specifically, applications of multiscale wavelet transforms to analyse and process remotely sensed images were explored, since these techniques proved to be superior to others for answering some of the research questions. The core chapters were developed and applied to aid the solution of problems related to mapping forests and deforestation through the use of advanced tools for geoinformation gathering, feature extraction and knowledge discovery. Multiscale methods for processing 'hyperdimensional' and noisy remotely sensed data are proposed and exemplified in case studies within the "*Vale do Alto Rio Grande*", southeastern Brazil.

The thesis is organised in eight chapters. Most of these individual chapters provide an extensive literature review on the subject and a comparison of existing techniques. A short overview of each chapter is elaborated in the following paragraphs and a schematic outline of the processing steps carried out in this study is illustrated in figure 1.2.

Chapter 1 starts with a description of my reasons for embarking on this project followed by the definition of research questions and objectives. The chapter ends with an outline of the thesis contents.

Chapter 2 brings a detailed description of the study site and of the Atlantic forest domain in Brazil with emphasis on its seasonal variant: *The Semideciduous Atlantic Forest*.

Chapter 3 presents the theoretical background on geographical information processing with the basic aspects of remote sensing, multiscale analysis, and machine learning techniques.

Chapter 4 presents a new method to denoise remotely sensed time series. In particular, to remove outliers due to the presence of clouds and associated shadows.

Chapter 5 explores the use of a declouded time series of NDVI (Normalised Difference Vegetation Index) data, terrain elevation, slope and aspect, and spectral data to improve discrimination of forested areas. Additionally, classifiers based on artificial intelligence are compared to the traditional maximum likelihood classifier.

Chapter 6 introduces a new approach to improve the results of digital change detection by discriminating changed sites according to size classes. The technique facilitates a rapid assessment of deforested areas to warn authorities and to enable a rapid response.

Chapter 7 describes a compound procedure for automated GIS updating based on the approach developed in chapter 6, on image segmentation, and on subsequent classification.

Chapter 8 evaluates the main outcomes of each chapter and of the thesis as a whole. It brings answers to the research questions as well as recommendations for future research and operational applications.

Main objectives: (1) Definition of a mapping strategy for semideciduous Atlantic forest in the "*Vale do Alto Rio Grande*" region.
(2) Development of a deforestation warning system.

Data preparation: preprocessing time series to eliminate corrupted observations, to facilitate further analysis, and to enable extraction of meaningful information.

[Chapter four]

Supervised classification: exploratory experiment on mapping forested areas using different sets of attributes and a number of algorithms for pattern recognition.

[Chapter five]

Multiscale change analysis: methodology development to improve digital change detection using remotely sensed images.

[Chapter six]

Automation of change detection: system development for GIS updating based on feature extraction with *multiscale change analysis*, segmentation with a region growing algorithm, and *supervised classification* of remotely sensed images that have undergone *data preparation*.

[Chapter seven]

Figure 1.2 Schematic outline of the main processing steps carried out in this thesis to achieve the given objectives.

CHAPTER TWO

An Area of Semideciduous Atlantic Forest

There are two different definitions of Atlantic forest currently in use. The more traditional one, the Atlantic forest *sensu strictu*, is defined by the areas of dense and open evergreen forests (Veloso *et al.* 1991) that occur along the Brazilian coast and extending 300 Km inland. The other definition (*sensu lato*), more complete and increasingly used nowadays, adds the seasonal semideciduous and the mixed umbrophilus (Araucaria forests) forests. Therefore, the Atlantic forest *sensu lato* is divided in approximately 45% of semideciduous forest, 18% of mixed forest, and 37% of evergreen forest.

The semideciduous forest included in the *sensu lato* definition occurs between the evergreen Atlantic forest and the "*Cerrado*" (Brazilian savanna) domains. Up to now it has been called dry semideciduous forest (Rizzini 1979), subtropical forest (Hueck 1972), seasonal tropical forest (Andrade-Lima 1966), and tropical caducifolious forest (Veloso 1982) but no scientific consensus has been reached concerning a proper label. Recently, a meticulous study on floristic similarities among savanna woodlands, Amazonian, and Atlantic forests has shown that the semideciduous forest of southeastern Brazil is in fact a subdomain of the Atlantic forest (Oliveira-Filho and Fontes 2000). Hence, it will be called *semideciduous Atlantic forest* throughout this thesis. Another good reason to call it this way is that if included in the Atlantic forest domain it will inherit world-wide charisma and the legal instruments of protection that the Atlantic forest already possesses.

2.1 Historical aspects

It is supposed that the Brazilian Atlantic forests have once covered about one million square kilometres (Mori *et al.* 1981), corresponding to almost 12% of the country's area. Unfortunately, only approximations can be obtained because deforestation started just after colonisation and in the nineteenth century most of the forest was already cut down. Rizzini (1979) suggests that its northern limit was located at about 5° S in the state of Rio Grande do Norte. Its southern limit is probably the current one, at about 30° S along the river Taquari in the north of the state of Rio Grande do Sul (Por 1992). Nowadays, estimated figures indicate that it has been reduced to less than 5% of the original cover and has become one of the most important examples of the radical destruction of tropical forests reported in any book concerned with the subject (e.g., Whitmore 1990, Terborgh 1992, Whitmore and Sayer 1992).

The area chosen to study the semideciduous Atlantic forest is located in the "*Vale do Alto Rio Grande*" region in the south of Minas Gerais, southeastern Brazil. The occupation of this region was characterised by four economic cycles (SEBRAE 1998), viz. gold mining, ranching and agriculture, coffee, and industrialisation. Gold mining in the eighteenth century was the first important activity in the region. Mining was soon abandoned giving room to ranching and agriculture. In the nineteenth century, the region was the main furnisher of cattle and working animals to the market of Rio de Janeiro, which was by that time the capital of Brazil (Filetto 2000). The main agricultural crops included cotton, tobacco and sugar cane. Later in this century, the culture of coffee was introduced and increased very fast to become one of the main causes of deforestation in the region (Oliveir-Filho *et al.* 1994). Nowadays, besides the increasing industrialisation, coffee and milk production form the main economical activities in the region.

This complex land use pattern has major consequences for interpretation and automatic analysis of remotely sensed images. Problems related to spectral overlap, spatial variability, mixed observations (i.e., various land cover types represented with a single value), and the multiscale nature of the sensed scenes are increased considerably. In addition, forest distribution patterns are strongly related to human occupation as mentioned before.

2.2 Physiographic characteristics

The following items provide a description of the area chosen to study the semideciduous Atlantic forest (figures 1.1 and 2.1).

Location

The study area shown in figure 1.1 is delimited by the coordinates 21° 04'49" - 21° 47'05" S and 44° 01'31" - 45° 03'52" W (figure 2.1). This area was chosen because it is one of the study areas of the large scale project mentioned in chapter 1 and is very representative of the fragmented landscapes that occur in the semideciduous forest domain.

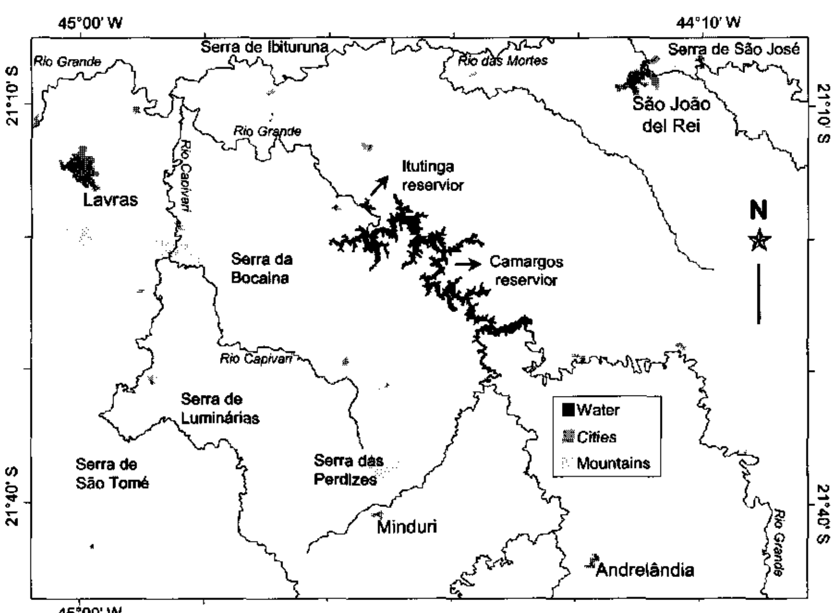

Figure 2.1 Water resources, urbanisation, and principal mountain chains of the study area.

Geology and lithology

Arquean, Proterozoic, and Tertiary-Quaternary Litho-Stratigraphical geological units occur in the region (Lacerda 1999). Arquean units are composed of calcic alcaline potassic granulites, granitic granodioritic gneisses, mafic and ultramafic rocks, anfibolits and metabasalts of the greenstone-belt of Lavras and of the greenstone-belt of the Rio das Mortes. Proterozoic units are composed of a series of granitic granodioritic plutons and metasedimentary formations of the Serra de Bom Sucesso. Tertiary-Quaternary units are represented by alluvial covers (Lacerda 1999). Geology and lithology are perhaps the primary factors that will determine other physiographic aspects such as geomorphology, drainage network and distribution of soil types. All these factors have some impact on forest distribution and consequently on remote sensing observations as described in the items below.

Geomorphology

The "*Vale do Alto Rio Grande*" is characterised by gentle hills, with altitudes ranging, in most of the region, between 700 and 1000 m. However, altitudes between 1100 and 1400 m occur on the steeper ridges of the mountain chains shown in figure 2.1 (Oliveira-Filho *et al.* 1994). Additionally, flat areas are represented mainly by flood plains at the rivers' margins and by a few localised plateaus. It is supposed that geomorphology has an influence in the distribution pattern of forests in the region, since they determine the land suitability for agricultural practices. Besides, mountainous relief in combination with the position of the sun by the time of image generation affects the reflectance of terrain objects by forming shadows in the scene.

Climate

The climate of the region is classified as Cwb and Cwa types of Köppen's system (Köppen 1931), i.e. temperate to subtropical temperate climate with wet summer and dry winter. Although lying in the tropics, its altitude explains the Cwa and Cwb climate types (Eidt 1968). Data collected by the Meteorological Station of Lavras (21° 13' 40'' S, 44° 22' 35'' W, 900 - 950 m altitude) provided the following average figures for the period 1960 - 1992: annual air temperature of 19.03 °C with monthly temperatures ranging from 16.03 °C (July) to 21.82 °C (February); annual rainfall of 1517.0 mm (93% occurring between October and April) with monthly rainfall ranging from 19.2 mm (July) to 293.3 mm (January). The deciduous nature of the forests in the region is certainly a reflex of this strong climatic seasonality described above, which in turn increases the variability of temporal remote sensing observations.

Hydrography

The main river in the study area is the "*Rio Grande*". After merging with the "*Rio Parnaíba*" in western Minas Gerais, the Rio Grande becomes the "*Rio Paraná*", which is the main watercourse of the second largest river system of South America. Other important watercourses crossing the study area are the "*Rio das Mortes*" and the "*Rio Capivari*", besides a number of small contributors. Additionally, two artificial water reservoirs, Camargos and Itutinga, were built in the region to generate hydroelectric energy (figure 2.1). Semideciduous Atlantic forests are strongly related to gallery forest formations (i.e., that protect watercourses). The consequences for remote sensing observations is that a dendritic spatial pattern is evident from the drainage network, characterising a high complexity of forest boundaries associated with gallery forests.

Soils

The main soil types of the region are Latosols, Cambisols, Lithosols, Podzolic soils, Hydromorphic soils, and Alluvial soils (Brazilian Classification System). Latosols occur predominantly where the slope gradient is lower than 12%, although Hidromorphic and Alluvial soils might occur at flooded plains where the slope gradient is lower then 3%. Podzolic soils occur where the slope gradient is higher than 12% and lower than 45%, although Cambisols and Lithosols might occur locally where the slope gradient is higher than 24% (Lacerda 1999).

Soils are probably the most important natural factor that drives the distribution of forests in the region. Semideciduous Atlantic forests are very interspersed with savanna formations as a function of changes in soil fertility (Ratter 1992).

2.3 Available data

The main remote sensing data used in this thesis came from the Landsat Earth observation satellite program. One image from the Landsat Multi-Spectral Scanner (MSS) acquired in July 1981 and 27 images from the Landsat Thematic

Mapper (TM) acquired from 1984 till 1999 (table 2.1) were available for this study. Landsat TM images were purchased with three spectral bands, viz. red (band 3), near infrared (band 4) and mid infrared (band 5), except for the image of August 1998, which had all six TM optical bands included. The main reasons to use only three TM spectral bands were: (1) less amount of data to be analysed and consequently less disk space needed for storage, (2) the selected bands represent more than 80% of the spectral information (i.e., the excluded bands are highly correlated with the selected ones), and (3) the costs per scene were considerably reduced. Auxiliary data comprised orthophotos (1:10.000) and digitised contour lines with 20 m of vertical resolution.

Table 2.1 Acquisition dates (day/month/year) of Landsat TM images used in this study.

12/10/84	04/06/89	05/06/95
09/06/85	22/07/89	31/01/96
15/10/85	26/10/89	07/06/96
16/11/85	25/07/90	28/07/97
14/07/86	23/04/91	01/11/97
03/11/86	14/09/91	16/08/98
17/07/87	30/07/92	29/04/99
13/03/88	01/07/93	19/08/99
03/07/88	05/08/94	23/11/99

CHAPTER THREE

Geographical Information Processing

Advanced tools for data gathering and analysis have been developed using techniques that resemble biological systems. Man-made devices measure physical quantities in an attempt to mimic sensing strategies found in nature. In fact, they have gone beyond biological sensors to *register signals* that range from molecules to outer space with ever-increasing capabilities for spatial, spectral, temporal and geometric resolutions. The way living beings perceive the environment to *extract features* of interest motivated the development of multiscale analysis tools, where the sensed signals are first evaluated as a whole and then searched for important structures in a range of 'size' classes. Finally, artificial intelligence approaches were developed based on the learning strategy of biological systems, which experiment with the features extracted from the environment and 'learn' or *recognise patterns* of events and relationships.

Some peculiarities of modelling the signals sensed by these remote 'eyes' in a land observation context will be described in section 3.1. The chapter continues with a detailed description of one particular approach to feature extraction, the multiresolution wavelet analysis, which is presented in section 3.2 and extensively used throughout the thesis. In section 3.3, methods used in further chapters for pattern recognition and knowledge generation from geographical data will be briefly introduced.

3.1 Sensing the Earth's surface

One of the most basic and important procedures in geographical information sciences is appropriate data acquisition. This task has been accomplished with field surveys and remote sensing techniques. Remotely sensed data are generated by measuring devices that record a physical quantity of interest, which has interacted with the Earth's surface. It could be compared to the retina of the human visual system, forming images to be further processed by the brain. The measured radiation gives an indirect link with environmental variables of interest (e.g., tree density) through the use of state variables (e.g., vegetation indices) that can be estimated directly with remote sensing (Curran *et al.* 1998). Hence, remote sensing techniques provide an acquisition oriented data model representing conceptual views or images of the world (Molenaar 1996), which are structured in some way and subject to a number of processing routines in an attempt to increase our understanding of the environment.

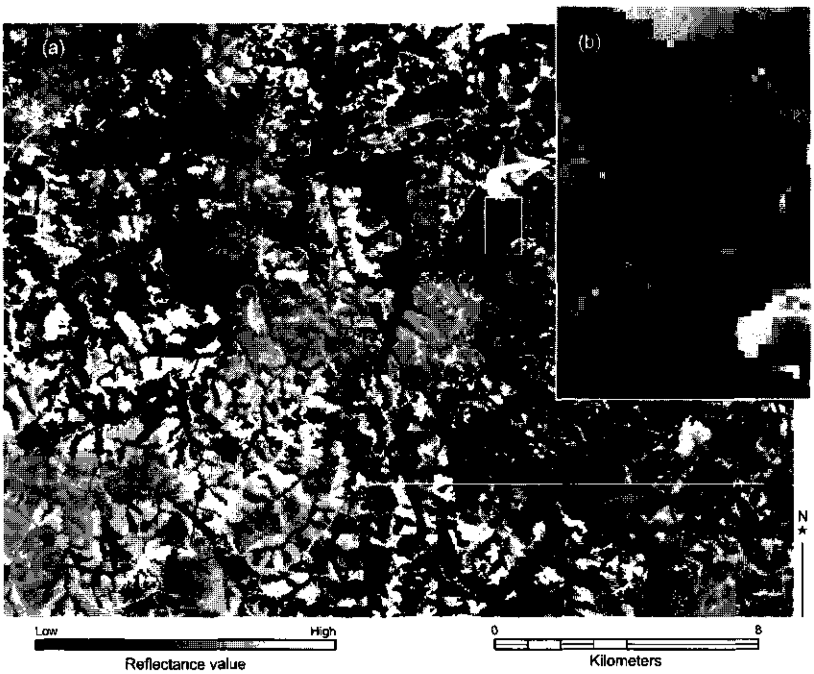

Figure 3.1 (a) Example of the discretization of a continuous field (i.e., the Earth's surface) illustrating the raster structure used to represent reflectance measurements. Each square in (b) has a unique value of reflectance. Image of the water reservoirs located within the study site.

A remotely sensed image represents a description of a region on the Earth's surface at one specific point in time. The radiation measurements are normally organised as a regular tessellation of cells, called pixels, each representing a mixed value of reflectance or emittance of an area on the ground (30 x 30m in the case of the image in figure 3.1). The set of adjacent pixels is then a discretization of a continuous field or surface of attribute values (e.g., reflectance), where the values are assumed to vary somewhat smoothly over a certain region (Burrough and McDonnell 1998). This statement describes a conceptual model of the real world known as the *continuous field* and a related data structure known as *raster* (Peuquet 1990), which are widely used in GIS. Because the raster is a collection of elements in a regular grid, it can be ordered in rows and columns, indexed accordingly and linked to a coordinate system. In this way, multivalued raster structures (Molenaar 1998) can be built to provide more complete characterisations using more than one attribute for each image pixel (figure 3.2), for instance, reflectance features sampled in various portions of the electromagnetic spectrum (multispectral images) or in different points in time (multitemporal images).

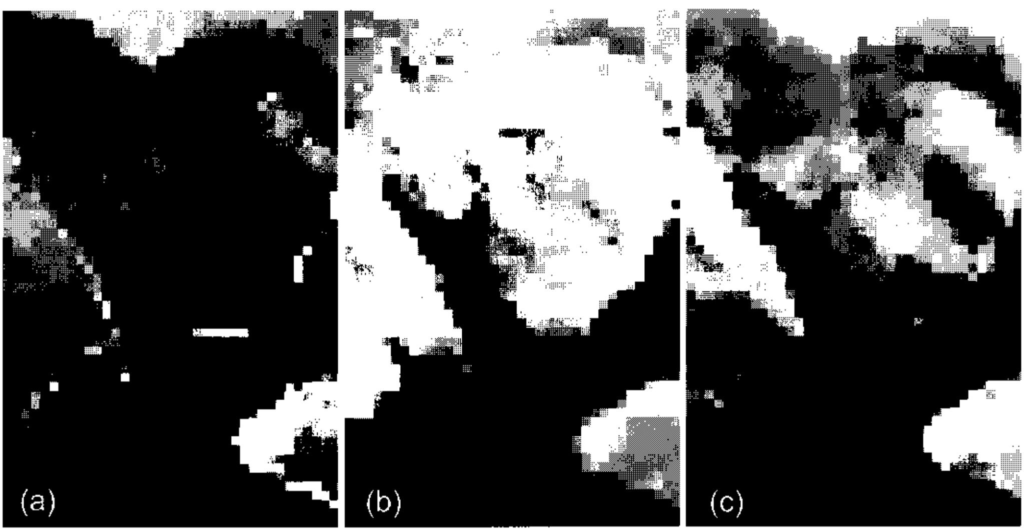

Figure 3.2 Example of a multivalued raster representing different reflectance characteristics of terrain objects along the electromagnetic spectrum. Landsat TM (a) band 3, (b) band 4, and (c) band 5.

The size of the sides of an image pixel defines the resolution of the raster. In principle, the smaller the pixel, the better the objects can be resolved in detail. The final geometric resolution of a raster is then a compromise between the required spatial detail and the amount of data to be acquired and processed. For a complete specification of a given scene, the pixel size should be less than half of the size of the smallest detail to be evaluated (i.e., Nyquist rate) (Molenaar 1998). However, an excessive increase in variability within 'homogeneous' terrain objects (e.g., a forest patch) may happen if very small pixels are used (Townshend 1981).

3.2 Perceiving the environment

In the last decades, much attention has been paid to the multiresolution characteristic of processes and patterns in general. Good examples are remotely sensed images, which provide different information and noise at various spatial scales. Analysts have become aware that image processing is considerably improved if the scenes are viewed at multiple resolutions because the information of interest might be characteristic of just a few scale levels. In this context, the capacity of perceiving scales might be the key for a better understanding of our landscapes and an aid to the automatic analysis of remotely sensed images. It is a common belief that biological visual systems first evaluate the overall scene (i.e., coarse information manifested at large scales) of reflected energy and then analyse edges and objects of interest (i.e., detailed information appearing at a range of scales).

A note on scale

The meaning of scale varies so much between and within disciplines that care should be taken to avoid terminological confusion. The ratio between a segment on a map and the corresponding segment on the Earth's surface is probably the oldest and the most popular notion of scale. Scale is also used to indicate the spatial extent of a study area. Comparing the two connotations above, a 'large scale map' provides more detailed and, consequently, voluminous information, which is usually limited to small geographical areas. On the other hand, a 'large scale study' covers a large geographical area and usually omits detailed information. Besides the two described concepts of *cartographic scale* (map scale) and *geographic scale* (extent or domain), other important notions of scale include the *resolution* (grain or sampling interval) and the *operational scale*. The term resolution is used to refer, for instance, to the size of the smallest observable object or to the pixel size, which defines, together with the geographic scale, the limitations to represent a given scene. Finally, the operational scale refers to the interval at which a phenomenon operates (Lam and Quattrochi 1992). In this thesis, the meaning of scale will always be clear from the context and used mostly in the sense of resolution or geographic scale, where small scales present detailed information and large scales represent coarse views of the scenes or signals.

These important aspects of scale are useful and obvious when we make observations as a function of space (i.e., position), but the same principles apply to the temporal, spectral or other dimensions of the world and are fundamental to their proper characterisation. Even so, the vast majority of techniques for geographical information processing have been driven by the 'fixed scale paradigm'. Regarding remote sensing and GIS, resolution-invariant methods have proliferated mainly because of simpler data structures and analysis (Csillag 1997). In this framework, the information contained in the multiple scales of the data cannot be analysed or used separately yielding results that also combine the influence of variables that might be characteristic of just a few scale levels. Environmental processes operate at multiple scales generating patterns that have a multiscale nature as well. Like the real world they portray, remotely sensed data 'show' different or complementary information at different scale levels. This fact has important implications for analyses, representations and interpretations of data and accuracy.

The almost infinite resolutions of our world in all of its dimensions have raised an increasing interest in scale issues, which are now recognised as fundamental to any research area. Nevertheless, only a few (under-development) tools exist, which are appropriate to derive and study the information contained in multiple scales of the data.

Introduction to a potential tool

We now come back to the device measuring a physical quantity of interest. In application fields ranging from chemometrics to astronomy, the device is a remote sensor and the physical quantity is the reflected electromagnetic energy, which is recorded in digital or analogue format usually as a function of space $f(x,y)$, e.g. a raster. Lets pick, as an example, one line of our digital image and plot it (figure 3.3) as a function of just one variable $f(t)$ to simplify presentation.

One common way to extract information from this function is to compare it with a set of test functions. Basically, a high coefficient results from this comparison where the function under evaluation is more similar to the test functions. Well-known sets of test functions are the dilations by a factor ω of a single periodic function e^{it} in Fourier transformations (Fourier 1822).

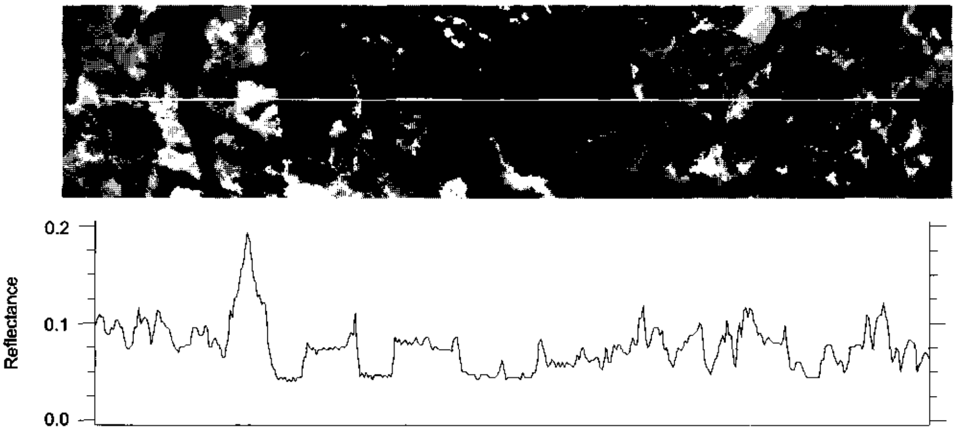

Figure 3.3 Plot of reflectance values referent to the white line of the image on top.

The Fourier transform accurately reflects in a_ω *which* frequencies occur in the input signal:

$$a_\omega = \langle f(t), e^{i\omega t} \rangle . \tag{3.1}$$

Where, i is the imaginary unit ($i^2 = -1$) and $\langle \ , \ \rangle$ stands for the inner (or scalar) product in the space L^2 of square integrable functions. If $h(t)$ and $g(t)$ are two functions in L^2, their inner product in the interval [a,b] is a measure of similarity between the two functions, which is defined by:

$$\langle h(t), g(t) \rangle = \int_a^b h(t) \cdot \overline{g(t)}\, dt . \tag{3.2}$$

Where " $\overline{}$ " stands for complex conjugate, such that the conjugate of $a + ib$ is $a - ib$, with i being the imaginary part of the complex number ib. For example, using the complex conjugate of $e^{i\omega t}$, the inner product of equation (3.1) becomes:

$$\langle f(t), e^{i\omega t} \rangle = \int_{-\infty}^{+\infty} f(t) \cdot e^{-i\omega t}\, dt$$

Besides the frequency localisation property mentioned above, practical applications require good time (or space) localisation as well. This requirement was partially achieved by the windowed Fourier transform (Gabor 1946), which uses pieces of periodic functions instead of infinite waves as test functions. However, sudden breaks between pieces might generate artefacts, especially in 2D signals. Moreover, a choice has to be made concerning the size of the analysing pieces, generating a compromise towards local or, otherwise, global characterisation. The new set of test functions $\psi_{jk}(t)$ in the wavelet transform goes a step further and tells us *when* (or *where*) each frequency component occurs more efficiently than the windowed Fourier transform. One of its aims is to provide an easily interpretable visual representation of signals. While Fourier coefficients in (1) have an index ω related to the frequency, the wavelet coefficients are characterised by a parameter j, referring to a scale of octaves (doubling the frequency when $\Delta j = 1$), and a positional parameter k:

$$a_{jk} = \langle f(t), \psi_{jk}(t) \rangle . \tag{3.3}$$

This comparison might operate in continuous time (on functions) or in discrete time (on vectors). The raster data structure presented before is strictly discrete and consequently, the wavelet transforms used here will also be discrete. Fortunately, multiresolution analysis and wavelet transforms have a strong connection with the discrete filters of signal processing, which will serve as the basis for the following presentation.

The remainder of this section provides a textual overview of wavelet transforms and multiresolution analysis with emphasis on aspects used in further chapters. For a complete mathematical characterisation of wavelets, which is not the purpose and not even achievable in one section, a whole thesis would be necessary. Extensive literature exists on the subject and a few recent references will be recommended here. Strang and Nguyen (1997) bring a comprehensive introduction to the theory of wavelets and filter banks, whereas Prasad and Iyengar (1997) provide a basic mathematical background and some practical applications to image processing. Daubechies (1992) and Mallat (1998) present in-depth developments, whereas Starck *et al.* (1998) present application oriented material with numerous examples in various fields, including geoinformation sciences.

Digital filters and filter banks

In signal processing, a digital filter is a time-invariant operator, which acts on an input vector (i.e., digital signal), producing a transformed vector by means of mathematical convolution. Let the operator be h = [1/2,1/2] acting on an input vector x, with N elements. Then, the n^{th} element of the transformed output vector y is computed from two consecutive elements of x:

$$y(n) = \sum_{l} h(l)x(n-l). \tag{3.4}$$

Where, $h(l)$ is the l^{th} element in the operator.

This is the so-called moving average, because the output averages the current element $x(n)$ with the previous one as the operator moves forward over x. The moving average smoothes out the bumps in the signal. It is also called lowpass filter because it reduces the high frequency components (i.e., the bumps) keeping only the low frequency components of the signal. Now, let the operator be g = [1/2, -1/2] acting on the same input vector x to produce another output vector. This operator computes "moving differences". It picks out the bumps or high frequencies in the signal and thus, is called highpass filter. Figure 3.4 illustrates the convolution of the example signal with a lowpass and a highpass filter.

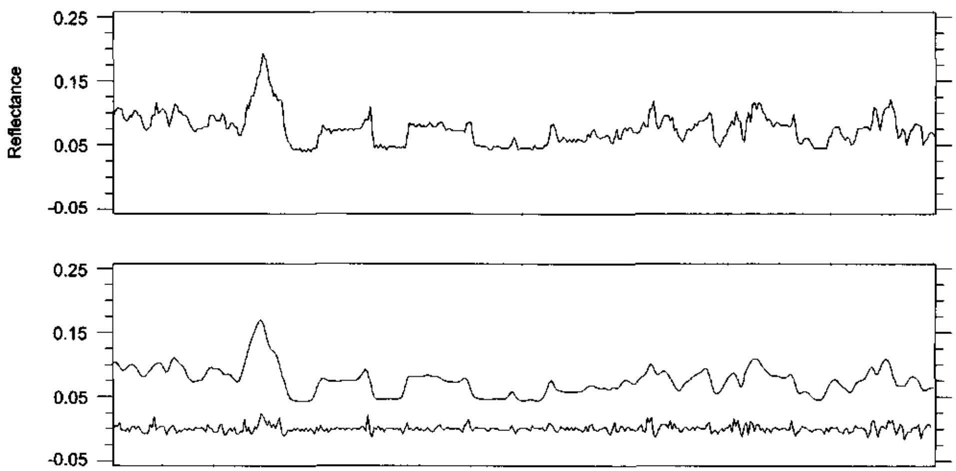

Figure 3.4 (a) Line-profile of figure 3.3 with (b) respective low frequency (top) and high frequency (bottom) components.

These kinds of filtering operations are well known in geoinformation sciences and for long have been used to smooth images and enhance objects' edges (Burrough and McDonnell 1998), but they can do a lot more. The lowpass and highpass filters alone lack the desirable property of invertibility because one cannot recover x from y. Together, they separate the input x into complementary frequency bands that can be combined to recover the original signal. This combination is termed filter bank or quadrature mirror filters (QMF) (Esteban and Galand 1977), which only recently have gained attention from the geoinformation community and turned out to be extremely useful. The advantages are that the subband signals can be efficiently filtered, compressed, enhanced, transmitted, and then reassembled if so desired. Figure 3.5 illustrates a complete two-channel filter bank with analysis (decomposition), sub-band manipulation (e.g., filtering), and synthesis (reconstruction).

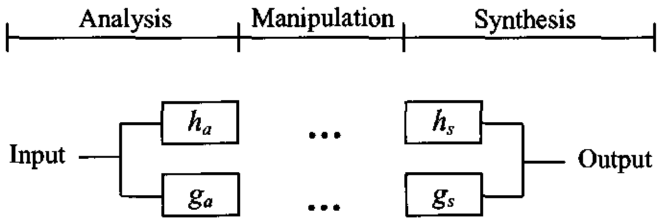

Figure 3.5 Schematic representation of a filter bank.

Perfect reconstruction (i.e., output = input) is achieved if no manipulation is carried out and if the synthesis bank (h_s and g_s) is the inverse of the analysis bank (h_a and g_a). In this sense, the filter banks might be orthogonal, biorthogonal (h orthogonal to g, h and g independently orthogonal), semiorthogonal (h and g independently orthogonal, but spaces associated with h and g are not individually orthogonal) or even nonorthogonal (Stark *et al.* 1998).

The novelty about wavelets and the key concept of "scale" come from a procedure of *recursive* implementation of the filter bank: signals are represented with variable resolutions when we apply the same transform (lowpass and highpass filtering) on the outputs of the analysis bank. If this process iterates, we move to coarser scales as far as desired, depending on the length of the input signal and on the objectives of the analysis. Usually, we consider only the outputs of the lowpass filter for iteration (figure 3.6), but other possibilities exist; the complete tree (lowpass and highpass are iterated) and the wavelet packets (lowpass and/or highpass are iterated).

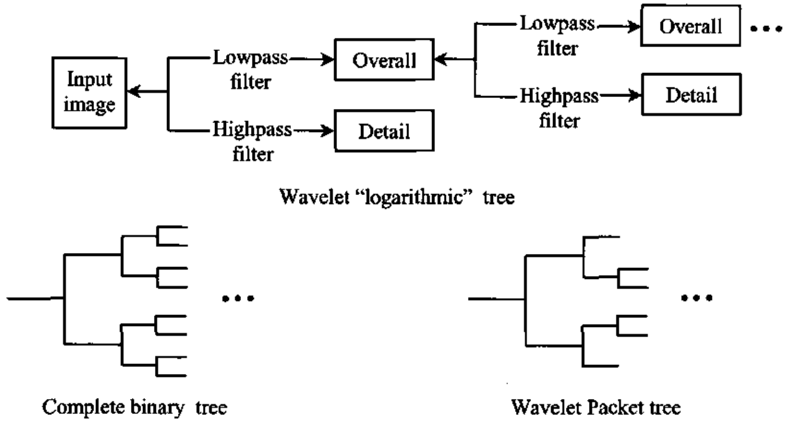

Figure 3.6 Schematic representation of three possible structures for recursive implementation of filter banks.

Wavelets and multiresolution

In continuous-time, there exist a scaling function $\phi(t)$, also known as the father wavelet, corresponding to the lowpass filter and a wavelet function $w(t)$, also known as the mother wavelet, corresponding to the highpass filter. They both involve the sets of filter coefficients $h(l)$ and $g(l)$ from discrete time. The scaling function is produced by the so-called dilation equation, whereas the wavelet function is produced by the wavelet equation:

Dilation equation: $$\phi(t) = 2\sum_l h(l)\phi(2t-l). \tag{3.5}$$

Wavelet equation: $$w(t) = 2\sum_l g(l)\phi(2t-l). \tag{3.6}$$

Considering the filter coefficients of our example (1/2, 1/2 and 1/2, -1/2), we have the dilation equation and the wavelet equation from h and g:

$$\phi(t) = \phi(2t) + \phi(2t-1) \text{ and } w(t) = \phi(2t) - \phi(2t-1).$$

In this case the dilation equation produces the box function and the wavelet equation produces the Haar function (figure 3.7).

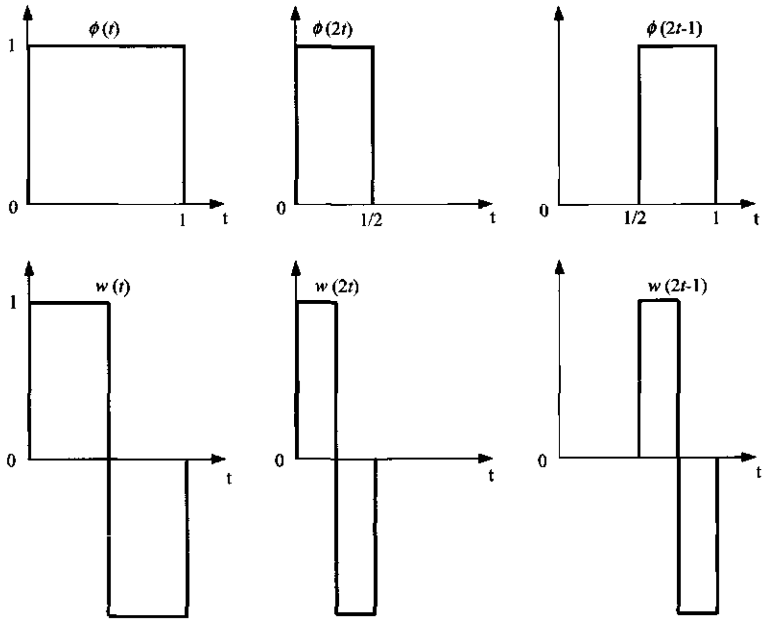

Figure 3.7 The box function (top) and the Haar wavelets (bottom).

Wavelet stands for 'small wave' (a pulse). In the case of the Haar wavelet (figure 3.7) it is a 'square' wave. It is one of the simplest wavelets and a standard example, which is used to demonstrate the principles in most textbooks because the idea is fundamental to all others. Alfred Haar introduced it almost 70 years before the concept of "*ondelette*" (wavelet) was born in France (Haar 1910). Again, the novelty concerns the recursive implementation and not the functions; wavelets might be piecewise constant functions, continuous piecewise linear functions, splines etc.

The simultaneous appearance of t and $2t$ in the dilation and wavelet equations characterises its multiscale nature. Meyer (1989) introduces multiresolution using a metaphor: *"From a subtle and complicated image, one may extract...a schematic version...being a sketchy approximation resembling the pictures one can find in cartoons."* Then, a set of better and better sketchy approximations of the original image resembles a multiresolution representation.

The goal in multiresolution analysis is the decomposition of the whole space of functions into subspaces V_j. Functions are projected at each step of the analysis onto finer subspaces such that each V_j is contained in the previous subspace V_{j-1}:

$$\ldots \subset V_4 \subset V_3 \subset V_2 \subset V_1 \subset V_0 \subset \ldots$$

The function $f(t)$ in the whole space has a projection in each subspace. These projections represent the information contained in $f(t)$ in an increasing fashion, such that $f_j(t)$ (i.e., the projection of $f(t)$ in V_j) approaches $f(t)$ for decreasing j. Besides the hierarchic and complete scale of (sub-)spaces other requirements are crucial to the notion of multiresolution. The dilation requirement states that if a function $\phi(t)$ is in V_j, then $\phi(2t)$ is in V_{j-1}. The translation requirement states that if $\phi(t)$ is in V_0, then so are all its translates $\phi(t - k)$. The final requirement states that the function $\phi(t)$ with translates $\phi(t - 1)$ must form a stable basis for V_0, i.e. a Riesz basis: a complete set of linearly independent testing functions, say $\phi_i(t)$, that represents in a unique way every function in V_0 as $\sum a_i\phi_i(t)$, with $\sum |a_i|^2$ being finite.

Then, considering dilations by j and translations by k, the basis is generated by $\phi_{jk}(t) = 2^{j/2}\phi(2^jt - k)$ and we have:

$$f_j(t) = \sum_k a_{jk}\phi_{jk}(t), \tag{3.7}$$

representing the projection of $f(t)$ in V_j.

The associated error space when moving from V_j to V_{j+1} is the wavelet space W_{j+1}. The wavelet space, which is seemingly generated by dilations and translations of a single function, contains the "difference in information" $\Delta f_{j+1}(t) = f_j(t) - f_{j+1}(t)$, which is the "detail" at level j+1. Each function in V_j is then the sum of two parts, $f_{j+1}(t)$ in V_{j+1} and $\Delta f_{j+1}(t)$ in W_{j+1}. Considering the subspaces they lie in, we have:

$$V_{j+1} + W_{j+1} = V_j\,. \tag{3.8}$$

Then,

$$V_2 + W_2 = V_1 \text{ and } V_1 + W_1 = V_0,$$

hence,

$$V_2 + W_2 + W_1 = V_0\,.$$

Seemingly, if $w_{jk}(t) = 2^{j/2}w(2^j t - k)$ is a stable basis for W_j and calling the set of associated coefficients by d_{jk} we have the complete information of $f(t)$:

$$f(t)=\sum_k a_{Jk}\phi_{Jk}(t)+\sum_{j=1}^{J}\sum_k d_{jk}w_{jk}(t). \tag{3.9}$$

Then, the coefficients a_{jk}, representing the projection $f_j(t)$ on V_j are obtained with the inner product $\langle f(t), \phi_{jk}(t)\rangle$, whereas the coefficients d_{jk}, representing the projections $\Delta f_j(t)$ on W_j are obtained with the inner product $\langle f(t), w_{jk}(t)\rangle$.

Concluding, wavelets come from the iteration of a filter bank (Daubechies 1989) and because of the repeated rescaling, they decompose a signal into details at different resolutions. If the signals under consideration are remotely sensed images, the scale parameter corresponds to the size of objects on the Earth surface, which are effectively modelled with this new multiresolution representation revealing patterns that are not so clear in "subtle and complicated" remotely sensed images.

Algorithms for implementation

Part of the success of the wavelet transform is due to the existence of fast algorithms. They rarely compute inner products with wavelet templates directly. Rather, implementation is normally achieved via simple discrete convolutions, where the filters and filter banks play a major role. Two basic and very popular algorithms will be presented now and applied in further chapters. Variations of these two as well as other algorithms exist. Some of them will be only cited here and the interested reader should refer to the following references. The previously mentioned "*Wavelet Packet*" is described in Coifman *et al.* (1992). Stark *et al.* (1999) proposed a fusion of the wavelet transform (WT) and the pyramidal median transform (PMT), called "*PMWT*", which combines the advantages of both methods in one algorithm. The "*Laplacian Pyramid*" by Burt and Adelson (1983) was one of the first schemes for multiresolution decomposition and afterwards related to the wavelet transform. Bijaoui *et al.* (1992) proposed a scheme similar to the Laplacian pyramid called "*Half Pyramidal Wavelet Transform*" in order to reduce some drawbacks of the former. Finally, the so-called "*Lifting Scheme*" (Sweldens 1996) is probably the most famous and innovative algorithm proposed recently for implementation of the wavelet transform.

Because of simplified notation, the following algorithms will be described considering that our input signal is a function of one variable $f(t)$. Extensions to $f(\mathbf{T})$, with $\mathbf{T} = (t_1,\ldots t_n)$, are straightforward.

The "algorithme à trous" (Holschneider *et al.* 1989):

Let $f(t) = a_0$, and l be symmetric around zero, i.e. $l = (\ldots,-1, 0, 1,\ldots)$.

Then, the projections onto V_j are:

$$a_{j,k} = \sum_l h(l)\, a_{j-1,k+2^{j-1}l}\text{, for all } j > 0,\ k. \tag{3.10}$$

Whereas, the projections onto W_j are:

$$d_{j,k} = a_{j-1,k} - a_{j,k}\text{, for all } j > 0,\ k. \tag{3.11}$$

The reconstruction formula is:

$$a_{0,k} = a_{J,k} + \sum_{j=1}^{J} d_{j,k}\text{, for all } k. \tag{3.12}$$

Schematically:

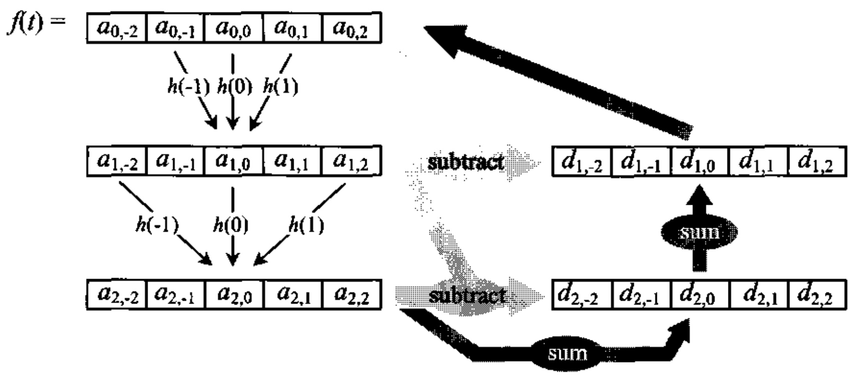

Figure 3.8 Schematic representation of the "à trous" algorithm with decomposition (⟶ and ⇨) and reconstruction (➡) paths.

As an example, let the operator be $h(-1) = 1/4$, $h(0) = 1/2$, $h(1) = 1/4$, then the 0^{th} element of a_1 is:

$$a_{1,0} = \frac{1}{4}a_{0,-1} + \frac{1}{2}a_{0,0} + \frac{1}{4}a_{0,1}.$$

Then, for the next resolution level, the 0^{th} element of a_2 is:

$$a_{2,0} = \frac{1}{4}a_{1,-2} + \frac{1}{2}a_{1,0} + \frac{1}{4}a_{1,2}.$$

The 0^{th} element of d_1 and d_2 are:

$$d_{1,0} = a_{0,0} - a_{1,0} \text{ and } d_{2,0} = a_{1,0} - a_{2,0}.$$

With reconstruction:

$$a_{0,0} = a_{2,0} + d_{2,0} + d_{1,0}.$$

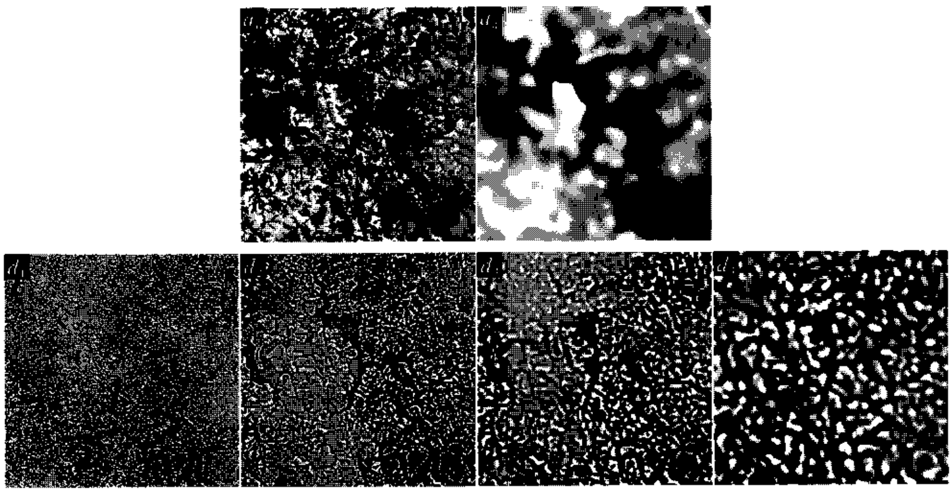

Figure 3.9 Example of a 2D decomposition using the "*à trous*" algorithm.

Remarks:

1) The operator forgets all signal samples but every $k + 2^{j-1}l$. This is achieved by inserting zeros between samples of the operator when moving from j to j+1. That is the reason why the algorithm bears its name, "*à trous*" means 'with holes'.

2) 2D signals (figure 3.9) require 2D operators: $\begin{pmatrix} 1/4 & 1/2 & 1/4 \end{pmatrix} \otimes \begin{pmatrix} 1/4 \\ 1/2 \\ 1/4 \end{pmatrix} = \begin{pmatrix} 1/16 & 1/8 & 1/16 \\ 1/8 & 1/4 & 1/8 \\ 1/16 & 1/8 & 1/16 \end{pmatrix}$.

3) Values at the boundaries of the signal are normally obtained by reflection, periodicity or continuity.

4) Operators must have an odd number of elements.

Stéphane Mallat's algorithm (Mallat 1989):

The projections onto V_j are given by:

$$a_{j,k} = \sum_l h(l - 2k)\, a_{j-1,l}, \text{ for all } j > 0,\ k. \tag{3.13}$$

Whereas, the projections onto W_j are given by:

$$d_{j,k} = \sum_l g(l-2k)\, d_{j-1,l}\text{, for all } j > 0,\ k. \tag{3.14}$$

The reconstruction formula is:

$$a_{j,k} = \sum_l \left[h(k-2l)\, a_{j+1,l} + g(k-2l)\, d_{j+1,l}\right]\text{, for all } j,\ k. \tag{3.15}$$

Schematically:

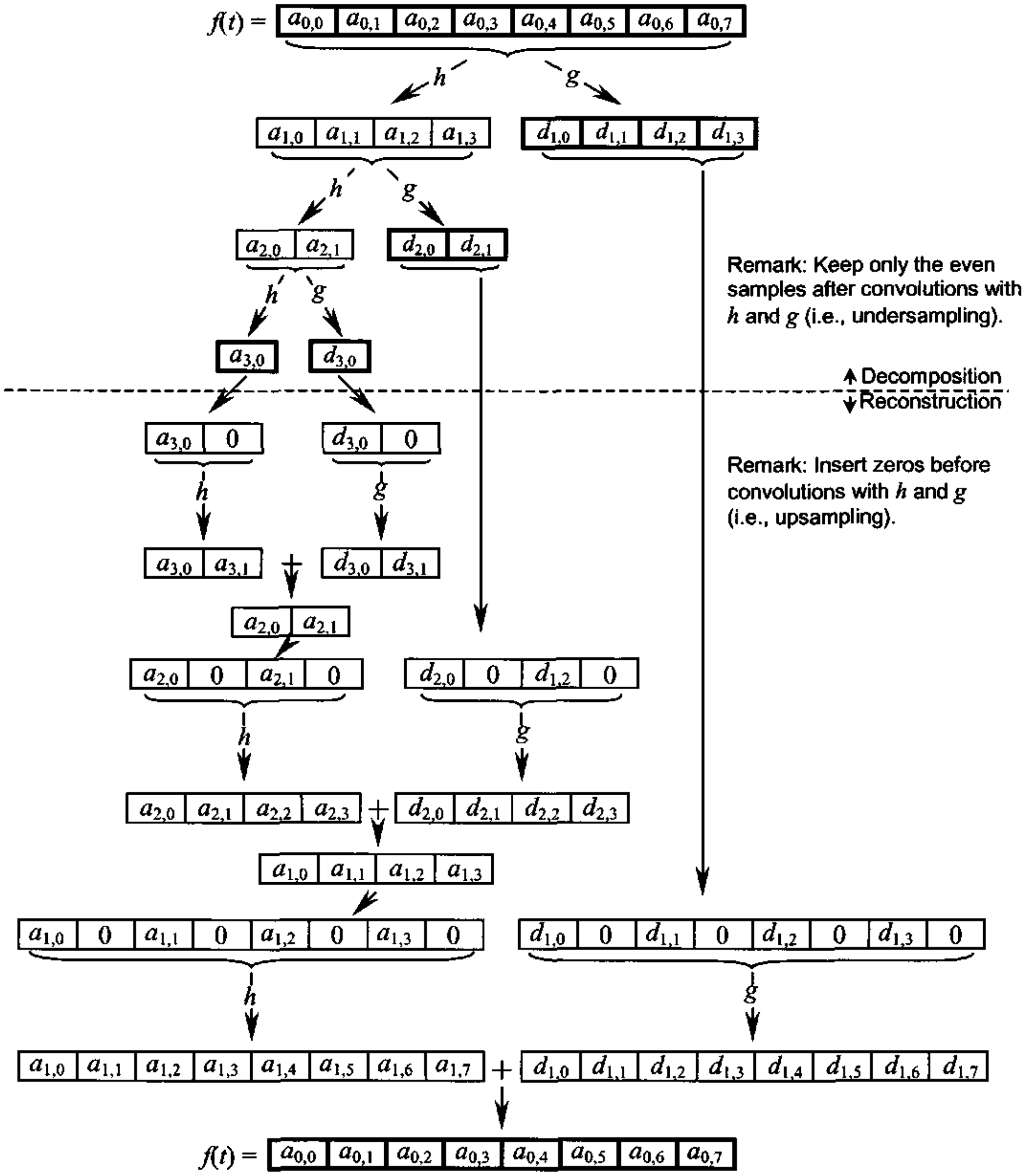

Figure 3.10 Schematic representation of Mallat's algorithm with decomposition and reconstruction stages.

As an example, let the operators be $h = (1/2, 1/2)$ and $g = (1/2, -1/2)$, then the 0[th] element of a_1 and d_1 are:

$$a_{1,0} = \frac{1}{2}a_{0,0} + \frac{1}{2}a_{0,1} \text{ and } d_{1,0} = \frac{1}{2}a_{0,0} - \frac{1}{2}a_{0,1}.$$

Then, after undersampling a_1 and d_1, the 0[th] element of a_2 and d_2 are:

$$a_{2,0} = \frac{1}{2}a_{1,0} + \frac{1}{2}a_{1,1} \text{ and } d_{2,0} = \frac{1}{2}a_{1,0} - \frac{1}{2}a_{1,1}.$$

With reconstruction (after upsampling):

$$a_{0,0} = \frac{1}{2}a_{1,0} + \frac{1}{2}d_{1,0}.$$

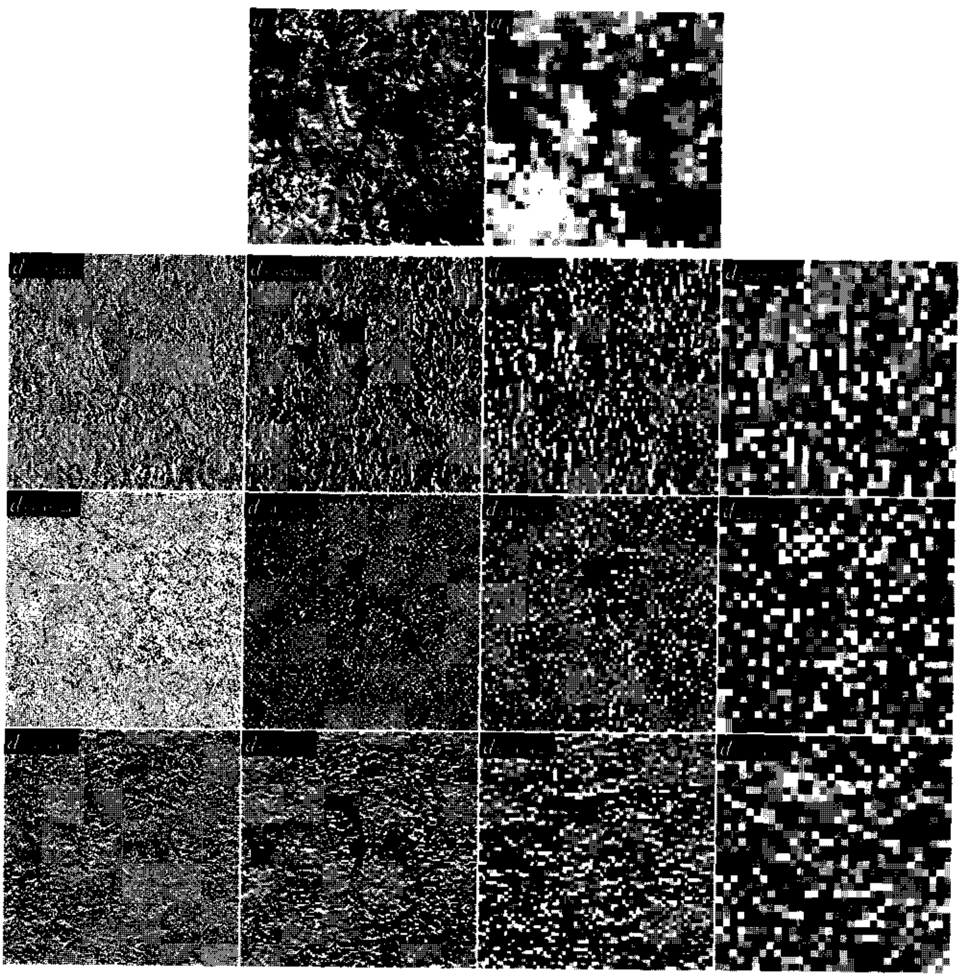

Figure 3.11 Example of a 2D decomposition using Mallat's directional analysis.

Remarks:

1) Mallat's algorithm requires the length of the input signal to be power of 2.

2) Extension to 2D signals is implemented by applying the same 1D scheme first to the rows and then to the columns of the 2D signal. In this way, Mallat's algorithm might generate three sets of detail coefficients at each scale *j*, depicting high frequencies according to their orientation in the raster, i.e. vertical, diagonal and horizontal (figure 3.11).

3) Values at the boundaries are also obtained by reflection, periodicity or continuity.

Other mutiresolution decompositions

Stark *et al.* (1998) developed a robust multiresolution decomposition based on the median transform. The median transform is nonlinear, and offers advantages for dealing with outliers in the data. Basically, the result from a convolution with a median filter is subtracted from the original signal and followed by iteration, which leads to multiresolution representations. Similarly, multiresolution decomposition based on mathematical morphology (Serra 1982) can be realised by taking the difference between the original image and its opening. In both alternative transforms, undersampling can be introduced (Stark *et al.* 1998), which leads to pyramidal structures like in Mallat's algorithm.

3.3 Knowledge generation

Machine learning techniques have been developed for some decades within the larger field of Artificial Intelligence. The objective of Artificial Intelligence is to understand the way human beings recognise patterns and to develop intelligent systems. Nowadays, machine learning techniques have been increasingly applied to develop computational learning (the 6th generation computing), solve decision-making problems (e.g., classifications), and discovery of knowledge (data mining) (Eijkel 1999). Neural nets and rule induction, two popular paradigms of the machine learning field, will be described in this section and used in further chapters. They have been applied recently to classification problems in geoinformation sciences showing promising results. The basic idea in classification of multidimensional data is to identify clusters in the multidimensional feature space and isolate them by using some decision boundaries. Machine learning techniques gained considerable attention for classification tasks because they provide partitions of feature spaces in an essentially non-linear and non-parametric way.

Artificial Neural networks

Basically, artificial neural networks identify data clusters through experiencing and gradual learning from the experience. This is very much the strategy of the brain's nervous systems, strengthening the knowledge after each experience and storing information as patterns (Silipo 1999). Once the patterns in the data are learned, the classifier uses them to generalise across related, but not experienced, instances of the data. For classifying a new instance (e.g., an unknown pixel), the model uses knowledge learned from previous experiences (e.g., known pixels). The most used neural network model in geoinformation sciences will be described in this section. The model is called multilayer perceptron (MLP) (figure 3.12). It is characterised by an input layer that receives and presents the data to the network, an output layer that stores the final results and one or more intermediate layers, which process the data in a number of inter-connected processing elements called nodes.

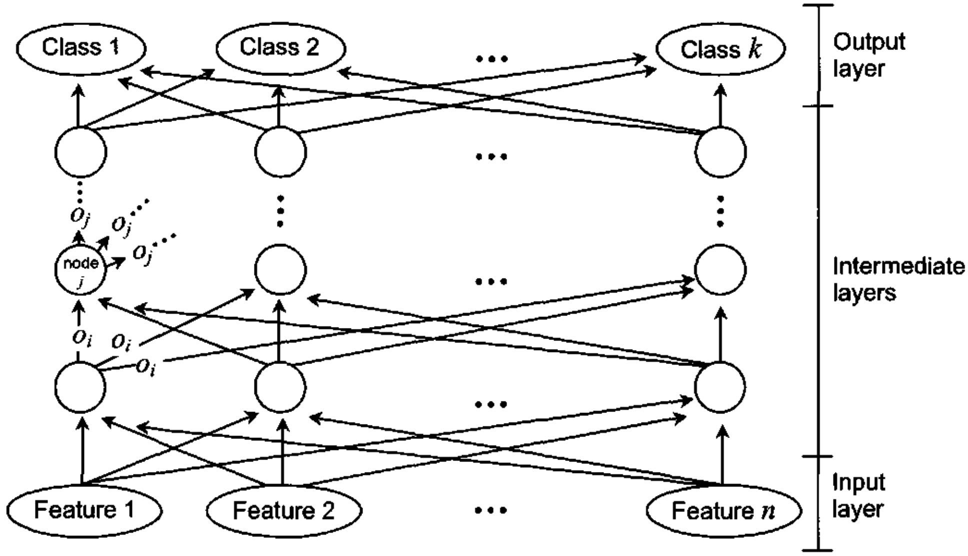

Figure 3.12 The multilayer perceptron neural network model.

The network node j, receives the output o_i of each node i in the preceding layer, weights them as ω_{ji} and combines all calculated weights with some mathematical function, usually a simple summation, generating a measure of node activity:

$$I_j = \sum_i \omega_{ji} o_i \tag{3.16}$$

The output o_j of node j is then computed by the so-called transfer function f, usually a variant of the sigmoid function, before being passed to the next layer:

$$o_j = f(I_j) \tag{3.17}$$

This process continues until the data reaches the output layer. The processing of weighted connections provide differentiated strength to favour a certain combination of paths for the present input instance, and hence leading it to a given output node. The transfer function introduces non-linearity and is used to prevent problems caused by large summation results.

In supervised classification, the output node that an instance of the data must reach is known, enabling interactive refinement of the model to correctly classify all instances in the training set. The model refinement has been successfully achieved by propagating the classification error back to the network and updating the set of connection weights $W = \{\omega_{ji}\}$ with the so-called *delta* learning rule, which is used to minimise the global error of the network. This updating procedure is based on reducing the error between actual (o_j) and desired (d_j) outputs.

The model refinement can be summarised as follows (Bishop 1995):

1. Calculate an error measure E in the output layer, e.g., $E(W) = 1/2\sum(o_j - d_j)^2$.
2. Compute the delta learning rules of the output layer as $\delta_j = f'(I_j)\,(o_j - d_j)$.
3. Compute the delta learning rules of the preceding layer as $\delta_i = f'(I_i)\sum_j \omega_{ji}\,\delta_j$.
4. Use $\Delta\omega_{ji} = -\,\eta\delta_i\,o_j$ for all ω_{ji} of the network.

Where η is a small positive number called learning rate parameter.

This is a refinement procedure (back-propagation learning paradigm) widely used for classification tasks, during which the neural network is said to be 'learning' the patterns in the input data. The learning process stops when some threshold error measure or a maximum number of iterations is reached, after which the neural network can be recalled to classify unknown similar data.

Decision trees

Inductive learning is another approach for artificial intelligence. The rationale behind it is very simple and intuitive: starting from a set of examples (e.g., training pixels) described by a set of features (e.g., a multivalued raster), a binary decision rule is defined to split the data into subsets more homogeneous than the original (figure 3.13). Each subset is then subject to a new split generating even more homogeneous (sub-)subsets. Theoretically, the procedure iterates until 'pure' subsets are obtained. Decision rules at each split are normally obtained by thresholding the best discriminant attribute (univariate tree) or by defining the best discriminant function based on linear combinations of attributes (multivariate tree) (Brodley and Utgoff 1995). The choice of attributes to be used in each split is guided by a quality measure applied to the generated subset.

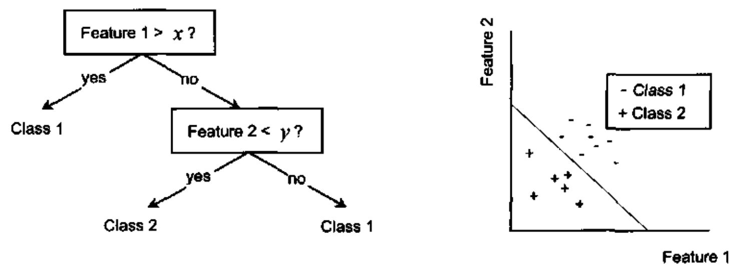

Figure 3.13 Illustration of an univariate tree (left) and multivariate decision boundary (right).

The goal is to induce rules that correctly classify all objects in the training sample. However, uncertainty in the data can yield very large trees with few pixels in some terminal nodes. Many of the branches leading to these relatively empty terminal nodes reflect chance rather than underlying patterns. To mitigate this specificity, large trees are then pruned by removing the least statistically reliable branches. This is done at the expense of increasing impurity in the terminal nodes when classifying the training set, but decreasing it on independent test data (Mingers 1989). In the present study, induction of univariate and multivariate decision trees was performed with Classification And Regression Trees (CART) (Breiman *et al.* 1984). The 'goodness of split' of different attributes was compared by the GINI index[1] of diversity, whereas pruning was based on the error-complexity method.

[1] named after the Italian economist Corrado Gini (1884-1965) (Murthy 1998).

For attribute selection, the GINI index is calculated for each discriminant attribute to measure how well they separate classes:

$$1-\sum_i P^2(C_i \mid t) \tag{3.18}$$

where, at node t, a randomly selected sample is assigned to class C_i with probability $P(C_i \mid t)$:

$$P(C_i \mid t) = \frac{P(C_i)N_i(t)/N_i}{\sum_i P(C_i)N_i(t)/N_i} \tag{3.19}$$

where, $P(C_i)$ is the Bayes' prior probability for class C_i, N_i is the number of samples from class C_i in the training set, and $N_i(t)$ is the number of samples from class C_i in node t.

Tree pruning was carried out with the error-complexity method, which is implemented in two stages as follows:

1) All possible sub-trees are considered and the one giving the smallest reduction in error is selected for pruning. By repeating this process, increasingly pruned trees are generated. The measure of reduction in error when evaluating sub-trees in this first stage is give by:

$$\alpha = \frac{R(t)-R(T_t)}{N_t-1} \tag{3.20}$$

where, $R(t)$ is the error cost of node t after pruned, defined by the number of wrongly classified samples in node t multiplied by the number of samples that reached node t, $R(T_t)$ is the summation of error costs from the N_t terminal nodes if node t was not pruned.

2) The best tree is then selected based on classification errors they make with test data. The standard error (SE) of the misclassification rate used in this second stage is:

$$SE = \sqrt{\frac{R\times(1000-R)}{N}} \tag{3.21}$$

where, R is the misclassification rate of the pruned tree, and N is the number of samples in the test data.

Like trained neural networks, classification of new instances with the final decision tree is straightforward.

CHAPTER FOUR[*]

Removal of Clouds from Remotely Sensed Time Series

The occurrence of *clouds* prevents the solar energy from "colouring" the environment. This fact poses at least three limitations to the extraction of land cover information from remotely sensed images: a cloud hides landscape features in the scene, shadows other areas on the ground, and if the aircraft flies below the clouds, the radiometric resolution is dramatically reduced. If a temporal snap shot meets the objectives for a given application, careful selection of a cloud free image might provide enough information, but if the analysis of dynamic aspects is the aim, one needs repeated observations of the same area, part of which will be eventually covered by clouds.

The *time series* provided by Earth observation systems are important sources of information. In an analogy to hyperspectral imagery, we can already use *hypertemporal* data sets to analyse and model the environment. The Landsat system, for instance, has been acquiring images almost weekly since 1971 and producing valuable inputs for historical characterisations, predictive modelling,

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[*] Based on:
Carvalho L.M.T. de, Clevers J.G.P.W, Skidmore A.K. & Jong S.M. de, 2001. Robust nonlinear wavelet regression for denoising remotely sensed time series. *Photogrammetric Engineering & Remote Sensing* (submitted).

decision-making etc. Other systems, like the NOAA AVHRR, acquire images on a daily basis revealing detailed temporal information about the Earth's surface. Nevertheless, it is still difficult to perform spatio-temporal analysis of long time series acquired by such systems, in special Landsat, because of *cloud contamination* and other distortions. Image analysis techniques to support processing and information extraction from existing temporal data must be developed. Long term studies on land surface, water, carbon and energy fluxes require corrected time series to provide more realistic temporal parameters (Los *et al.* 2000). In this context, our task is to reconstruct as close as possible an estimate of the observations, which have been corrupted (e.g., obscured by clouds). Then, past records might be effectively used to provide as important information as upcoming data of new Earth observation systems.

The general problem of detecting and estimating corrupted values has been tackled before with *wavelet transforms* (Starck *et al.* 1998, Donoho 1993). The technique is particularly appealing to study signals that are "smooth" in some sense and have singularities of short duration. Despite sudden changes in land cover, the smoothness requirement is normally met by remotely sensed time series, where clouds, shadows, and other anomalies appear as narrow peaks in the otherwise smooth temporal profile.

This chapter can be viewed as a preprocessing step for further analyses conducted in the thesis. It describes the application of the *product of wavelet scales* (Sandler & Swami 1999) to generate binary masks of corrupted observations. The *robust smoother-cleaner wavelets* method (Bruce *et al.* 1994) is then applied to each temporal profile where anomalous values were detected. The interpolation step is based on nonparametric function estimation applying *wavelet shrinkage* (Donoho & Johnstone 1992) to the "clean" time series. The results were compared to other methods applied to the same synthetic data set.

4.1 Dealing with cloud contamination in remote sensing

Cloud contamination has been a major limitation of land observation with systems that operate in the optical part of the electromagnetic spectrum. Especially over tropical regions, where the weather can be overcast for long periods, cloud cover hampers the potential use of time series derived from optical remote sensing. Yet, clouds might also adversely affect passive microwave remote sensing by modifying brightness temperatures of the Earth's surface (Long *et al.* 1999). In any case, cloud contaminated pixels are marked and treated as missing data that must be estimated using additional information, e.g., spectral (Guo and Moore 1993, Derrien *et al.* 1993), spatial and/or temporal (Addink and Stein 1999, Roerink *et al.* 2000).

An operational procedure for automatic cloud detection in NOAA AVHRR imagery was developed by Saunders and Kriebel (1988) and Derrien *et al.* (1993). Their pioneering algorithm uses different threshold tests applied to various combinations of channels. Pixels are identified as cloudy if one test is successful. The development was based on scenes from Western Europe and the authors highlight the necessity of tuning the algorithm if other regions are to be processed. Wang *et al.* (1999) proposed automatic cloud detection in a set of two temporal Landsat TM images by simply thresholding the differences. For shadow detection they thresholded high frequency components as extracted by a 2D discrete wavelet transform of both images. Roerink *et al.* (2000) developed the Harmonic ANalysis of Time Series (HANTS) and reported considerable improvements over the standard Fourier transform. The algorithm is based on an iterative procedure of least squares fitting based on harmonic components. Recursively, the outliers are removed and the curve fitting recomputed until it reaches a maximum acceptable error or a minimum number of remaining points. In this way, clouds and shadows are automatically detected as outliers in the temporal profile.

Once marked, be it manually or automatically, the contaminated pixels are replaced to yield cloud free products. Long *et al.* (1999) compared several methods for cloud replacement in images from the Special Sensor Microwave/Imager (SSM/I) radiometer. They found that the combination of maximum value and mean methods produces better results than any of the approaches individually. Addink and Stein (1999) proposed new approaches to replace clouded pixels based on geostatistics. They concluded that instead of conventional methods, like the widely used maximum value composite (Moody and Strahler 1994), unstratified co-kriging using another temporal observation as co-variable should be used to replace clouds from NOAA AVHRR images. Nevertheless, they also pointed out that the quality of the images used as co-variables must be very good; otherwise, unstratified kriging is the better option. In the algorithm of Wang *et al.* (1999) mentioned before, they recover the missing data by fusing the two images with the inverse wavelet transform. Binary decision maps of clouds and shadows are used to mask contaminated pixels during the inverse transform. Thus, masked pixels are reconstructed using complementary information, which must be available in at least one of the images. The HANTS algorithm is the only procedure listed above which is able to deal with long time series in an automatic fashion. It replaces all instances of temporal profiles by the respective values of the fitted curves, enabling the estimation of cloud free images at any moment in the time series. Similarly, Los *et al.* (2000) developed a corrected data set (FASIR NDVI), which also includes steps of Fourier adjustments, interpolation, and reconstruction of cloud free NDVI (Normalised Difference Vegetation Index) time series derived from NOAA imagery.

4.2 Automatic detection of cloud contaminated pixels

Detection of outliers in diverse types of signals has been carried out effectively in wavelet transformed space (Starck *et al.* 1998). In remote sensing, outliers caused by clouds and shadows appear as peaks of narrow bandwidth in the temporal spectrum. They appear similarly in the spatial domain, but with variable bandwidth. If we consider the presence of clouds and shadows as signal response against a "noisy" background, a framework for their detection can be set forth based on noise modelling in transformed space.

Recall from chapter 3 that wavelet analysis transforms a given signal (e.g., figure 4.1a) to a set of resolution related views, which are by definition of zero mean with variance σ^2 (figure 4.1b, and c). The discrete wavelet transform was implemented with the 'à trous' algorithm (Holschneider *et al.* 1989) with a linear spline as the wavelet prototype. It produces a vector of wavelet coefficients d at each scale j, with $j = 0,\ldots, J$. The original function f was then expressed as the sum of all wavelet scales and the smoothed version a_J:

$$f(t) = a_J(t) + \sum_{j=1}^{J} d_j(t). \tag{4.1}$$

In order to further enhance singularities (i.e., edges and peaks) in the signal, interscale correlation was explored by forming multiscale point-wise products (figure 4.2). The multiscale product (Sadler and Swami, 1999) of an arbitrary set K of wavelet scales is given by:

$$p(t) = \prod_{j \in K} d_j(t). \tag{4.2}$$

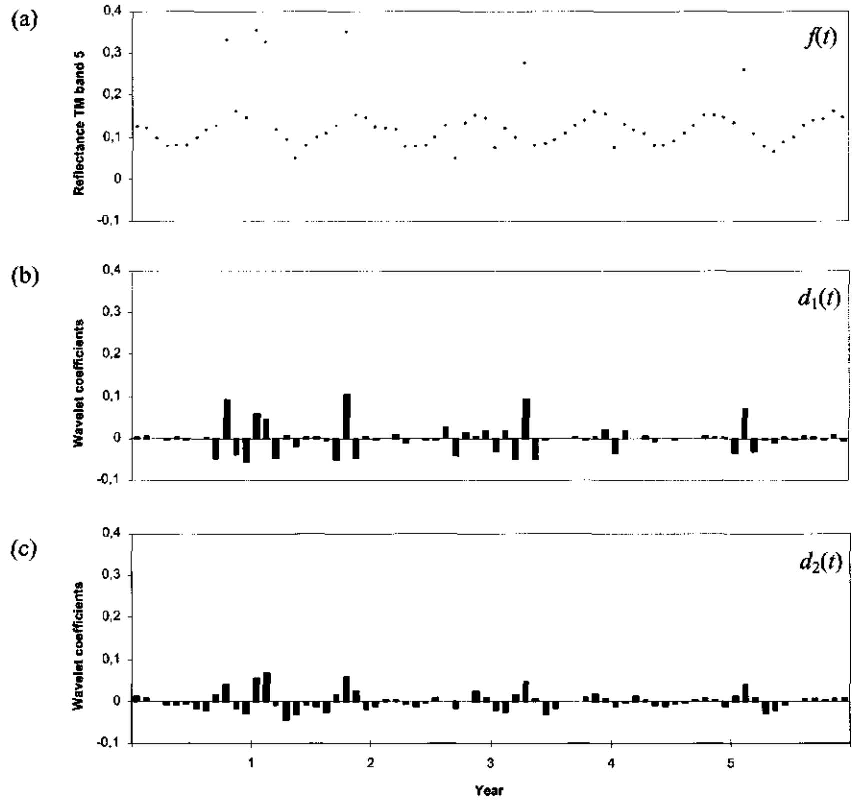

Figure 4.1 (a) Simulated temporal profile with cloud contamination. (b) Wavelet coefficients at first scale level. (c) Wavelet coefficients at second scale level.

Moreover, by using an even number of scales in the product, positive and negative singularities in wavelet space are represented only as positive singularities in the multiscale product space facilitating the detection procedure (Figure 4.2). The detection hypothesis is that the signal is locally constant around $p(t)$. Then, a simple approach to model noise that follows an unknown distribution is to consider it locally Gaussian. If $\sigma_j(t)$ is the local standard deviation within the support of the wavelet template at scale j, we have a significant singularity when $p(t) > C\sigma_j(t)$. In this study, we used wavelet scales d_1 and d_2 in the multiscale product and the constant C was empirically set to 2. Increasing the detection level might avoid false detection, but also excludes weaker singularities.

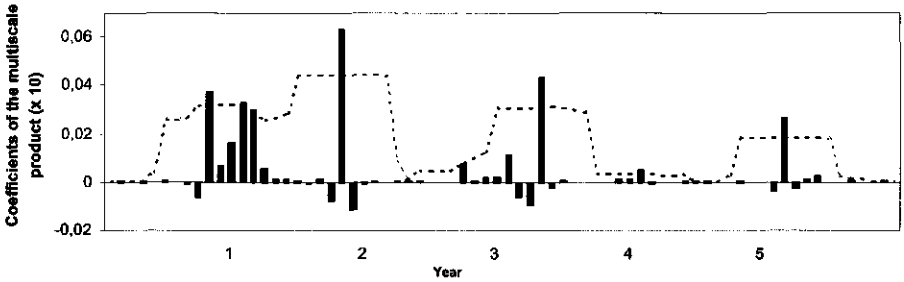

Figure 4.2 Product of wavelet coefficients (bars) and the detection limit (dashed line).

4.3 Robust nonlinear wavelet regression

Recovering information obscured by clouds and shadows consists of estimating the missing data assuming that land cover varies smoothly over space and time. This is a fundamental requirement to the proper utilisation of nonparametric regression techniques. Then, wavelet methods might be applied to the problem of modelling a given digital signal y by estimating the unknown mean response function f:

$$y(t) = f(t) + \varepsilon , \tag{4.3}$$

where the vector ε represents noise.

The wavelet approach to regression estimators brings a useful new set of basis for orthogonal series estimation, which allows characterisations of functions in terms of both time and frequency. The estimation is based on the representation of the mean response function as a linear combination of basis functions ψ_i:

$$f(t) = \sum_i a_i \psi_i(t), \tag{4.4}$$

where the coefficients a_i are given by:

$$a_i = \langle f(t), \psi_i(t) \rangle . \tag{4.5}$$

The vector a of associated coefficients is called the transform of f. Thus, the problem of estimating f using the known vector y consists of three main steps:

(1) calculate the transform of y:

$$\tilde{a}_i = \langle y(t), \psi_i(t) \rangle ,$$

(2) select a subset S of important coefficients from $\tilde{a}$ in an attempt to remove the noise component ε from the regression model (equation 4.1), and

(3) invert the transform using the selected coefficients to obtain the regression curve:

$$\hat{f}(t) = \hat{y}(t) - \varepsilon = \sum_{i \in S} \tilde{a}_i \psi_i(t). \tag{4.6}$$

The subset S might be obtained with a suitable threshold function applied to the wavelet coefficients. In this study the so-called soft threshold (Donoho and Johnstone 1994) was used:

$$\delta_T(t) = \begin{cases} 0 & \text{if } |a_i| \le T \\ \text{sign}[a_i](|a_i| - T) & \text{if } |a_i| > T \end{cases} \tag{4.7}$$

Note that the threshold value T may vary from level to level resulting in a locally adaptive function evaluation.

The robust smoother-cleaner wavelets (Bruce *et al.* 1994) were used in the present study to reduce the sensitivity of regression smoothers to outliers. Let the input signal be $f = a_0$, which is first convolved with a median filter. The array of robust residuals r in every scale j is given by:

$$r_j = \delta_T(a_j - a_j^*), \tag{4.8}$$

where, a^*_j is the median filtered version of a_j and δ_T is a suitable threshold function, like in equation (4.7).

The cleaned version c_j is obtained by subtracting the residual r_j from the original vector a_j:

$$c_j = a_j - r_j . \tag{4.9}$$

In practice, it is enough to repeat this procedure twice to remove the outliers from the data, which is then ready to be modelled with nonlinear estimators such as wavelet shrinkage (Donoho and Johnstone 1992).

Thus, wavelet regression (Bruce and Gao 1994) consists of carrying out some modification to the data in the wavelet space and recombining, in a linear or nonlinear way, the modified wavelet functions to represent the data. The 'à trous' algorithm with spline wavelets was also used for nonlinear regression and the data were regarded as regularly sampled in the time domain.

4.4 Test Data and Validation

The reference cloud-free time series consisted of twenty-six co-registered subsets (256 x 256 pixels) of a Landsat TM scene (path 218, row 75). The images were acquired in varying intervals of time, from 1984 till 1999. In this study, we used TM band 5 images as input to the detection and replacement procedures. In a first simulation, real clouds and respective shadows were extracted from an image acquired in April 1989 that was not included in the time series, and placed over the same area of a cloud-free image acquired in June 1989, which was included in the time series. Thus, a simulated data set with cloud contamination was generated (figure 4.3) in order to test the procedures for cloud detection and replacement. A second simulated time series was generated for a single forest pixel to illustrate the potential of wavelet regression. In this case, the following images were assumed to be representative of a one year cycle: Jan 1996, Mar 1988, Apr 1991, Jun 1989, Jul 1989, Aug 1991, Sep 1991, Oct 1985, and Nov 1985. This cycle was repeated four times and non-Gausian noise was added, resulting in a 5-year time series (figure 4.1a).

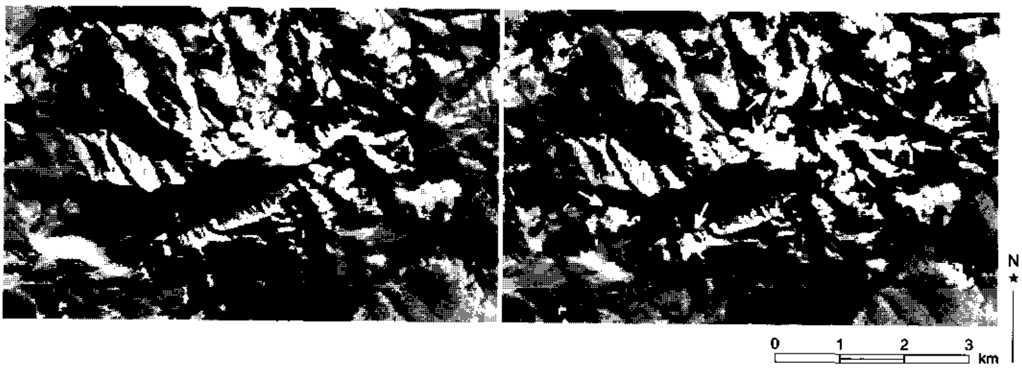

Figure 4.3 Band 5 of Landsat TM scene acquired in June 1989. Original (left) and simulated (right) images. White arrows indicate the locations of the added clouds.

The first simulated time series had the missing values estimated using five methods: 1) mean value, 2) minimum value, 3) maximum value, 4) linear regression, and 5) the wavelet-based procedure for nonparametric regression described above. Root mean square errors (RMSE) were calculated for the cloud-contaminated areas to evaluate the performance of each method in terms of accuracy of estimation:

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{N} (\hat{g}_i - g_i)^2}}{N}, \qquad (4.10)$$

where, $\hat{g}_i$ is the ith estimated pixel, g_i is the ith original pixel, and N is the number of contaminated pixels. In addition, as methods 4 and 5 might replace all values in the time series when the spatial localisation of corrupted observations are not known in advance, RMSE were also calculated for the whole estimated images of 1989 produced by these methods.

4.5 Results and Discussion

In total, 2508 out of 3715 contaminated pixels were detected by applying the automatic detection procedure described in section 4.2. The pixels that were not detected represented fuzzy boundaries of clouds and shadows, as well as shadowed forests that already had low reflectance, or even clouded areas of bare soil that had high reflectance values in the reference image. These contaminated pixels could not be detected because the reflectance values were only slightly affected by cloud and shadow cover. For some applications, such small variation in reflectance is not significant and may be disregarded. For others, specific solutions must be devised to detect cloud and shadow edges.

Because of their high reflectance values, clouds have been normally detected by simply thresholding the original image or a difference image (Wang *et al.*, 1999). In the first case, other objects of high reflectance could be misdetected as clouds. In the second case, misdetection might occur in areas of significant land cover change. Moreover, the contaminated instance to be thresholded must be known in advance and the definition of proper thresholds for actual reflectance values could be difficult. Automatic cloud detection for NOAA imagery is described in Derrien *et al.* (1993). Their procedure is based on a series of tests and thresholds, which must be updated for different areas or illumination conditions. The advantage of the method described in this chapter is that detection of outliers in multiscale product space is completely data driven and independent of the shape and magnitude of the original signal, avoiding false detection and aiding automation. In addition, other anomalies, like geometric misregistration, were also detected. Note in figure 4.4, the clouds and shadows depicted with the multiscale product in 1989 and the misregistration effects depicted in 1992. Burned areas (white patch in the upper left corner of the image from 1992 in figure 4.4) due to agricultural practices are susceptible to be misdetected as shadows and consequently removed from the time series.

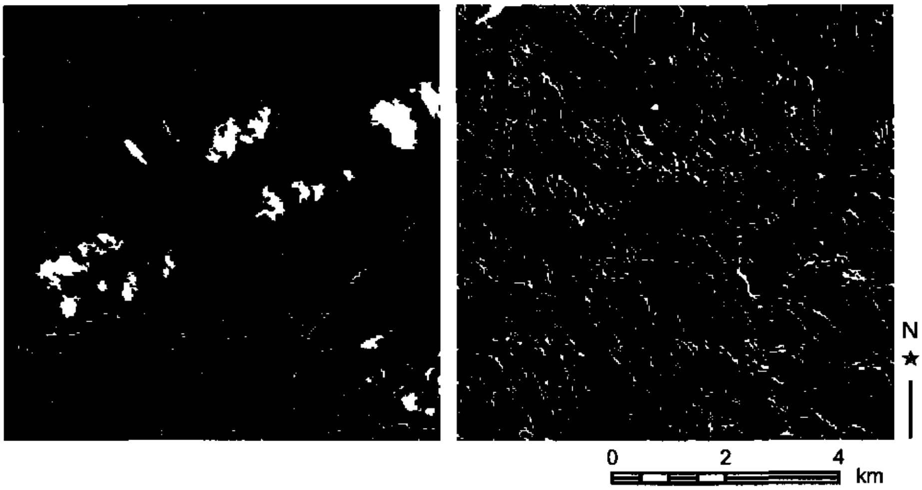

Figure 4.4 Binary mask of corrupted values produced by thresholding the multiscale product. Time slices are 1989 (left) and 1992 (right).

The calculated RMSE for the first simulation shows clearly that replacement methods widely used for declouding NOAA time series were very inaccurate in comparison to regression methods (table 4.1). Specially, the maximum value composite gave the worst results for both clouded and shadowed areas. The wavelet-based approach was more accurate for clouded areas while linear regression performed better in shadowed areas. Even then, the time series used in the first simulation represented wet and dry seasons sequentially, leading to an up and down pattern which is easy to be modelled with linear regression. More complete time series, like our second simulation, would certainly demand more elaborated regression techniques if one wants to keep track of real trends in the time series.

Table 4.1 Root mean square errors (x 1000) for the five interpolation methods.

Interpolation Method	Clouded Areas	Shadowed areas
Minimum value	1.8364	1.3319
Mean value	1.0286	0.6250
Maximum value	3.2227	2.0406
Linear regression	0.6699	**0.4197**
Wavelet regression	**0.5757**	0.4339

Figure 4.5 shows the regression curve obtained with the robust nonlinear wavelet analysis applied to the simulated forest pixel. Note that the influence of outliers was completely removed and the nonlinear estimation could be properly applied. The technique is also useful to reduce geometric misregistration, radiometric noise, and other anomalies from long time series of remotely sensed data. Figure 4.6 shows a small subset contaminated with the larger shadow in the

upper right corner of figure 4.4. The image estimated with nonlinear wavelet regression maintained even the spatial contrast of the reference image, different from linear estimation that tends to smooth out the object's edges.

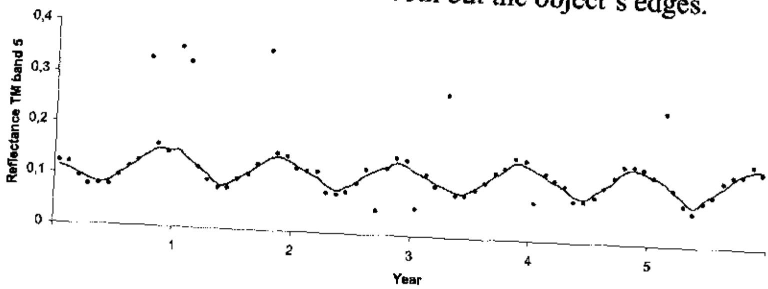

Figure 4.5 Regression curve obtained with the robust smoother-cleaner wavelets followed by wavelet shrinkage.

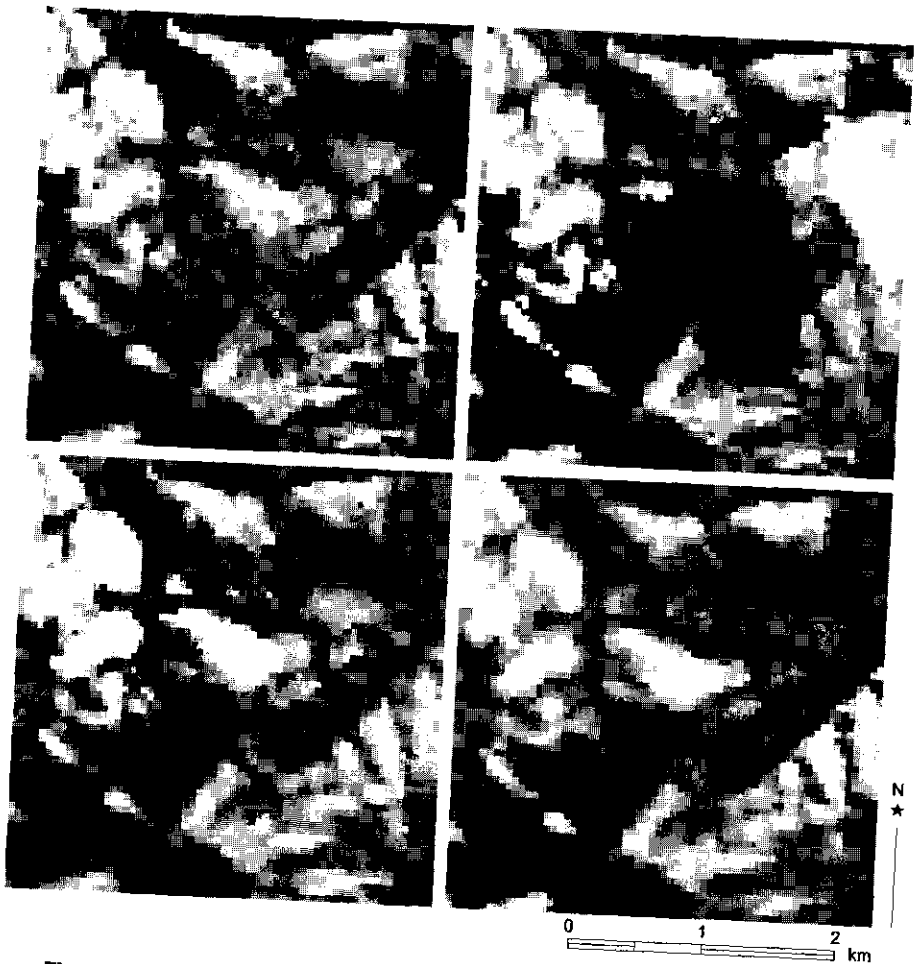

Figure 4.6 Reference cloud free image (upper left), simulated cloud contamination (upper right), nonlinear estimation (lower left), and linear estimation (lower right).

4.6 Conclusions

A framework for (non-Gaussian) noise suppression (i.e., cloud removal) from remotely sensed time series was presented and demonstrated. The procedure is a step towards automation because the contaminated instances of the time series do not need to be known in advance. Multiscale products of wavelet scales might be effectively used to automatically mask corrupted values for further replacement with any desired method. The method proposed here not only identified clouded and shadowed pixels but also other anomalies like misregistration effects and changes of short duration (e.g., burn scars). The robust nonlinear wavelet regression can do both, detection and estimation, at the same time and produce noise reduced images at any point in the time series. Thus, the wavelet approach is promising as a preprocessing step for effective time series analysis. It can be adapted to reduce radiometric discrepancies among images in the time series, acting as a temporal smoothing operator.

Although not compared directly with Fourier-based methods (e.g., HANTS, FASIR), some advantages of the wavelet-based method may be highlighted: (1) lower computational complexity, (2) simultaneous detection of positive and negative anomalies in the time series, and (3) patches of outliers (e.g., cloud contamination observed sequentially for a given location) are efficiently removed from the time series with the robust smoother-cleaner wavelets. In the approach proposed by Addink and Stein (1999), the image to be declouded as well as the image used as the second variable in co-kriging must have low cloud cover because the presence of clouded pixels among the interpolators decreases the reliability of the method.

Considering the comparisons presented in this chapter, wavelet regression predicted the reference values for clouded areas better than all others did, and performed almost equivalent to linear prediction in shadowed areas. Even so, more complete time series, like in our second simulation, would certainly be better modelled with nonparametric regression methods.

A similar approach might be used in the spatial domain and combined with the temporal analysis presented here. Further research on this direction and on more complete data sets (daily or monthly series) will bring insights to other possibilities and improvements of the procedure.

CHAPTER FIVE*

Classification of Forest Remnants

It was acknowledged at the environmental conferences in Rio de Janeiro and Kyoto that satellite imagery offers the most promising and probably the only feasible way for detailed mapping and monitoring of forests over large geographical areas. Indeed, the available image processing tools have the potential to provide repeatable procedures for analysing standard data sets in a comparable framework. Nevertheless, operational applications of remote sensing for forest mapping at regional and local scales have many theoretical and practical challenges that must be met in order to realise its potential. For example, there is a need for effective information extraction and knowledge generation from high-resolution (spatial, temporal, and spectral) data sets. The preprocessing and analysis tools should be able to deal with a variety of data types, sources and distortions to improve our ability to distinguish between different landscape features. The need for improved mapping methods is evident from our still poor knowledge on basic information about forest extent and condition.

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* based on:
Carvalho L.M.T. de, Clevers J.G.P.W, Skidmore A.K. & Jong S.M. de, 2001. Features for mapping semideciduous Atlantic forest: overcoming spectral overlap with remotely sensed time series. *Remote Sensing of Environment.* (submitted).

Coarse spatial resolution sensors such as the NOAA AVHRR have been widely used for forest and land cover mapping (Mücher *et al.* 2000, Lucas *et al.* 2000a). However, the results are also spatially coarse and, thus, inaccurate for analysing fragmented landscapes (Foody *et al.* 1997, Lucas *et al.* 2000b). Recently, attempts to overcome the spatial constrains imposed by sensors such as AVHRR have explored the use of mixture models, fuzzy clustering and artificial neural networks (Atkinson *et al.* 1997, Tatem 2001). Higher spatial resolution images (e.g., SPOT and TM imagery) have proven to be suitable for mapping forests with the accuracy required by regional-scale models (Frohn *et al.* 1996). A significant limitation for their fully operational use has been spectral overlap problems, large data volumes, and consequently the computational costs needed for large areas mapping (Kontoes and Rokos 1996, Townshend *et al.* 1997, Suzen and Toprak 1998). Even then, higher spatial resolution images still provide the only way of dealing with situations where sufficient level of detail must be observed.

The issues discussed above are evident in the case study presented in this chapter: mapping semideciduous Atlantic forest in southeastern Brazil. By estimating its actual cover using NOAA imagery, one would probably conclude that this forest ecosystem has been completely removed due to its strongly fragmented state (see figure 5.1). Spectral overlap affects the use of Landsat imagery because of the co-occurrence of land cover types such as coffee and eucalyptus plantations (Varona 2000, Raga 2001).

The operational use of high spatial resolution images for forest mapping is still premature, especially within complex and fragmented agricultural systems. There is a need for an effective classification procedure that: (a) distinguishes among natural forest and classes that spectrally overlap with it, (b) gets the most from available features for classification, and (c) requires less human intervention, if reliable estimates of forest cover are to be made frequently over large geographical areas. Thus, this study intends to evaluate the suitability of the following variables to distinguish natural forests from coffee and eucalyptus plantations in the study site:

– Terrain topography,
– Temporal and spectral information of yearly cycles,
– Long time series of NDVI (Normalised Difference Vegetation Index) data,
– Spatial and temporal texture measures, and
– Classifiers (viz., maximum likelihood, neural networks, and decision trees).

5.1 State-of-the-art in land cover mapping

Since the first images from the Landsat Multi-Spectral Scanner (MSS) reached the scientific community, a number of studies have demonstrated the applicability of spectral information for discrimination among land cover types. Together with the capabilities of multispectral analysis, its limitations were also revealed. Scientists found out that some objects on the Earth's surface reflect the electromagnetic energy in the same way when sensed at this coarse spectral resolution (Skidmore *et al.* 1988, Ma and Olson 1989), and consequently, their discrimination using spectral information was not possible. In addition, objects' reflectance may vary according to growth stage, phenology, humidity, atmospheric transparency, illumination conditions etc. These drawbacks led to a search for alternatives to enable the discrimination of land cover classes with similar reflectance behaviour.

The developed approaches rely on the addition of multisource information mainly related to topography, geology, historical imagery, land cover data, image textural measures, and multisensor imagery. Skidmore (1989) successfully mapped different eucalyptus species in Australia by incorporating information on their preferred terrain positions, whereas Bruin (2000) obtained up to 14% better classification results by using geological stratification. Temporal information has been considered in an attempt to distinguish agricultural crops using their developmental trajectories (Clevers *et al.* 1990, Ortiz *et al.* 1997). Temporal signatures are then treated in the same way as spectral signatures. An exception is a recent methodology developed by Vieira *et al.* (2000), the so-called spectral temporal response surface (STRS), which characterises the pixel's reflectance over time for each waveband by means of analytical surface fitting. Janssen and Middelkoop (1992) used relative transitions of land cover in the classification procedure increasing its accuracy from 76 to 82 per cent. Seemingly, Jong and Riezebos (1991) improved classification by 20% using agroecological zones and the probabilities of a land cover type to occur within these zones. Xia (1996) was able to identify five additional classes when information about objects' form was combined with spectral classification results. Image texture had little effect on improving classification accuracy according to Dikshit (1996). In contradiction, Haralick (1979) obtained highly accurate results when using textural features derived from co-occurrence matrices. Seemingly, Manian *et al.* (2000) and Zhu and Yang (1998) reported promising results when texture features were extracted with logical operators and with wavelet transforms. Texture measures have proven to be of utmost importance for the analysis of SAR images (Soares *et al.* 1997, Fukuda and Hirosawa 1999, Simard *et al.* 2000). The synergistic use of optical and radar remote sensing holds new opportunities for land cover classification (Clevers *et al.* 2000, Kuplich *et al.* 2000) since the latter provides additional data on vegetation structure and on areas frequently covered by clouds (Leeuwen *et al.* 1994).

The multisource information has been fed into a variety of classification schemes. The algorithms evolved beyond the traditional probabilistic classifiers to accommodate these heterogeneous data sets. Three approaches based on intelligent data analysis are being increasingly applied in the field of remote sensing. The first, known as expert systems, works with encoded information termed knowledge base, which is generated by domain specialists. Unlike conventional mathematical models, the knowledge is stored in a separate file, which is evaluated within a set of rules also defined by specialists (Eijkel 1999). Some references cited above have used these models for land cover mapping (e.g., Skidmore 1989, Jong and Riezebos 1991).

The second family of intelligent models is known as artificial neural networks. The most popular neural network model for classification of remotely sensed data is the Multi-Layer Perceptron (MLP). Skidmore (1997) used the backpropagation learning algorithm with a MLP model and reported no statistically significant improvements in classification accuracy for mapping forest types. New architectures have been developed in an attempt to improve over MLP, like the fuzzy ARTMAP (Carpenter *et al.* 1992), textural neural networks (Kaminsky *et al.* 1997) and combinations of neural networks and expert systems (Murai and Omatu 1997).

Decision trees are the third family of 'intelligent' algorithms used for geographical analysis (Skidmore *et al.* 1996, Simard *et al.* 2000, Friedl *et al.* 2000, Gahegan 2000). Induction of decision trees enables learning from pattern and is useful in selecting relevant features for classification (Borak and Strahler 1999). It has been extensively used in other disciplines as a means of discovering and explicating knowledge for expert systems (Quinlan 1986). Surprisingly, despite these attractive characteristics and rare investigations in the past (Swain and Hauska 1977, Lee and Richards 1985, Belward and Dehoyos 1987), decision trees have only recently been considered for classification of remotely sensed images and not much work has been done up to now (Friedl and Brodley 1997, DeFries *et al.* 1998, Friedl *et al.* 1999, Borak and Strahler 1999).

Finally, large-scale mapping projects using an increasing amount of remotely sensed data demand methods that are less dependent on human interventions and more capable of handling spectral, spatial, temporal and ancillary data from a variety of sources. In this context, decision trees have been regarded as one of the most important alternatives (DeFries and Townshend 1999).

5.2 Inputs, transforms and feature sets definition

A subset area in the "*Vale do Alto Rio Grande*", representing a complex and fragmented land cover pattern, was chosen for the analysis (figure 5.1). The main land cover types in this area are perennial crops like coffee, eucalyptus and pasture, enclosing remnants of semideciduous Atlantic forest and savanna-related formations. Both natural formations are confused with planted crops because of their similar reflectance characteristics. Thus, the potential of variables derived from time series of reflectance data, spatial and temporal texture, and terrain topography were assessed to define a mapping strategy for semideciduous Atlantic forest.

Figure 5.1 Image used in the present study. The area within dashed lines is the subset shown in figure 5.2

The input data set consisted of a declouded time series of twenty-seven co-registered subsets (figure 5.1) of a Landsat TM scene (path 218, row 75) and digitised contour lines with 20 m of vertical resolution. Seven sets of features were input to four classification algorithms. Descriptions of derived features, as well as the motivation for construction of each feature set, are listed below:

SET 1 – One year of multispectral data – Bands 3, 4, and 5 of TM data acquired in August 1998, April 1999, August 1999, and November 1999 were combined to form a set of 12 features. This data set was motivated by the assumption that different land cover types exhibit different dynamics throughout the year, which might aid the discrimination of spectrally similar objects.

SET 2 – 15 years of NDVI data – This data set was created from 15 NDVI images. They were calculated from TM images acquired yearly from 1985 till 1999. NDVI was chosen because it is thought to represent not only phenological variation but also rotation and management practices in perennial crops. It is assumed that natural forests exhibit a relatively constant temporal profile in relation to eucalyptus and coffee plantations.

SET 3 – Topography – From the digitised contour lines, a regular grid of elevation data with 30 m of spatial resolution was generated using Delaunay triangulation with linear interpolation. This grid was then used to derive slope and aspect information. Elevation, slope and aspect features were combined with all TM bands (except for the thermal channel) of an image acquired in August 1998, thus forming a set with 9 features. The assumption here was that topography determines agricultural land use and might provide discriminating information for forest classification.

SET 4 – Spatial texture – Multiscale texture descriptors were extracted in the spatial domain using a 2D discrete wavelet transform (see chapter 3, page 26). Using this transform, four high-frequency images, representing textural variations at increasing scale levels, were obtained for three TM bands (3, 4, and 5) from 1999. Thus, 15 features (12 texture features and three TM bands) composed this set. The '*à trous*' algorithm with linear spline basis (Holschneider *et al.* 1989, Carvalho *et al.* 2001) was used for wavelet decomposition.

SET 5 – Temporal texture – The 1D discrete wavelet transform was applied to extract temporal texture descriptors from the NDVI time series. Temporal profiles were decomposed pixel-wise using the Haar wavelet basis and pyramidal decomposition (see chapter 3, page 27). Different from the 'à trous' algorithm, the pyramidal algorithm is non-redundant, i.e. generates two transformed vectors with half of the elements in the original vector; one representing low-frequency components and the other high-frequency components. One-level decomposition was applied to 14 NDVI images resulting in 7 high-frequency texture features. These were stacked with TM bands 3, 4, and 5 from 1999 generating a set with 10 features for classification.

SET 6 – The spectral-temporal response surface (STRS) – Bands 3, 4, and 5 from 27 images acquired from 1984 to 1999 were used to calculate coefficients of the spectral-temporal response surface (Vieira *et al.* 2000). The coefficients of fitted analytical surfaces describe pixels as a function of time and wavelength, and represent the spectral-temporal relations. In two dimensions, i.e. spectral (x coordinate) and temporal (y coordinate), polynomials derived by multiple regression for each pixel in the image are surfaces of the form (Burrough and McDonnell 1998):

$$f\{(x,y)\} = \sum_{r+s\leq p} \left(b_{rs} x^r y^s\right) \tag{5.1}$$

of which the first three are:

$$b_0 \qquad \text{zero order}$$

$$b_0 + b_1 x + b_2 y \qquad \text{first order}$$

$$b_0 + b_1 x + b_2 y + b_3 x^2 + b_4 xy + b_5 y^2 \qquad \text{second order}$$

The integer p is the order of the polynomial fit. A horizontal plane is zero order, an inclined plane is first order, a quadratic surface is second order, and a cubic surface is third order. As suggested by Vieira *et al.* (2000), a polynomial fit of third order was used to generate a set of 10 coefficients (i.e., features) for each pixel in the subset scene used in this study.

SET 7 – Mined features – The 59 features described previously were fed into a data mining package called Classification And Regression Trees-CART (Breiman *et al.* 1984) for exploratory analysis with decision trees (see chapter 3, page 33). The top 10 discriminating features were selected to compose the last set for classification. The automatically selected features were 6 NDVI images from 1985 till 1987 and from 1992 till 1994, band 5 from April 1999 and the 2nd, 4th and 7th coefficient images of the STRS.

In this way, sets 1 to 6 reflected expert knowledge on how different information might contribute to class discrimination, whereas in set 7, this knowledge was automatically generated based on relationships not always clear to domain experts. For the purpose of mapping semideciduous Atlantic forests, we hypothesise that feature sets 2, 5, 6, and 7, which include long time series, should be more relevant than the other feature sets that represent yearly cycles or have no temporal information included.

5.3 Supervised pattern recognition

The classification task is concerned with the identification of clusters and characterisation of their boundaries in multidimensional space, to decide if a given image pixel belongs to a certain cluster, i.e. a thematic class. The boundaries can be obtained by parametric or nonparametric techniques. Parametric classification makes assumptions about the shape of the data distributions and defines decision hyper-volumes as a function of estimated parameters (e.g., mean), whereas nonparametric classifiers assume that the data clusters can be isolated by some discriminant function (e.g., thresholding). In supervised classification, the necessary parameters or discriminant functions are calculated using predefined samples of known type.

Maximum likelihood

This algorithm has been the most popular for classification of remote sensing imagery. As a parametric classifier, it assumes that a hyper-ellipsoid decision volume can approximate the shape of the data clusters. For a given unknown pixel, described by a vector of attribute features, the probability of membership in each class is calculated using the classes' mean feature vectors, covariance matrices and prior probabilities (Duda and Hart 1973). The unknown pixel is considered to belong to the class with maximum probability of membership.

Artificial neural networks

This algorithm has capability for self-learning. It has proliferated in the remote sensing literature as a promising technique for a number of situations such as non-normality, complex feature spaces and multivariate data types, where traditional methods fail to give good results (Atkinson and Tatnall 1997). The MLP model with backpropagation learning algorithm (see chapter 3, page 31) was used in the present case. The network architecture was set as follows: two hidden layers with 18 nodes each using the sigmoid function as activation method, a fixed learning rate set to 0.9 and learning momentum set to 0.7. These settings were suggested by Henk van Oosten, author of the software and experienced user of neural networks for classification of remotely sensed data.

Decision trees

Decision trees share the same advantages of neural networks compared with traditional probabilistic algorithms because they are strictly nonparametric, free from distribution assumptions, able to deal with nonlinear relations, insensitive to missing values, and capable of handling numerical and categorical inputs. CART was used in this study to generated univariate and multivariate classification trees (see chapter 3, page 33). We expected neural networks and decision trees to perform better than the maximum likelihood classifier because of the advantages mentioned above and the complex land cover pattern in the study site.

5.4 Classification procedure and accuracy measures

Classifiers were trained with the same set of 700 sample pixels equally distributed in seven main land cover types: natural forest, savanna, coffee, eucalyptus, annual crops, grass land and bare land. In addition, decision trees were pruned with another set of 700 sample pixels different from the training set. A class-oriented approach was chosen and all classes, except forest, were merged in a single class named non-forest.

Each forest/non-forest output map was tested for accuracy using a unique set of 2000 pixels selected with simple random sampling. Training, pruning and testing pixels were checked during field campaigns in 1999 aided by visual interpretation of small-format aerial photos and Landsat TM images.

The chosen accuracy measure for classification comparisons was the class mapping accuracy proposed by Kalensky and Scherk (1975):

$$A_i = \frac{N_i}{N_i + E_i}, \tag{5.2}$$

where, A_i is the percentage mapping accuracy of class C_i, N_i is the number of correctly classified pixels in class C_i, and E_i is the sum of omissions and commissions in class C_i. This measure was chosen instead of the overall classification accuracy or the Kappa statistics because the former might overestimate positional class accuracy (Skidmore 1999) and the latter lack probabilistic interpretation due to adjustments for hypothetical chance agreement (Stehman 1997). Although included in the calculations of A_i, the number of omissions and commissions are also presented along with A_i in table 5.1 because they provide meaningful raw indicators of classification performance. In addition, entire confusion matrices are shown for the three best combinations of classifier and feature set.

5.5 Results and discussion

Table 5.1 shows an overview of the results for each combination of classifier and feature set. Forest mapping accuracy was higher when using temporal texture as input for maximum likelihood classification as shown in bold type in table 5.1. Some classifier-feature set combinations omitted less forest pixels than the most accurate ones, whereas others classified fewer non-forest pixels as forest. For example, when mined features were input to neural networks, only six forest pixels were omitted from this class, but 658 non-forest pixels were classified as forest. On the other hand, neural networks with spatial texture showed a few commissions but more omissions than the best combination. The third best combination, univariate tree with mined features, provided a good balance between omissions and commissions, seemingly to multivariate tree with spatial texture, but yet with high accuracy. The worst classification accuracy (19%) was provided by the combination of neural networks with mined features mainly due to the large number of commissions.

Maximum likelihood performed relatively well with all input feature sets (table 5.1) with accuracy ranging from 34.5% to 51.3%. In contrast, neural networks showed the greatest variation, with accuracy ranging from 19.0% to

45.2%. Seemingly, commissions made by this type of classifier range from 72 to 658 pixels (out of 2000 pixels), the lowest and highest commission values in table 5.1. Univariate trees provided the most robust results for different feature sets. Classification accuracy ranged from 39.6% to 46.7%.

Table 5.1 Forest mapping accuracy with 99% confidence interval according to Thomas and Allcock (1984) with omissions and commissions for each combination of feature set/classifier evaluated in this study.

	Classifiers			
	Maximum Likelihood		Neural Networks	
Feature Sets	Forest accuracy (%)	Omissions / Commissions (pixels)	Forest accuracy (%)	Omissions / Commissions (pixels)
1. One Year cycle	**46.9 ± 2.4**	**16 / 149**	44.2 ± 2.2	16 / 168
2. NDVI time series	44.2 ± 2.2	16 / 168	20.8 ± 0.8	9 / 574
3. Topography	34.5 ± 1.7	16 / 261	33.8 ± 2.4	29 / 231
4. Spatial texture	39.8 ± 1.6	11 / 217	40.2 ± 5.2	68 / 72
5. Temporal texture	**51.3 ± 3.0**	**21 / 113**	35.1 ± 2.2	23 / 234
6. STRS	34.7 ± 1.0	6 / 287	**45.2 ± 2.7**	**22 / 148**
7. Mined features	42.8 ± 1.5	8 / 198	19.0 ± 0.6	6 / 658
	Univariate Tree		Multivariate Tree	
1. One Year cycle	41.8 ± 3.1	32 / 149	38.4 ± 2.4	23 / 200
2. NDVI time series	43.3 ± 1.9	13 / 182	36.0 ± 1.4	10 / 260
3. Topography	41.8 ± 3.1	32 / 149	44.0 ± 2.9	26 / 147
4. Spatial texture	39.6 ± 3.4	40 / 146	40.1 ± 4.6	59 / 95
5. Temporal texture	42.0 ± 2.5	21 / 174	32.1 ± 1.8	19 / 283
6. STRS	44.4 ± 2.5	23 / 182	43.4 ± 2.7	23 / 158
7. Mined features	**46.7 ± 4.3**	**43 / 93**	35.8 ± 1.7	14 / 251

As expected, classification confusion (arrows in Figure 5.2) occurred mainly with coffee and eucalyptus plantations, but neural networks and univariate trees also misclassified deforested areas currently covered with pasture.

Features and classifiers for mapping semideciduous Atlantic forest

The information provided by high frequency components extracted from temporal profiles was relevant in this experiment probably because of the different dynamics exhibited by natural forests and managed land cover types with similar reflectance characteristics. Considering that temporal information provides discriminating features for a given application, we suggest that these findings could be applied to other areas as well, and high frequency coefficients as extracted with pyramidal wavelet transforms might provide data reduction and yet enough information for class discrimination. The Haar wavelet was chosen for this study because it is equivalent to subtract subsequent years and, thus, represents differences in land cover characteristics between the considered years. Wavelet coefficients captured land cover dynamics enabling change information to be used effectively during classification. Note that this feature set provided more accurate results than the NDVI time series from which wavelet coefficients were extracted. This fact may be explained by the so-called curse of dimensionality: provided that the number of training samples per class is fixed, the classification accuracy decreases as the number of input features increases (Bishop 1995). In contrast to the results presented here, Borak and Strahler (1999) concluded that features representing time had minor importance for class discrimination, but their temporal data set included only images from one-year cycle. Long time series (e.g., years or decades) can be very effective for class discrimination if the goal is comparisons between natural and managed land cover types, since the latter normally exhibits strong dynamics. Another reason for this different conclusion could have been the pronounced spectral overlap of forests with perennial crops in our study site, preventing the efficient use of spectral features for class separation. Neural networks combined with STRS coefficients and univariate trees combined with mined features misclassified deforested areas currently covered with pasture (black arrows in figure 5.2), probably because of not effectively used temporal information. The fact that forests once covered these areas might have been more important for the mentioned combinations of classifiers-feature set.

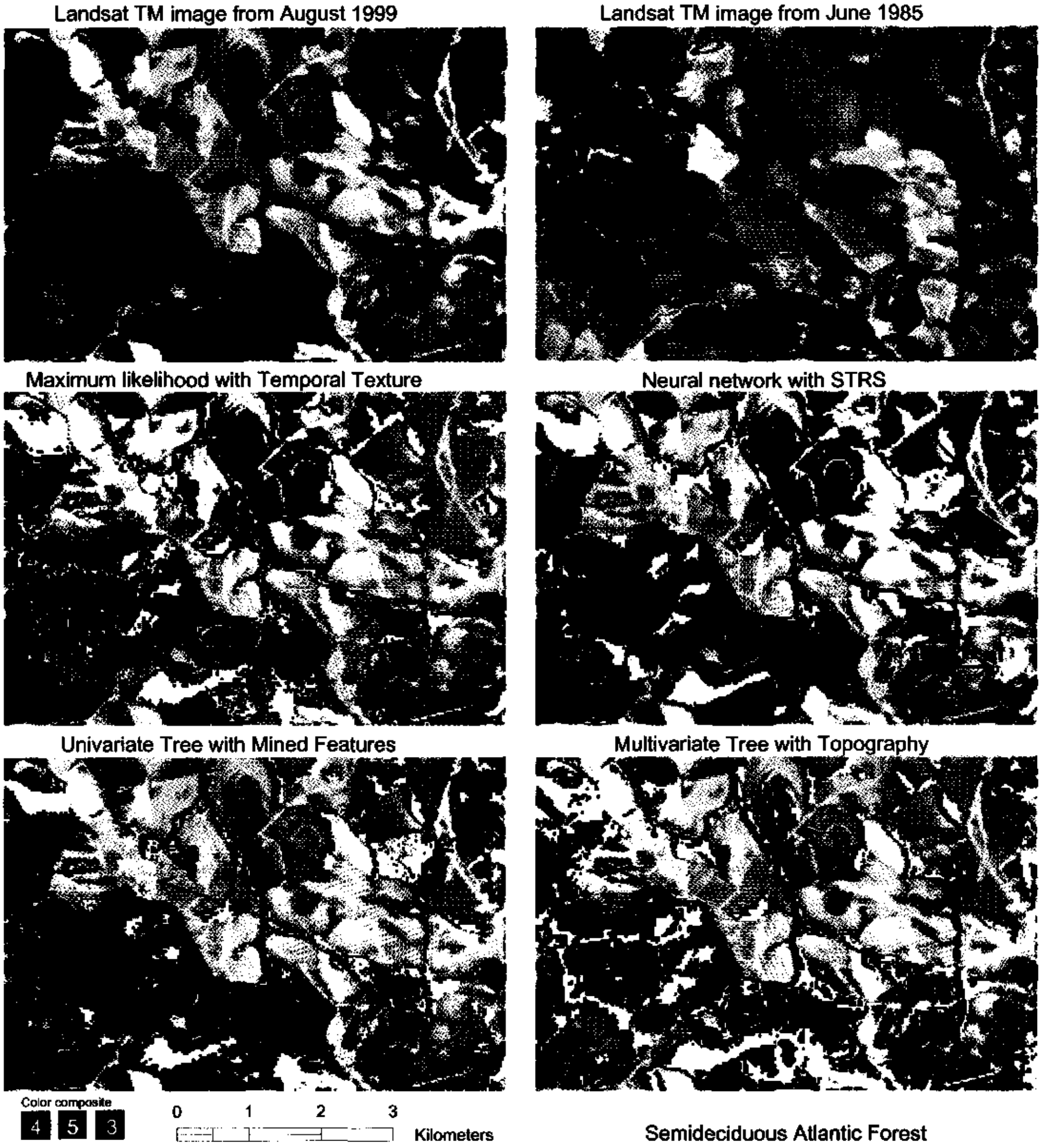

Figure 5.2 Comparison of the best four combinations of features set and classifier. Black arrows indicate misclassifications.

From the seven feature sets evaluated, only sets 3 (topography) and 4 (spatial texture) represented static information. Probably because of the explicit combination of features to define discriminant functions, multivariate trees performed well when sets 3 and 4 were supplied for classification. For example, when a multivariate tree was grown using topographic information, a discriminant function for forests was defined such that:

if (NIR - 0.0021) * slope ≤ -0.199154, ***then*** class = forest.

This important relationship between slope and near-infrared reflectance (NIR) could have been hidden for other classifiers hampering their ability to use topographic features for classification. Another indication for the lesser importance of topography and spatial texture comes from the fact that they were rarely selected during data mining and hence considered to have low discriminating power. Data mining with decision trees provided effective feature selection and reduction, but classification accuracy was improved only when the mined features were used to grow another decision tree. Eighty-one features were reduced to ten coefficients of the STRS, which kept most of the relevant information and showed good accuracy when input to neural networks, univariate and multivariate decision trees. Although preprocessing with data mining decreased the neural network accuracy, the good results provided by feature reduction with the STRS shows the benefit of using data transformations and preprocessing before neural network classification.

It is important to mention that equal prior probabilities were provided to the maximum likelihood classifier, whereas neural networks and decision trees learned the different prior probabilities from training data distributions. Even then, maximum likelihood was the best classifier in this study from which improved results can still be achieved by provision of prior probabilities for each land cover class. On the other hand, the unpredictable behaviour of neural networks could be a reflection of its lack of interpretability, demanding careful experimentation before use in particular situations.

Univariate trees performed better than multivariate trees whenever temporal information was used. Classifiers with learning capabilities generally improve when more examples (i.e., training samples) are provided. In this study, only 100 pixels per class were used for training and that could have limited the accuracy levels obtained with decision trees.

Mapping accuracy

As for the choice of classifiers, decision of what should be considered the best or worst in terms of accuracy depends largely on the objectives of the mapping project (Stehman 1997). Because the aim of this study was to evaluate classification of forests as a whole, the total number of misclassifications was the arbitrarily chosen indicator. As opposed to measures based on indicators of type I and type II errors (e.g., user and producer accuracy), the class mapping accuracy proposed by Kalensky and Scherk (1987) takes omissions and commissions into account generating an unbiased estimator of positional class accuracy (Skidmore 1999) (compare Tables 5.2 and 5.3). The combination shown in Table 5.4 would be considered the best for forest mapping if one used producer accuracy as indicator. Considering the class-oriented approach and the binary classification problem presented in this study, overall accuracy would yield similar results, but still, the combination of neural network with spatial texture (overall accuracy of 93%) would be misinterpreted as giving the second best result even omitting a large number of forest pixels. Stehman (1997) criticised the lack of probabilistic interpretation when using coefficients like Kappa and conditional Kappa, but in the present study they did not lead to misinterpretation of the case mentioned above (compare tables 5.3 and 5.4).

Table 5.2 Accuracy measures for the map produced with maximum likelihood classifier applied to feature set 5 (temporal texture). Values in the contingency table are number of pixels.

Mapped class	Ground truth			Commission error	User accuracy
	Forest	Non-forest	Total		
Forest	141	113	254	44.49%	**55.51%**
Non-forest	21	1725	1746	1.20%	98.80%
Total	162	1838	2000		
Omission error	12.96%	6.15%			
Producer accuracy	**87.04%**	93.85%			
Overall accuracy = **93.30%**	Kappa coefficient = **0.6425**				

Table 5.3 Accuracy measures for the map produced with neural network classifier applied to feature set 4 (spatial texture). Values in the contingency table are number of pixels.

Mapped class	Ground truth			Commission error	User accuracy
	Forest	Non-forest	Total		
Forest	94	72	166	43.37%	**56.63%**
Non-forest	68	1766	1834	3.71%	96.29%
Total	162	1838	2000		
Omission error	41.98%	3.92%			
Producer accuracy	**58.02%**	96.08%			
Overall accuracy = **93.00%**	Kappa coefficient = **0.5351**				

Table 5.4 Accuracy measures for the map produced with maximum likelihood applied to feature set 1 (yearly cycle). Values in the contingency table are number of pixels.

	Ground truth				
Mapped class	Forest	Non-forest	Total	Commission error	User accuracy
Forest	146	149	295	50.51%	**49.49%**
Non-forest	16	1689	1705	0.94%	99.06%
Total	162	1838	2000		
Omission error	9.88%	8.11%			
Producer accuracy	**90.12%**	91.89%			
Overall accuracy = **91.75%**	Kappa coefficient = **0.5968**				

5.6 Conclusions

Considering the study set up and its outcomes, the following statements could be drawn about mapping the semideciduous Atlantic forest:

Temporal information of vegetation indices was more important than image texture, terrain topography and raw spectral information for discriminating semideciduous Atlantic forest in the present study site.

Nevertheless, spatial texture and topographical features were still important when neural networks and multivariate trees were used for classification.

The choice of classifiers is dependent on the data, objectives, resources, and expertise available for a given mapping project. Aiming at accurate mapping of semideciduous Atlantic forest in the "Vale do Alto Rio Grande", using the data set available for this study and considering the other factors granted, one is advised to use maximum likelihood classification and temporal texture descriptors of NDVI time series as input data.

*CHAPTER SIX**

Multiscale Change Analysis

Digital change detection as commonly applied to temporal remotely sensed images produces another digital image, where pixel values represent the degree of difference between the temporal scenes under investigation. In the ideal case, areas of land cover change would show high positive or negative values, whereas non-changed areas would be zero-valued. Nevertheless, additional sources of noise and the spatial multiscale nature of input images are propagated to the outputs of digital change detection, demanding the use of tools that take these characteristics into consideration. The present chapter gives an in depth characterisation of a new approach to deal with noise and multiple spatial scales during change detection. The methodology is based on noise modelling in wavelet space for efficient and automatic thresholding. The objective of this new method was to reduce the sensitivity of digital change detection to the effects of radiometric and geometric misregistration by extracting changes according to size classes using a multiscale approach.

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* based on:

Carvalho L.M.T., 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* (in press).

6.1 Problems of digital change detection

Current methods used to compare two or more remotely sensed images and to detect differences among them are dependent on accurate radiometric normalisation and geometric rectification (Dai and Khorram 1998, Schott *et al.* 1988). These prerequisites are generally hard to achieve in many situations due to the lack of (radiometric) calibration data and difficulties in locating (geometric) control points. In addition, a threshold value to separate change from no-change areas must be defined. In the absence of noise, thresholding a difference image would be an easy procedure leading to reasonable results. Unfortunately, discrepancies in sensor characteristics, atmospheric transparency, vegetation phenology and errors in geometric registration are a few examples of noise sources present in every multitemporal/multisensor data set derived from optical remote sensing.

In the operational context, digital change detection has been normally performed with a category-based approach that compares land cover maps produced at different points in time. The choice for this approach is motivated by the straightforward information about old and new land cover classes represented by each image pixel that has undergone land cover change. However, uncertainty propagation reduces considerably the confidence level of change detection results obtained with map comparisons (Shi and Ehlers 1996, Bruin and Grote 2000). For example, two highly accurate classification results, say 80%, would produce a mere 64% accurate change detection result (Stow *et al.* 1980). In the research context, radiometric-based change detection techniques are more popular than category-based ones because of their ability to overcome the above-mentioned drawback, but as pointed out before, they are more sensitive to errors in geometric and radiometric registration. This becomes even more important when different sensors with different spatial and radiometric resolutions are used for change detection. Moreover, the amount of change is dependent on the empirically defined thresholds, to which there is no theoretical guidance.

Consequently, a need for automatic analysis tools able to minimise these requirements has been recognised (Singh 1989). The dilemma relies on how to differentiate real changes from misregistration (geometric and radiometric) noise.

6.2 Multiscale feature extraction

Wavelet analysis in discrete time corresponds to successive band pass filters decomposing the signal at each step into details and overall pattern (chapter 3). In a two-channel filter bank it separates the high from the low frequencies recursively using the same transform at a new scale (Strang and Nguyen 1997). A change image, produced by any of the standard radiometric change detection methods (e.g., image differencing), is decomposed into several high frequency bands with variable resolutions plus a low frequency band at the coarsest resolution. The decomposition was obtained by applying the 2D extension of the algorithm "*à trous*" (Holschneider *et al.* 1989) with a cubic spline as the scaling function: After decomposition, the differences between the images are separated into five detail levels ranging from fine to coarse, as well as a smoothed representation of the original difference image (Figure 6.1). At this stage, changed sites are discriminated according to size classes. Small area changes and geometric misregistration are captured in the fine details representation whereas overall changes, like variations due to phenology, are captured at the coarse details levels and at the smoothed representation of the original difference image. Thus, by solely using information provided by intermediate scale levels, spurious effects of misregistration are filtered out and the search space is considerably reduced.

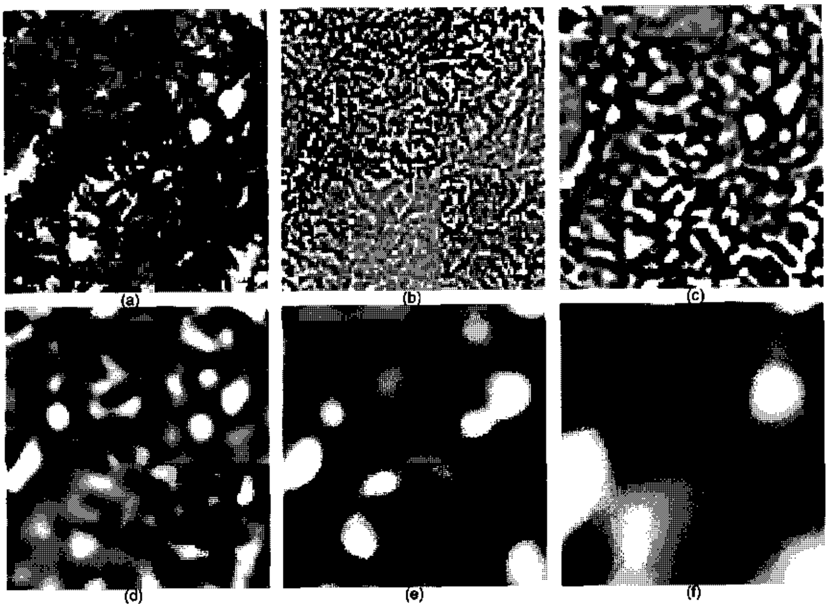

Figure 6.1 (a) Result of image differencing (TM band 3 from 1998 and MSS band 2 from 1981). (b, c, d and e) Detail images ranging from fine to coarse and (f) smoothed version of (a) decomposed with the "*à trous*" algorithm.

Landsat TM bands 2 (520-600 nm), 3 (630-690 nm), 4 (760-900 nm) and Landsat MSS bands 1 (500-590 nm), 2 (610-680 nm), 3 (790-890 nm) were chosen to perform this experiment because they cover relatively comparable portions of the electromagnetic spectrum (Buiten and Clevers 1996). Note that spatial resolution, sensor characteristics and phenological conditions are very heterogeneous among these images (Figure 6.2). The images were reduced to the same pixel size by applying a one level pyramidal wavelet transform using a cubic spline as scaling function. Due to decimation, the pixel size for the Landsat TM images became 60x60m after the transformation. The Landsat MSS image, preprocessed by the U.S. Geological Survey and purchased with a pixel size of 57x57m, was resampled to 60x60m with a nearest neighbour algorithm. No radiometric rectification was applied to the input images and spatial misregistration (RMS error < 1 pixel) ranged from one to three pixels when evaluated visually.

Ground data were recorded during field visits in 1999 when sites of deforestation, new rock exploitation, annual crops, and forest regrowth were located in the field and over orthophotos (scale 1:10,000) acquired in 1984.

6.5 Results and Discussion

Using the multiscale product in a simple colour composite, visualisation of changed sites can be readily done. To visualise changes from dark to light (e.g. deforestation in TM band 3), one must use the oldest image to make the composite (Figure 6.3). Changes from light to dark (e.g. reforestation in TM band 3) are better visualised when using the most recent image. This is because the background at sites where changes are to be visualised must be dark so that the changes of interest are emphasised. All changes detected by this visualisation procedure did occur although their quantification was not possible. Note that, in Figure 6.3, the whole triangular forest fragment at the bottom right disappeared between 1985 and 1998 although only its centre is being enhanced. This straightforward visualisation might be of much use when large areas are to be evaluated. Misregistration effects and small area changes were isolated as fine details (Figure 6.4d), while differences in phenological characteristics and atmospheric conditions were captured in the smoothed representation as overall differences between the images (Figure 6.4e).

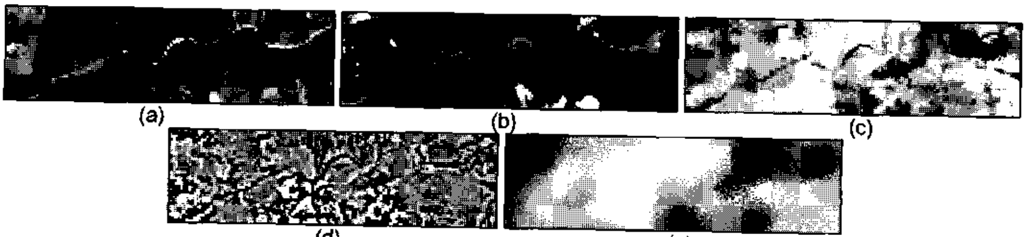

Figure 6.4 Landsat TM from (a) 1998, (b) 1985 and (c) respective difference image. (d) Details of the difference image at the first scale level. (e) Smoothed version of the difference image at the fourth scale level. Note the misregistered road depicted in (d), while overall differences like phenological condition of vegetation patches are depicted in (e).

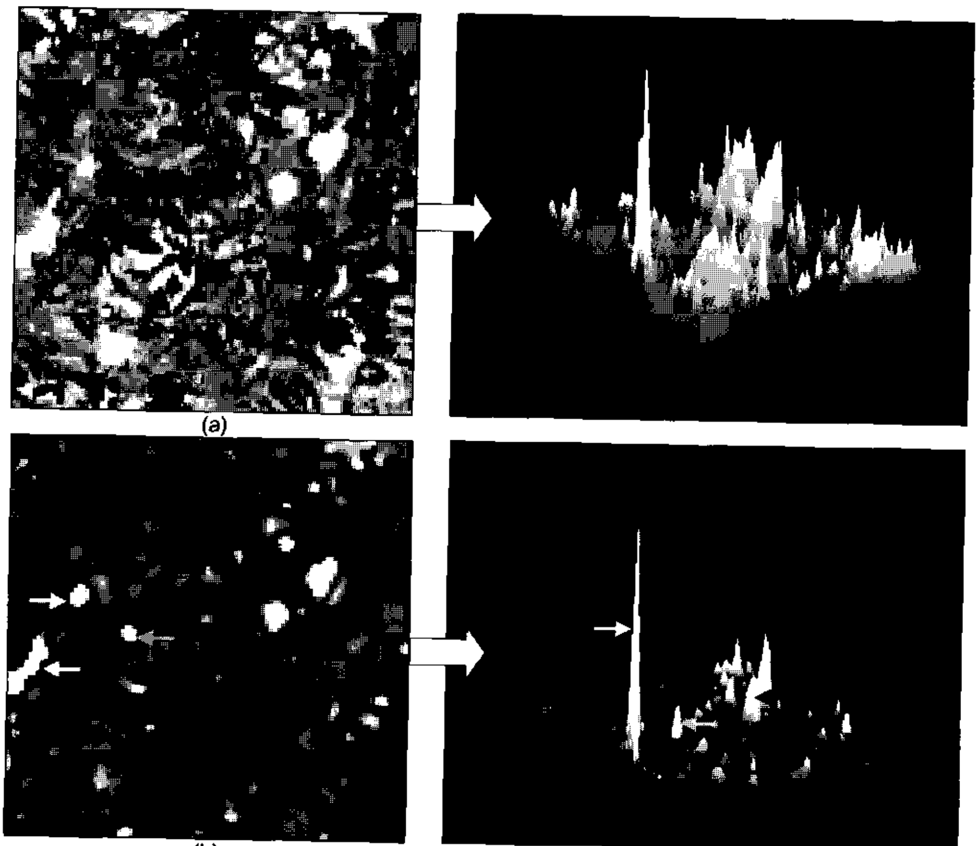

Figure 6.5 (a) Difference image between band 3 of Landsat TM from 1998 and band 2 of Landsat MSS from 1981 with respective 3D view. (b) Product of differences at second and third scales and respective 3D view.

Unrelevant information that could be considered noise in the difference image (figure 6.5a) does not appear in the change image built with the product of wavelet scales (figure 6.5b). This 'cleaning' effect facilitates the analysis and understanding of remotely sensed images. In figure 6.5, vegetation removal (black arrows), reforested areas (grey arrows) as well as new rock exploitation sites (white arrows) were pinpointed successfully without previous radiometric rectification or threshold definition while differences not related to land cover changes were bypassed.

6.6 Conclusions

The behaviour of changes at different scale levels as resulting from the new method presented here enables their discrimination according to size classes. Hence, using information from intermediate scale levels one can minimise the problems mentioned above. The method was found to be less sensitive to spatial and radiometric misregistration, although fine details are lost as well. It can be applied to the outputs of any change detection technique such as image rationing, principal components, change vector analysis etc.

As for the selection of significant wavelet coefficients, the selection of scale levels to be considered for further analysis can be driven by statistical tests, which are useful when no knowledge exists on the size of features of interest.

Changes in the study area were well discriminated but their quantification was not possible when using information from limited scale levels. Further research on the combination with other techniques, like region growing algorithms, could be a solution to determine the spatial extent of changed sites. Applications of the proposed method include, for instance, the automatic selection of changed sites for GIS updating and the fast identification of priority areas for field check when large data sets are to be evaluated. Finally, the visualisation of changed sites is straightforward with a simple colour composite avoiding any threshold definition, radiometric rectification or accurate geometric registration.

Chapter Seven[*]

Automatic Deforestation Detection

Remote sensing and GIS are being increasingly used in combination. GIS databases are used to improve the extraction of relevant information from remote sensing imagery, whereas remote sensing data provide periodic pictures of geometric and thematic characteristics of terrain objects, improving our ability to detect changes and update GIS databases (Janssen 1993). In the previous chapter, a method to extract change information at varying spatial scales was presented and discussed. This chapter incorporates the multiscale change analysis in an operational environment to automatically detect changes and to update GIS databases using multitemporal remote sensing imagery.

Most research efforts for monitoring land cover change with remote sensing have dealt with localised case studies of an experimental nature (Wyatt 2000). Considering monitoring of forests, the PRODES project (Estimate of Amazon gross deforestation) from the Brazilian Institute for Space Research (INPE) is one of the few examples of operational application of high spatial resolution remote sensing data for change analysis over large geographical areas.

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[*] based on:

Carvalho L.M.T., Clevers J.G.P.W., Jong S. & Skidmore A. 2001. Automatic GIS updating using feature extraction, segmentation and classification of remote sensing imagery. *International Journal of Geographic Information Sciences* (submitted).

It has been providing valuable estimates of deforestation since 1974. The methodology used by PRODES still relies on manual delineation of deforested areas involving for each assessment approximately 50,000 man-hours with a team of 70 remote sensing specialists supervised by 15 researchers (INPE 2000). Such a framework would be inapplicable for complex fragmented landscapes, as in the case studies presented in this thesis, unless automation of some tasks is achieved. The Landsat Pathfinder project (deforestation in the humid tropics) is another relevant attempt to monitor land cover at large scales with high spatial resolution imagery, which gave strong evidence for the need of automated approaches as well (Townshend *et al.* 1997).

The difficulties with land cover change detection are further complicated when compared to land cover mapping, imposing limits to automation. In fact, as change analysis with remote sensing compares image snap shots acquired at intervals of time, they inevitably inherit problems of single-date image analysis and rise new ones related to the integration of multitemporal data sets. The first difficulty while handling time-series of remotely sensed data is (1) the geometric transformation of each image in the series to match a reference image or map. Errors result from this process and part of detected changes is caused by misregistration (Townshend *et al.* 1992). Another important spatial aspect is related to (2) the size of changes to be observed. Change detection is limited by the nominal spatial resolution of the sensor, the degree of fragmentation of the landscape and the nature of boundaries between objects. They influence land cover mixture in a pixel, which may vary from one date to the other, even if no land cover change occurs. (3) Temporal scales in which changes occur must be considered as well, and the choice of sensors to provide data should be guided by the nature of processes under investigation. (4) Atmospheric conditions by the time of image acquisition vary considerably and might weaken the signal that reaches the sensor or even obstruct it completely, generating differences that can be misinterpreted as land cover change. (5) Remote sensing-based land cover studies rely on the premise that the radiometric response of objects on the Earth's surface must differ in the spectral region covered by the sensor. Finally, (6) some changes are gradual and their detection is difficult. Forest degradation and regeneration, for instance, are much harder to quantify with remote sensing when compared to forest removal. Advances on hyper-spectral and -temporal data analysis may help to study such cases, but their use for change detection is still premature (Wyatt 2000).

7.1 Automation in digital change detection

Automation has been one of the early goals of geoinformation processing due to the potential of performing unsupervised tasks provided by computer-aided analysis (Tzschupke 1976, Dobson 1983). In digital change detection, little work has been carried out in this direction and the few established procedures are related to image classification (Tou and Gonzales 1974). Automated change detection using remote sensing data is reported by a few recent studies (Chavez and Mackinnon 1994, Michener and Houhoulis 1997, Pristnall and Glover 1998, Hamë *et al.* 1998, Kwartenge and Chavez 1998, Salvador *et al.* 2000). Even so, the term 'automated' is causing confusion in literature, considering that the process of change detection is very broad and should not be misinterpreted as the simple act of automatically producing, for instance, a difference or ratio image.

The approach proposed by Priestnall and Glover (1998) for updating vector-based GIS represents an effective step towards automation of change detection. Yet, they concluded that the project is still in the beginning and many challenges are still to be met. This is because their aim is on cartographic-quality updating of high spatial resolution databases involving increased complexity of contextual information, which in turn makes the approach complex. Hamë *et al.* (1998) described an interesting procedure (called "AutoChange") as a change detection and recognition system that could be considered automatic. The procedure is also complex and though the term 'recognition' was used to describe it, the outputs only provide changes and their magnitudes, but not labels. Furthermore, its best reported performance was below 66% of correct distinction between changed and unchanged pixels. Machine learning techniques are potential tools for automatic change detection, which were evaluated in recent studies by Abuelgasim *et al.* (1999) using fuzzy neural networks and Dai and Khorram (1999) using multi-layer perceptron (MLP).

The aim of this study was to develop an automated, simple and flexible procedure for raster-based GIS updating. Automated in the sense that changes are detected, segmented, classified, and the GIS layers updated without human interaction, though ground-truth for changed sites and spectral signatures of the new land cover classes must be known in advance. Note that this is also the case with the so-called unsupervised classification algorithms, where the analyst still has to label clusters. Flexibility relates to the possibility of accommodating various segmentation and classification schemes (e.g., machine learning algorithms, parametric classifiers), of taking into consideration knowledge on the changes of interest (i.e., denoising), and of using pixel- or object-oriented approaches during classification.

7.2 A compound procedure for automatic GIS updating

The procedure proposed and illustrated in this chapter (figure 7.1) uses as input two remotely sensed (RS) images acquired at different points in time (t_1 and t_2), GIS layers representing the land cover types under investigation, and a set of ground-truth data (GT) for the present land cover pattern and for changed sites. The most recent image is used to update the GIS layers based on radiometric differences with the oldest image. This latter should have been acquired near the map production date to give a representative picture of the land cover pattern by that time.

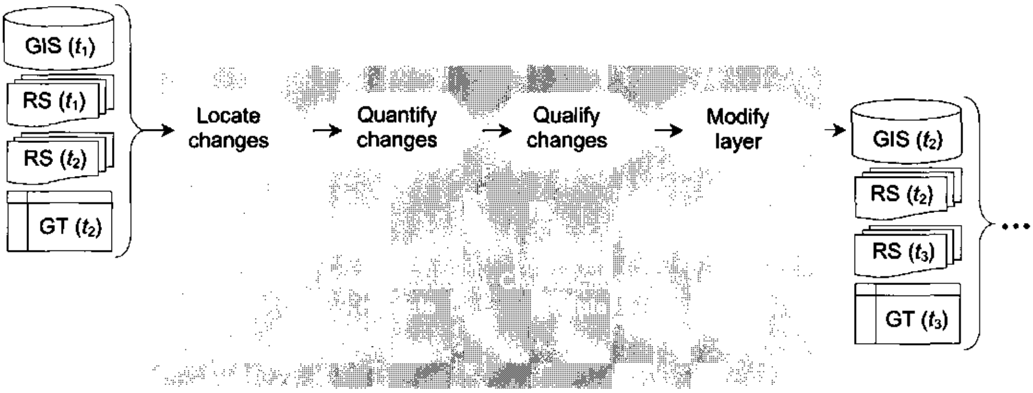

Figure 7.1 Flow diagram illustrating the main modules of the procedure.

Four modules compose the procedure according to the main tasks performed: (1) location of changed sites, (2) quantification of changed area, (3) classification of the new land cover type, and (4) updating the database. First, the difference image is decomposed with wavelet transforms and the maxima of multiscale products representing significant singularities are extracted at changed sites. Secondly, segmentation is performed on the difference image based on a decision rule to check if the pixels surrounding each detected maximum are spectrally similar. Thirdly, each changed pixel or each segmented region is assigned to the land cover class with the highest probability of membership. Then, the output is used to update all the GIS layers where changes took place. Each module is explained in more detail in the following sections.

Search module

The extraction of meaningful information from noisy, high-dimensional and multi-modal data sets is a complex task, which requires new and appropriate tools for tackling the problem. For the present algorithm, feature extraction is performed with the aid of multiresolution wavelet analysis and the so-called multiscale products (Sadler and Swami 1999, Carvalho *et al.* 2000), where maxima points are extracted at changed sites. Small area changes and geometric misregistration are captured in the fine wavelet scales whereas overall changes, such as variations due to phenology, are captured at the coarse wavelet scales and at the smoothed representation of the original difference image. Thus, multiscale products are calculated using only intermediate wavelet scales to filter out spurious effects of misregistration and to reduce the search space (see chapter 6). At this stage, maxima points are located in the filtered multiscale product if the value of a pixel is greater than its eight immediate neighbours. In this study, the difference image was produced by subtracting images of different dates.

Segmentation module

For abrupt radiometric changes (e.g. deforestation, burnings, geometric misregistration etc) the decision of what represents change is easily taken by level slicing the difference image. In this experiment, segmentation of changed areas was performed with a simple region-growing algorithm, where neighbouring pixels of the detected maxima were sequentially evaluated by a decision rule until no more neighbours of the grown region meet the defined criterion. The decision threshold used was empirically extracted from groundtruth as 1.5 standard deviations from the mean value of the difference image. For example, if some neighbours of the pixel under consideration are greater than a threshold, they are stored sequentially in a temporary array. The first one is now turned into the pixel under consideration and its neighbours, greater than the threshold, are stored at the end of the same temporary array. This process iterates until the pixel under consideration has no neighbours greater than the threshold. Then, the next pixel in the temporary array is considered. The segmentation stops when the end of the temporary array is reached. Alternatively, the module may use adaptive thresholding with parametric or non-parametric rules applied to the spatial context surrounding each seed pixel (i.e., detected maximum) in single band or multispectral difference images.

Classification module

The classification of changed areas may be performed according to any desired decision rule (e.g., maximum likelihood, minimum distance, neural networks, decision trees etc) or even by an unsupervised procedure. If classification is unsupervised, the output clusters will have no label. In the supervised case, groundtruth for land cover classes of the most recent image must exist with which to compare the segmented areas. The comparison might be performed pixel-by-pixel or assuming homogeneity within the segmented regions. In the first case, each pixel is assigned to the class that has the largest probability of membership. The second case can be viewed as an object-oriented approach, where each segmented area is considered a single object, which is assigned to the class that has the largest probability of membership. The output of this module is a thematic change layer where pixels that did not change are zero-valued. For this study a supervised scheme with maximum likelihood decision rules was used in a pixel-by-pixel base.

Updating module

This module assumes that GIS layers are input to the procedure as binary raster-based masks. Then, updating is straightforward with two simple conditional statements. (1) If a given location (i.e., pixel) in the change layer and in the GIS input layer are different from zero, then the land cover at this position has changed and the corresponding pixel in the GIS layer is assigned a value of zero. (2) If the changed pixel belongs to the land cover class represented by the input GIS layer, then a value of one is assigned to that location in the GIS layer under consideration. In this way, an updated binary mask representing the new land cover configuration is generated for each input GIS layer.

7.3 Other approaches to automatic change detection

Two other methods for change detection and identification were applied in this study: post classification comparison and direct multidate classification using artificial neural networks. The post classification comparison was chosen because it is the most popular in an operational context and a standard reference in change detection studies, whereas the neural network approach was chosen because it has been regarded as a promising tool for various automated tasks concerning geoinformation processing.

Post-classification comparison

This simple approach consists of comparing the properly coded results of two separate classifications. Normally, the map from time t_1 is compared with the map produced at time t_2, and a complete matrix of categorical changes is obtained. For comparison purposes, the post classification approach could be illustrated as in the diagram of figure 7.1, which would become:

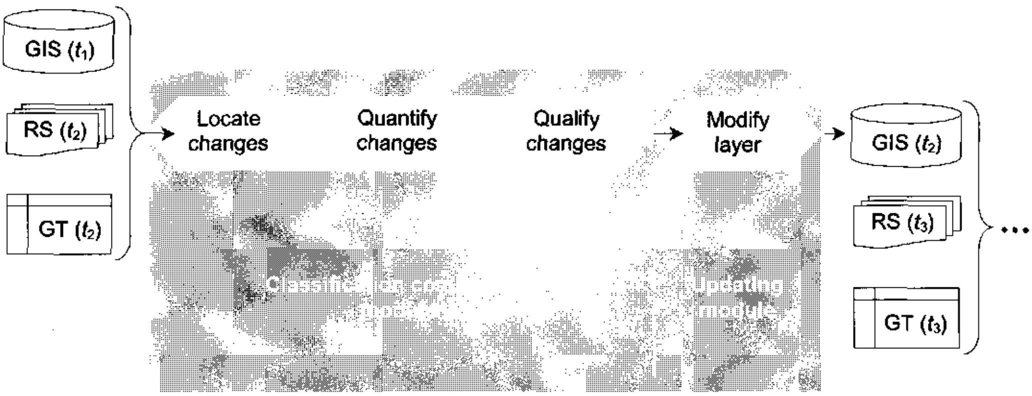

Figure 7.2 Flow diagram illustrating post classification comparison.

Artificial Neural networks

Neural network based change detection follows the same principles of traditional image classification, but includes the land cover classes of both times. The direct multidate classification procedure proposed and described in Dai and Khorran (1999) for change detection was implemented in the present study. The authors used the MLP neural network model (chapter 3, page 31) to classify a single data set composed by 12 Landsat TM bands, six from time t_1 and six from time t_2. Slightly different from the procedure used by Dai and Khorran (1999), our architectural settings were defined as follows: a four-layer fully interconnected network with back-propagation learning algorithm was used. The network had six nodes in the input layer because only three image bands were available for each date. The output layer had one node for each of the 16 change classes (i.e., direct output encoding) and the two intermediate (hidden) layers had 6 nodes each. The selected activation method was the sigmoid function with a fixed learning rate set to 0.001 and learning momentum set to 0.00005. Using neural networks for change detection, the base diagram of figure 7.1 would become:

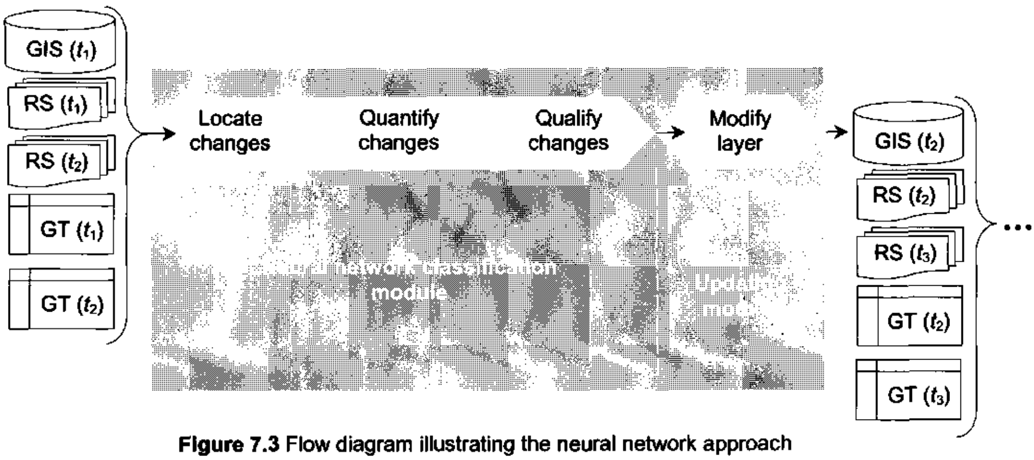

Figure 7.3 Flow diagram illustrating the neural network approach for change detection.

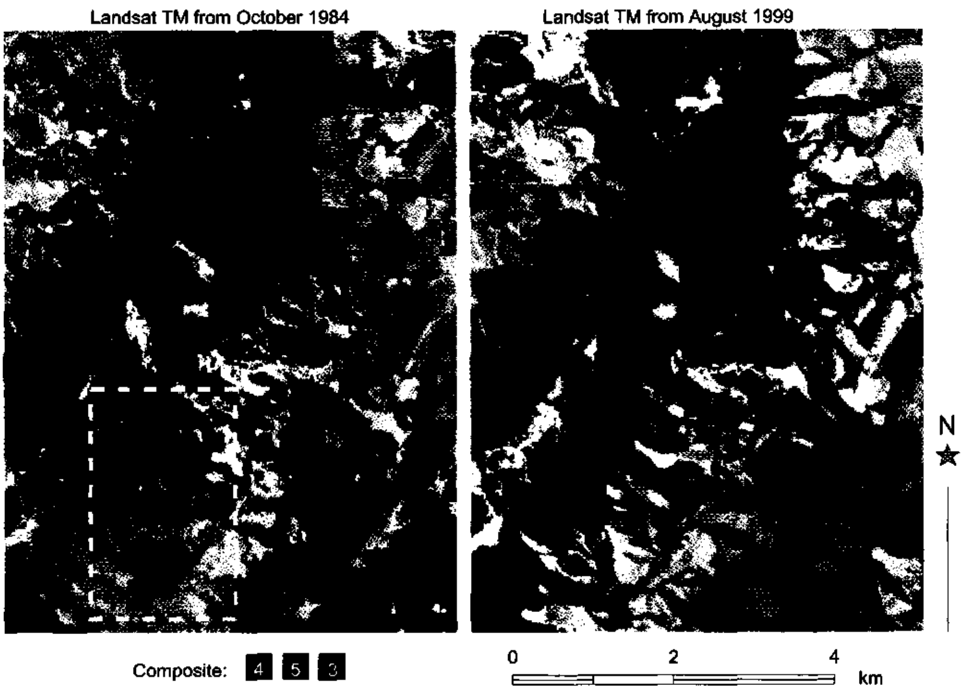

Figure 7.4 Image subsets used in this study.

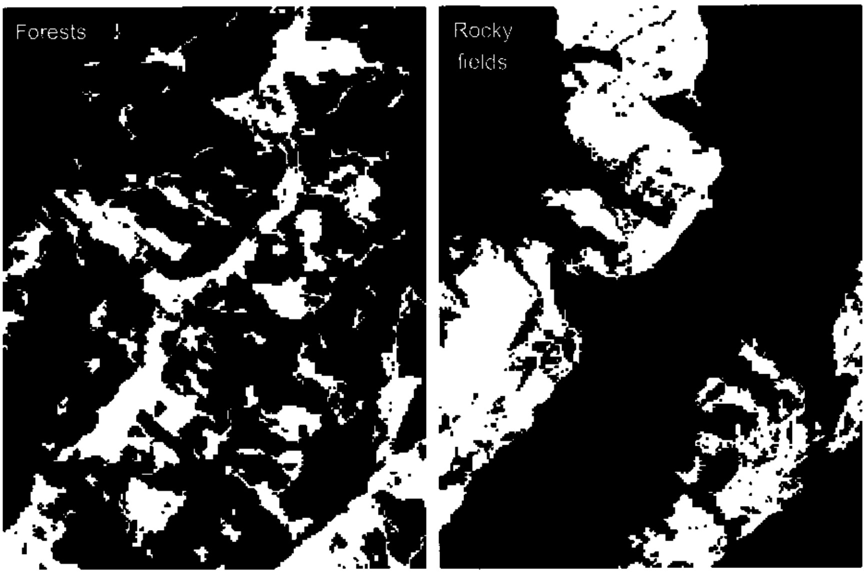

Figure 7.5 Land cover layers to be updated.

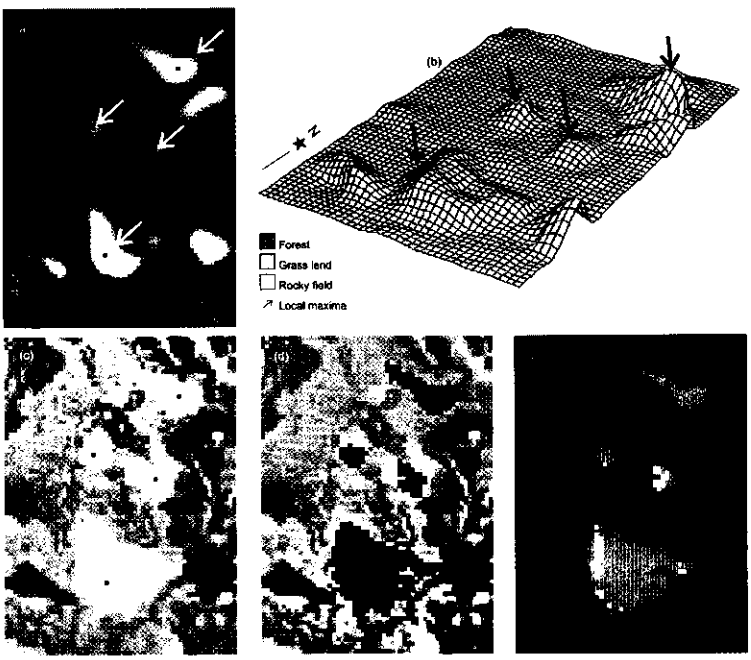

Figure 7.6 Sequence of the results produced by the first three modules of the procedure proposed in this chapter. (a and b) Identification of maxima points, (c) output from search module, (d) output from segmentation module, and (e) output from classification module.

7.4 Test site and data

The case study comprised subsets of 187 x 250 pixels of co-registered Landsat TM images (path 218, row 75) from October 1984 and August 1999 (figure 7.4), for which detailed ground truth was available. Two raster layers from a GIS database concerning semi-natural areas of forest and rocky-fields were used as the subjects to be updated (figure 7.5). Note that illumination and phenological conditions are distinct within the imagery set. The image from 1999 has more relief shadows and the overall reflectance of vegetated areas in 1984 is notably higher. Yet, no attempt was made to correct these differences, as we believe that the proposed method is insensitive to them. It is also important to mention that the proposed method is also considered to be less dependent on accurate image registration. Thus, only five ground control points (GCPs) were used to register a large image of 6500 x 4000 pixels, which was subset afterwards for this study. The root mean square error was 0.64 pixel, but visually evaluated displacements ranged from one to three pixels. TM band 3 was input to the search and segmentation modules whereas bands 3, 4 and 5 to the classification module.

Ancillary data comprised a complete orthophoto mosaic (1:10,000) from 1984, small-format aerial photos, and GPS measurements on the ground acquired during field campaigns in 1999. Orthophotos were used during field surveys to locate ground-truth samples. Thirty sample pixels of forest, rocky-field, grass land and rock exploitation sites were used to train the classifiers. In the neural network approach, training samples included all possible combinations of changes, whereas the other two approaches required only samples representing the four land cover classes occurring in the area. For accuracy assessment, deforestation and new rock exploitation sites were identified within a random set of 200 forest pixels and 200 rocky-field pixels. The change maps obtained with the proposed procedure, post-classification comparison, and neural networks were organised in contingency tables from which standard per pixel error estimates were extracted.

7.5 Results and discussion

Figure 7.6 (a) and (b) illustrate the local maxima (arrows) found in the multiscale product image. They correspond to sites where land cover has changed in the GIS layers under consideration. Note that the multiscale product image presented in figure 7.6(a) and (b) is almost flat everywhere except for changed sites facilitating their automatic location. The detected maxima are then located in the data set that will be subject to the region growing algorithm, which, in the present case corresponds to a single band difference image (figure 7.6c). The regions segmented with the region growing algorithm are illustrated in figure 7.6 (d). Pixels surrounding the detected maxima were considered to have changed and included in the region if they exceeded the threshold value. In this study, the threshold value was empirically determined because enough groundtruth data were available. Yet, this threshold might be automatically defined by considering the standard deviation of immediate neighbours of all detected maxima and by applying statistical significance tests. Finally, figure 7.6 (e) shows the segmented regions classified on a pixel-by-pixel basis. These results were then used to update the GIS layer representing forest areas.

Comparison with other approaches

Tables 7.1, 7.2, and 7.3 show the calculated change detection accuracy for the method proposed in this chapter, the neural network-based change detection, and for the classification comparison method, respectively. Although not significantly different (z = 0.1992) (Cohen 1960), artificial neural networks performed slightly better than our approach. On the other hand, post classification comparison results were far worse than the other approaches, confirming the expected error propagation of separate classifications.

Table 7.1 Confusion matrix of the change detection results produced by the method proposed in this chapter.

	Ground truth (pixels)				
Mapped class	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	14	0	0	0	14
Grass	1	21	0	3	25
Rocky field	4	1	181	1	187
Forest	0	4	0	170	174
Totals	19	26	181	174	400

Overall Accuracy = 96.5% (386/400) Kappa Coefficient = 0.9410

Table 7.2 Confusion matrix of the change detection results produced by the neural network-based change detection.

	Ground truth (pixels)				
Mapped class	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	15	0	0	0	15
Grass	0	21	0	3	25
Rocky field	4	0	181	1	186
Forest	0	5	0	170	175
Totals	19	26	181	174	400
Overall Accuracy = 96.75% (387/400)		Kappa Coefficient = 0.9452			

Table 7.3 Confusion matrix of change detection results produced by the post classification comparison method using maximum likelihood supervised classification.

	Ground truth (pixels)				
Mapped class	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	15	0	1	1	17
Grass	0	21	16	7	44
Rocky field	4	2	142	8	156
Forest	0	3	22	158	183
Totals	19	26	181	174	400
Overall Accuracy = 84.0% (336/400)		Kappa Coefficient = 0.7400			

Field surveys revealed that changed patches were converted to only one new cover type. Forest areas were replaced by grassland, and rocky-field areas by rock exploitation. Thus, the results provided by our approach might be further improved if an object-oriented approach is used. Each segmented region would then be treated as a single entity and assigned to a unique class. This would reduce the problem of speckled misclassification, which was not well represented in the test samples but visually detected as a considerable problem in changes from rocky-field to rock exploitation areas, mainly at the segments' edges. On the other hand, classification of deforested areas was well described by the confusion matrix, since visual evaluation showed just a few misclassifications.

Figure 7.7 shows the change maps produced by each method evaluated in this study to update the GIS layer representing forest cover. Note the strong effect of geometric misregistration represented by many small and linear change patterns depicted with post classification comparison (figure 7.7c) and the neural network-based change detection (figure 7.7b). The method proposed here (figure 7.7a) was more effective in depicting important changes.

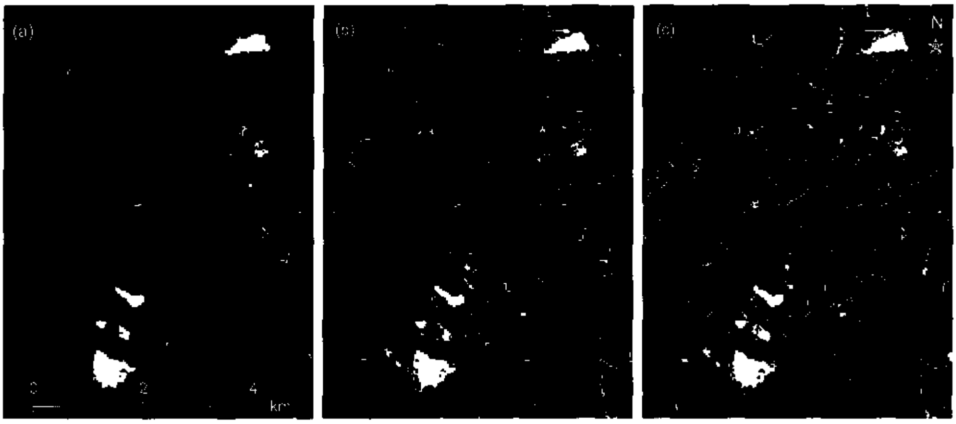

Figure 7.7 Change maps produced with our compound procedure (a), with artificial neural networks (b), and with post classification comparison (c).

The techniques currently available for detecting changes on remotely sensed data are dependent on accurate radiometric and geometric rectification (Dai and Khorram 1998, Schott *et al.* 1988), which are difficult tasks in most situations (e.g. poor quality of old sensors). The method proposed here detected changes using TM band 3, which is the one most influenced by atmospheric effects within the available set (i.e., bands 3, 4 and 5). Temporal images were acquired in different seasons of the year and were considerably misregistered. Even then, the procedure performed well and was insensitive to these problems. The methodology developed in an earlier work (Carvalho *et al.* 2000, chapter 6) and incorporated in the present procedure enabled the automation of change detection with remotely sensed data by taking advantage of singularity detection and denoising capabilities of wavelet transforms. These capabilities have already proven to be useful in the field of remote sensing to automate other tasks like GCPs definition for geometric registration (Djamdji *et al.* 1993) and extraction of linear features (Ji 1996). Furthermore, the wavelet approach eases change detection in images with different pixel sizes in a straightforward manner because of its multiresolution nature (Carvalho *et al.* 2000, chapter 6). Remotely sensed images are relatively noisy signals, which provide lots of information at different spatial scales. In this sense, the procedure presented in this chapter provides considerable improvements over post classification comparison and direct multidate classification (figure 7.7), even considering that the latter provided a slightly better classification accuracy (compare tables 7.1 and 7.2).

In spite of considering only one spectral band for analysis, the algorithm proposed here can be easily extended to the multispectral case by adding data integration steps during search and segmentation. Because information provided by various spectral bands is different, detected maxima in the search module would also differ from band to band. Segmentation in multidimensional space would have to evaluate the feature vector of each pixel being considered for inclusion in the region in the very same way as multispectral classification. These are two future directions to improve the procedure.

The possibility of using different decision rules in the segmentation and labelling modules is an important characteristic of the procedure to meet specific requirements in different situations. For instance, when classes under investigation are accurately modelled by unimodal probability distributions, a maximum likelihood decision rule would be well suited. Unfortunately, this is not always the case and the possibility of using other non-parametric rules is acknowledged. Finally, the procedure is especially attractive for monitoring large areas, where detailed inspection of difference images is prohibitive.

7.6 Conclusions

In this chapter, a framework for digital change detection and automatic GIS updating has been developed, demonstrated, and compared with other commonly used methods. The approach is relatively simple and provides advantages over traditional methods like post classification comparisons and direct multidate classifications. First, the method is less sensitive to geometric and radiometric misregistrations because of the multiresolution approach to feature extraction included in the search module. Second, different from post classification comparisons, it requires groundtruth data only for the present land cover pattern. In comparison to direct multidate classification, change-classes do not need to be defined or training samples to be collected at changed sites. Finally, an object-oriented approach might be used, avoiding speckled misclassifications, which could improve classification accuracy. Further refinements of the procedure include the automatic threshold definition and the possibility of working with multivariate difference images.

Chapter Eight

Conclusions

According to the main objectives of this thesis, a remote sensing-based strategy to map and monitor forest remnants in highly fragmented areas has been developed for the "*Vale do Alto Rio Grande*" region. The research was part of a larger project that investigates forests in southeastern and central Brazil, which is called "Strategy for Conservation and Management of biodiversity in fragments of semideciduous forests". A procedure that could be easily implemented by non-experts in image processing for rapid assessment of deforestation hot spots over large areas has been developed for and tested on a study area with a complex land cover pattern in southeastern Brazil. It has the potential to provide local authorities and governmental institutes with a deforestation warning system for the remnants of semideciduous Atlantic forest, where the visualisation of changed sites is straightforward with a simple colour composite avoiding any threshold definition, radiometric rectification or accurate geometric registration.

The use of temporal information was intensively explored not only for monitoring, but also for mapping purposes. In this context, methodologies had to be developed to correct, integrate and enable the proper use of time series of Landsat TM imagery.

This concluding chapter is organised as follows. In section 8.1, significant achievements of this study related to mapping and monitoring the semideciduous Atlantic forest with remotely sensed data are described. In section 8.2, a multiscale processing environment for high-dimensional data sets is proposed, which synthesises all the data processing carried out in this thesis and gives room for further improvements. Future research topics as well as possible directions for improvement are listed in section 8.3.

8.1 Answers to the research questions

The main research questions of this study will be listed again, followed by the respective answers proposed in this thesis.

Question: What are the preprocessing requirements to the application of remotely sensed time series in environmental modelling? How appropriate are the existing preprocessing techniques?

The effective application of multitemporal Landsat images to environmental modelling requires a great amount of preprocessing to bring the data to a usable format, mainly because of cloud cover and misregistrations. Clouded areas must be identified as well as replaced and image registration must be as accurate as possible. Existing preprocessing techniques can carry out these tasks but they are difficult and time consuming, requiring a great amount of human interaction. *The wavelet-based regression technique described in chapter 3 removed clouds and corrected for misregistration simultaneously and automatically, while providing reliable estimates for the values that were replaced.*

Question: How appropriate are the temporal analysis tools?

In terms of time series processing, *the multiscale approach provided an effective tool for studying remotely sensed images that were arbitrarily sampled in time, contaminated by clouds and shadows, corrupted by misregistration as well as random Gaussian noise.* In terms of traditional change detection using images of two distinct dates, *the framework described in chapter 6 and implemented in chapter 7 is less sensitive to noise caused by misregistration, it might be combined with any standard change detection technique and provides an aid to rapid change detection over large geographical areas.* A minor disadvantage of the method is that fine details are regarded as noise and removed as well.

Question: What kind of remotely sensed data is relevant to map semideciduous Atlantic forests? Can temporal information improve traditional multispectral classification?

The strong spectral similarity between natural forests and some planted crops hampers the use of single date remote sensing data for mapping forests in the study site. *Temporal information is of utmost importance for mapping the semideciduous Atlantic forest and particularly NDVI time series proved to be useful features for classification.* This fact could be explained by the contrasting long-term and seasonal dynamics exhibited by natural forests and planted crops. As shown in chapter 5, terrain elevation, slope and aspect are apparently less important than temporal information probably because forested areas occur across all relief types in the study site. Nevertheless, topographic properties still provide improvements in classification accuracy when compared to the use of spectral information alone.

Question: To what extent can geoinformation processing be automated?

Machine learning and multiscale approaches can facilitate automation, but even then, some degree of human input will always be necessary due to the complex nature of the Earth's surface. *Multiscale methods reduce the amount of information to be analysed when performing automated tasks, but knowledge on which scale levels to look at must exist. Similarly, neural networks and decision tree models must be carefully constructed with a considerable amount of training data before accurate generalisations over larger domains can be done.*

Question: How appropriate are the classification tools? Can artificial intelligence improve over traditional techniques?

In the experiment concerning mapping remnants of semideciduous Atlantic forest (chapter 5)*, the traditional maximum likelihood classification algorithm clearly outperformed the algorithms based on machine learning techniques when temporal features were used for classification.* This could be due to the fact that the distribution of forest pixels in multidimensional feature space (constructed with temporal information) was not so complex as expected, and could be accurately described with parametric models. Nevertheless, this is an intrinsic characteristic of specific thematic classes, which justify a class-oriented approach in classification. This observation suggests that probabilistic classifiers should always be considered and evaluated for future mapping projects.

Question: Can multiscale methods improve over traditional techniques?

The multiscale nature of our world is portrayed in remotely sensed data sets. These data sets also present intrinsic multiscale patterns (e.g., distortions) generated by the measuring devices, measuring conditions and integration processes. In this thesis, emphasis has been given to techniques that are able to separate the information contained in remotely sensed data sets according to the dominant scale levels in which the information manifests itself. The aim was to use this scale-specific information to improve over fixed-scale approaches to geographical information processing. As shown in this thesis, *multiscale analysis should be seen as a complement rather than a substitute for traditional geoinformation processing techniques. It provides a series of representations of the Earth's surface that isolates landscape features according to the dominant scale levels in which they appear.* It follows that traditional techniques might then be applied to selected scale levels according to the objectives of a given project.

It is concluded that postulates 1, 2 and 3 have been confirmed by the research described in this thesis, but postulate 4 has only partially been confirmed. Thus, based on the findings presented in this thesis, the postulates are reformulated as:

1) Nonlinear and nonparametric regression techniques are more effective to analyse and process time series of Landsat imagery in order to minimise the effects of cloud contamination and distortions caused by misregistration.

2) Long time series are useful to improve the separation of spectrally similar objects on the Earth's surface. It can be particularly useful to distinguish between natural and man-made land cover types.

3) Geographical data carry information at multiple spatial and temporal scales. Automation can be improved if this multiscale nature is taken into account during processing.

4) Multiscale methods can handle the increasing amount of available data more effectively than fixed-scale approaches. Traditional pattern recognition methods still provide important tools for geographical information processing.

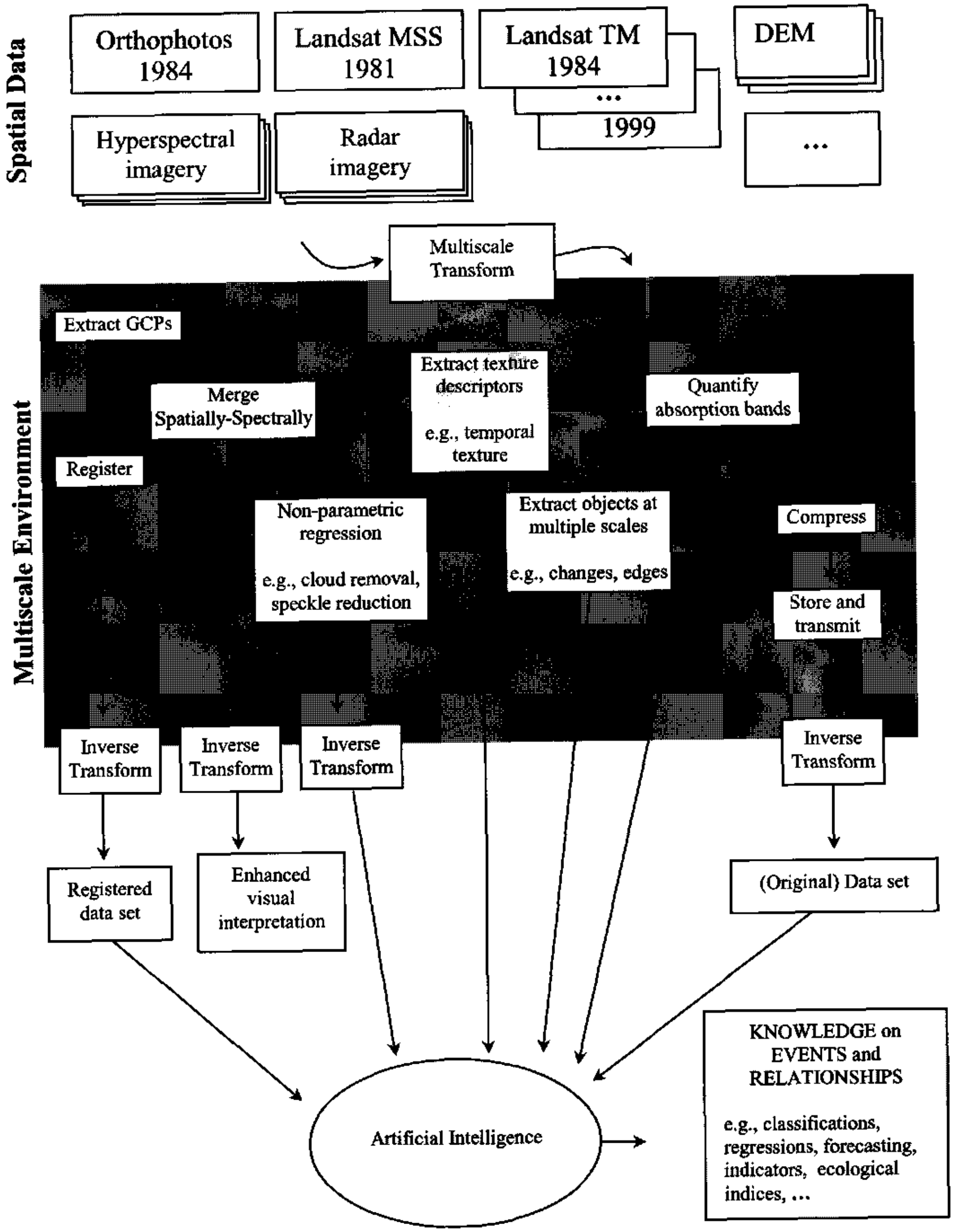

Figure 8.1 The multiscale processing environment.

8.2 A multiscale processing environment

The framework proposed here (figure 8.1) was based on multiscale transforms and artificial intelligence. Each raster data set was decomposed into a multiscale representation using wavelet transforms. Data integration, regression, compression and information extraction were carried out in the transformed domain (dark-grey area in figure 8.1).

The outputs, transformed back (or not) to the spatial-temporal-spectral domain in any desired resolution, were input to a machine learning system, which generated knowledge on events and relationships independently from data type or measurement scale. In this framework, events and relationships can then be translated into classifications, regressions, indicators, predictions etc.

The case studies presented in this thesis illustrate some of the possibilities when working within the proposed framework. The input data set comprised orthophotos, multi-temporal Landsat (MSS and TM) images and a digital elevation model. The tasks carried out in this thesis (light-grey boxes in figure 8.1) have included spatial resolution merging (chapter 6), nonparametric regression for cloud removal (chapter 4), extraction of texture descriptors for land cover classification (chapter 5), and extraction of objects at multiple spatial scales for change detection studies (chapter 7). Then, the knowledge generated with artificial intelligence was used to generate maps of forest cover and deforestation in an area of semideciduous Atlantic forest of southeastern Brazil.

8.3 Recommendations and perspectives

(Semi)Automatic change detection and GIS updating are feasible tasks that should be implemented by local authorities and planners to monitor and understand forest dynamics in the region. The procedure developed in this thesis enables a relatively easy implementation by non-experts in image processing, which might then concentrate on further aspects of landscape change or control of illegal activities.

Significant improvements in automatic change detection according to the proposed method include the development of algorithms for automatic scale selection within the multiscale approach. Even so, expert knowledge still has to be used to define the rules for such algorithms.

The preprocessing methodology presented in chapter 3 might be used to increase the temporal availability of Landsat images by replacing areas contaminated by clouds. Entire time series can be used to provide ecologically meaningful temporal profiles by reducing the variation caused by external sources. Institutes responsible for distribution of satellite sensor images could provide cloud free and/or estimated time series of high spatial resolution imagery increasing the levels of preprocessing currently available to the end users, e.g. GVI (Global Vegetation Index) and GIMMS-NDVI (Global Inventory, Modelling, and Monitoring System) data sets derived from NOAA AVHRR. Such a data set of high spatial resolution imagery would be a useful input for studies concerning vegetation dynamics, mapping, land transformation, ecological indicators and predictive modelling.

Effective classification of semideciduous Atlantic forest in the "*Vale do Alto Rio Grande*" should always take temporal information into account. The maximum likelihood classification algorithm is considered to be most appropriate in this study and is therefore recommended. Nevertheless, increased image size, landscape complexity and/or class complexity could generate more complex feature spaces and data distributions, where nonparametric classifiers are thought to be superior. A class-oriented approach is indicated whenever the objectives are exclusively focused on forest mapping. For mapping other land cover types, research should look for relevant features and suitable classifiers.

Concerning forest mapping in the region, further research should be directed to within-forest classification and to the definition of important features for this task. Again, temporal profiles preprocessed according to the proposed techniques are expected to play a decisive role for mapping forest subclasses.

Finally, the techniques described in this thesis have been developed to solve problems in the temporal and spatial domains. However, the same principles might be applied to the spectral domain as well, especially with the increasing availability of hyperspectral images. Applications in this direction include the identification and quantification of absorption features in spectral signatures, data reduction and denoising.

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SUMMARY

1. Introduction

The world leaders have recognised in unprecedented meetings that *forest ecosystems* play a fundamental role in vital processes such as carbon cycle, climate change, soil degradation, and water dynamics. One basic requirement to quantify and model these processes is the availability of *accurate maps* of forest cover. In this context, *remote sensing* and *geographical information* technologies represent promising tools, where data acquisition and analysis at *appropriate scales* are the keystone to achieve the mapping accuracy needed for development and reliable use of environmental models. The upcoming production of *high-resolution* data sets and the increasing *time series* that have been collected have the potential to improve dramatically our knowledge about the environment, but *data integration* and proper *analysis* of such data set is a challenge of utmost importance to realise this potential.

Hence, the following questions were addressed in this study:

(1) What are the preprocessing requirements to the application of remotely sensed time series with high spatial resolution in environmental modelling?
(2) What kinds of analytical tools and landscape features derived from remote sensing are relevant to map forests in the study area?
(3) To what extent can geoinformation processing be automated?
(4) Can artificial intelligence and multiscale methods improve over traditional techniques?

The questions were drawn based on the objectives listed below:

(1) to define a mapping strategy for forests in the study area,
(2) to develop a deforestation warning system to enable timely action to be taken,
(3) to develop a strategy to preprocess and extract information from long time series of Landsat data,
(4) to investigate methods to separate spectrally similar land cover types by using other information sources and/or alternative image analysis methods, and
(5) to develop an automatic approach for detection and quantification of land cover changes using remotely sensed images.

2. *An Area of Semideciduous Atlantic Forest*

It is supposed that the Brazilian Atlantic forests (evergreen, semideciduous, and Araucaria forests) have once covered about one million square kilometres, corresponding to almost 12% of the country's area. Estimated figures indicate that it is now reduced to less than 5% of the original cover. The *semideciduous Atlantic forest* represents an important subdomain of the Atlantic forest biome, which is eminently more threatened than the Amazonian, less studied than its evergreen counterpart, and even more degraded than both are.

The area chosen to study the semideciduous Atlantic forest is located in the "*Vale do Alto Rio Grande*" region in the south of Minas Gerais, southeastern Brazil. In the end of the nineteenth century, the culture of coffee was introduced in the region and increased very fast to become one of the main causes of deforestation. Nowadays, besides the increasing industrialisation, coffee and milk production form the main economical activities in the region. The study area is delimited by the coordinates 21° 05' - 21° 47' S and 44° 02' - 45° 04' W.

The area was studied using a long time series (28 images from 1981 to 1999) of remote sensing data, which came from the Landsat Earth observation satellite program. Auxiliary data comprised orthophotos (1:10.000) and digitised contour lines with 20 m of vertical resolution.

3. *Geographical Information Processing*

Observations with remote sensing are measurements of reflectance or emission after the radiation has interacted with the objects on the Earth's surface and with the atmosphere. The measurements are organised as an image or description of a region at a certain point in time. Repeated observations of the same area form a multitemporal data set. Seemingly, observations of the same area at a fixed point in time, but in different portions of the electromagnetic spectrum, form a multispectral data set.

Recently, much attention has been paid to the multiscale characteristic of environmental phenomena and, as a consequence, of our observations with remote sensing. Multiscale wavelet analysis separates the information of interest according to the dominant scales in which it appears, no matter the domain (i.e., spatial, spectral, temporal etc) under consideration. Wavelets come from the iteration of a filter bank and because of the repeated rescaling, they decompose a signal into details at different resolutions. If the signals under consideration are remotely sensed images, the scale parameter corresponds to the size of objects on the Earth surface, which are effectively modelled with this new multiresolution representation, revealing patterns that are not so clear in "subtle and complicated" remotely sensed images.

Machine learning techniques have been developed for some decades within the larger field of Artificial Intelligence. The objective of Artificial Intelligence is to understand the way human beings recognise patterns and to develop intelligent systems. Neural nets and rule induction, two popular paradigms of the machine learning field, have been applied recently to classification problems in geoinformation sciences showing promising results. The basic idea in classification of multidimensional data is to partition the multidimensional feature space by using some decision boundaries. Machine learning techniques gained considerable attention for classification tasks because they provide partitions of feature spaces in an essentially nonlinear and nonparametric way.

4. Removal of Clouds from Remotely Sensed Time Series

The use of temporal information is extensively explored in this thesis. Novel schemes based on multiresolution wavelet analysis are introduced in this chapter to preprocess long time series of Landsat data and improve its applicability on environmental assessment. Particularly, removal of clouds and their shadows is addressed. This chapter can be viewed as a necessary preprocessing step for further analyses conducted in the thesis. It describes the application of the *product of wavelet scales* to generate binary masks of corrupted observations. The *robust smoother-cleaner wavelets* method was then applied to each temporal profile where anomalous values have been detected. The interpolation step is based on nonparametric function estimation applying *wavelet shrinkage* to the "clean" time series. Cloud contamination was simulated in a cloud-free time series and the missing values were estimated using five methods: 1) mean value, 2) minimum value, 3) maximum value, 4) linear regression, and 5) the wavelet-based procedure for nonparametric regression proposed in this chapter. Comparisons were made on the basis of root mean square errors (RMSE). Contamination was simulated for 3715 pixels, but only 2508 were automatically detected by applying the procedure based on the product of wavelet scales. The contaminated pixels that were not detected represented fuzzy boundaries of clouds and shadows, shadowed forests that already had low reflectance, and clouded areas of bare soil that had high reflectance values in the reference image. In addition, other anomalies, like geometric misregistration, were also automatically detected. Concerning interpolation of the missing values, the wavelet-based approach was more accurate for clouded areas while linear regression performed better in shadowed areas.

Multiscale products of wavelet scales might be effectively used to automatically mask corrupted values for further replacement with any desired method. The method proposed here not only identified clouded and shadowed pixels but also other anomalies like misregistration effects and changes of short duration (e.g., burn scars). The robust nonlinear wavelet regression can do both, detection and estimation, at the same time and produce noise reduced images at any point in the time series. Thus, the wavelet approach holds promise as a preprocessing step for effective time series analysis.

5. Classification Forest Remnants

The need for improved mapping methods is evident from our still poor knowledge on basic information about forest extent and condition. Fragmented ecosystems such as the semideciduous Atlantic forest demand the use of high spatial resolution imagery. Nevertheless, because of spectral overlap problems, the occurrence of coffee and eucalyptus plantations in the region poses limitations to an accurate classification of forest remnants using the currently available high spatial resolution data. The experiment described in this chapter related attribute features derived from a digital elevation model, raw remote sensing data, and various transformations to enhance vegetation areas, image texture and spectro-temporal relations. Feature sets were defined based on expert knowledge and on data mining techniques to be input to traditional and machine learning algorithms for pattern recognition, viz. maximum likelihood, univariate decision trees, multivariate decision trees, and neural networks.

The results showed that maximum likelihood classification using temporal texture descriptors as extracted with wavelet transforms was most accurate to classify the semideciduous Atlantic forest in the study area. Maximum likelihood performed relatively well with all input feature sets, providing a forest mapping accuracy that ranged from 34.5% to 51.3%. In contrast, neural networks showed the greatest variation, with an accuracy that ranged from 19.0% to 45.2%. The worst classification accuracy (19%) was provided by the combination of neural networks with mined features mainly due to the large number of commissions. As expected, classification confusion occurred mainly with coffee and eucalyptus plantations, but neural networks and univariate trees also misclassified deforested areas currently covered with pasture. Univariate trees provided the most robust results for different feature sets, with a forest mapping accuracy that ranged from 39.6% to 46.7%. Temporal information of vegetation indices was more important than image texture, terrain topography and raw spectral information for discriminating semideciduous Atlantic forest in the present study site. Nevertheless, spatial texture and topographical features were still important when neural networks and multivariate trees were used for classification. Therefore, aiming at accurate mapping of semideciduous Atlantic forest in the "*Vale do Alto Rio Grande*", using the data set available for this study and considering the other factors granted, one is advised to use maximum likelihood classification and temporal texture descriptors of NDVI time series as input data.

6. *Multiscale Change Analysis*

Current methods used to compare two or more remotely sensed images and to detect differences among them are dependent on accurate radiometric normalisation and geometric rectification, which are hard to achieve in many situations due to the lack of (radiometric) calibration data and difficulties in locating (geometric) control points. The objective of the method proposed in this chapter was to reduce the sensitivity of digital change detection to the effects of radiometric and geometric misregistration by extracting changes according to size classes using a multiscale approach. A change image, produced by any of the standard radiometric change detection methods (e.g., image differencing), is decomposed into several high frequency bands with variable resolutions plus a low frequency band at the coarsest resolution by means of wavelet transforms. The product of wavelet scales was then used to enhance changed sites and suppress misregistration effects.

Using the multiscale product in a simple colour composite, visualisation of changed sites can be readily done. All changes detected by this visualisation procedure did occur although their quantification was not possible. This straightforward visualisation might be of much use when large areas are to be evaluated. Misregistration effects and small area changes were isolated as fine details, while differences in phenological characteristics and atmospheric conditions were captured in the smoothed representation as overall differences between the images. Vegetation removal, reforested areas, as well as new rock exploitation sites were pinpointed successfully without previous radiometric rectification or threshold definition, while differences not related to land cover changes were bypassed. The behaviour of changes at different scale levels as resulting from the new method presented here enables their discrimination according to size classes. The method was found to be less sensitive to spatial and radiometric misregistration, although fine details are lost as well. It can be applied to the outputs of any change detection technique such as image rationing, principal components, change vector analysis etc. Applications of the proposed method include, for instance, the automatic selection of changed sites for GIS updating and the fast identification of priority areas for field check when large data sets are to be evaluated. Finally, the visualisation of changed sites is straightforward with a simple colour composite avoiding any threshold definition, radiometric rectification or accurate geometric registration.

7. *Automatic Deforestation Detection*

Automation has been one of the early goals of geoinformation processing due to the potential of performing unsupervised tasks provided by computer-aided analysis. The difficulties with land cover change detection are further complicated when compared to land cover mapping, imposing limits to automation. The main difficulties while handling time series of remotely sensed data are related to (1) geometric transformations, (2) the size of changes to be observed, (3) the temporal scales in which changes occur, (4) atmospheric conditions, (5) the radiometric response of objects on the Earth's surface, and (6) the gradual nature of some types of changes. The aim of this study was to develop an automated, simple and flexible procedure for raster-based GIS updating.

The procedure proposed and illustrated in this chapter uses as input two remotely sensed images acquired at different points in time (t_1 and t_2), GIS layers representing the land cover types under investigation, and a set of groundtruth data for the present land cover pattern and for changed sites. The most recent image is used to update the GIS layers based on radiometric differences with the oldest image. Four modules compose the procedure according to the main tasks performed: (1) location of changed sites, (2) quantification of changed area, (3) classification of the new land cover type, and (4) updating the database. First, the difference image is decomposed with wavelet transforms and the maxima of multiscale products are extracted at changed sites according to the methodology developed in chapter 6. Secondly, segmentation is performed on the difference image based on a decision rule to check if the pixels surrounding each detected maximum are spectrally similar. Thirdly, each changed pixel or each segmented region is assigned to the land cover class with the highest probability of membership. Then, the output is used to update all the GIS layers where changes took place. This procedure was compared with two other approaches to change detection and identification, viz. post classification comparison and direct multidate classification.

The procedure described in this chapter was less sensitive to geometric and radiometric misregistrations because of the multiresolution approach to feature extraction included in the search module. Different from post classification comparisons, it requires ground truth data only for the present land cover pattern. In comparison to direct multidate classification, change-classes do not need to be defined or training samples to be collected at changed sites. Finally, segmented areas could be considered individual objects and classified as such, avoiding speckled misclassifications and improving classification accuracy. Further refinements of the procedure include the automatic threshold definition and the possibility of working with multivariate difference images.

8. Conclusions

According to the main objectives of this thesis, a remote sensing-based strategy to map and monitor forest remnants in highly fragmented areas was developed for the "*Vale do Alto Rio Grande*" region. A procedure that could be easily implemented by non-experts in image processing for rapid assessment of deforestation hot spots over large areas was proposed. It has the potential to provide local authorities and governmental institutes with a deforestation warning system for the remnants of semideciduous Atlantic forest.

The wavelet-based regression technique described in chapter 3 removed clouds and corrected for misregistration simultaneously and automatically, while providing reliable estimates for the values that were replaced. The multiscale approach provided an effective tool for studying remotely sensed images that were arbitrarily sampled in time, contaminated by clouds and shadows, corrupted by misregistration, as well as random Gaussian noise. The framework described in chapter 6 and implemented in chapter 7 is less sensitive to noise caused by misregistration, it might be combined with any standard change detection technique and provides an aid to rapid change detection over large geographical areas. Temporal information is of utmost importance for mapping the semideciduous Atlantic forest and particularly NDVI time series proved to be useful features for classification. Multiscale methods reduce the amount of information to be analysed when performing automated tasks, but knowledge on which scale levels to look at must exist. In chapter 4, the traditional maximum likelihood classification algorithm clearly outperformed the algorithms based on machine learning techniques when temporal features were used for classification. Multiscale analysis should be seen as a complement rather than a substitute for traditional geoinformation processing techniques. It provides a series of representations of the Earth's surface that isolates landscape features according to the dominant scale levels in which they appear. It follows that traditional techniques might then be applied to selected scale levels according to the objectives of a given project.

Based on the findings presented in this thesis, postulates 1 to 3 were confirmed, whereas the postulate 4 was partially confirmed:

1) Nonlinear and nonparametric regression techniques are more effective to analyse and process time series of Landsat imagery in order to minimise the effects of cloud contamination and distortions caused by misregistration.

2) Long time series are useful to improve the separation of spectrally similar objects on the Earth's surface. It can be particularly useful to distinguish between natural and man-made land cover types.

3) Geographical data carry information at multiple spatial and temporal scales. Automation can be improved if this multiscale nature is taken into account during processing.

4) Multiscale methods can handle the increasing amount of available data more effectively than fixed-scale approaches. Traditional pattern recognition methods still provide important tools for geographical information processing.

In the multiscale processing environment proposed in this thesis, each raster data set was decomposed into a multiscale representation using wavelet transforms. Data integration, regression, compression and information extraction was carried out in the transformed domain. The outputs, transformed back (or not) to the spatial, temporal and spectral domains in any desired resolution, were input to a machine learning system, which generated knowledge on events and relationships independently from data type or measurement scale. In this framework, events and relationships can then be translated to classifications, regressions, indicators, predictions etc.

(Semi)Automatic change detection and GIS updating are feasible tasks that should be implemented by local authorities and planners to monitor and understand forest dynamics in the region. Significant improvements in automatic change detection according to the proposed method include the development of algorithms for automatic scale selection within the multiscale approach. The preprocessing methodology presented in chapter 3 might be used to increase the temporal availability of Landsat images and entire time series can be used to provide ecologically meaningful temporal profiles. Effective classification of semideciduous Atlantic forest in the "*Vale do Alto Rio Grande*" should always take temporal information into account. A class-oriented approach is indicated whenever the objectives are exclusively focused on forest mapping. Concerning forest mapping in the region, further research should be directed to within-forest classification and to the definition of important features for this task. Finally, the techniques described in this thesis were developed to solve problems in the temporal and spatial domains. However, the same principles might be applied to the spectral domain as well, for identification and quantification of absorption features in spectral signatures, data reduction and denoising.

SAMENVATTING

1. Inleiding

De wereldleiders hebben tijdens de diverse klimaat- en milieuconferenties erkend dat *bos-ecosystemen* een essentiële rol spelen in processen zoals de koolstofcyclus, klimaatveranderingen, bodemdegradatie en de dynamiek van het water. Een eerste vereiste om deze processen te kwantificeren en te monitoren is de beschikbaarheid van *nauwkeurige kaarten* van bosgebieden. In dit verband spelen *remote sensing* en *geografische informatie-technieken* een cruciale rol. Gegevens-inwinning en -analyse op de *juiste schaalniveaus* vormen de basis om de karteringsnauwkeurigheid te bereiken die nodig is voor de ontwikkeling en het betrouwbaar gebruik van gebruikte milieumodellen. Binnen het aandachtsgebied van de aardobservatie bieden de opkomende productie van *hoge-resolutie* gegevens en de beschikbaarheid van steeds verder reikende *tijdseries* de mogelijkheid om onze kennis over het milieu aanzienlijk te verbeteren, maar *gegevens-integratie* en de juiste *analyse* van dergelijke gegevens is een zeer belangrijke uitdaging om deze mogelijkheden te benutten.

Gebaseerd op het bovenstaande werden de volgende vragen in deze studie aan de orde gesteld:

(1) Welke eisen moeten worden gesteld aan de voorbewerking van remote sensing-tijdseries met een hoge ruimtelijke resolutie voor toepassing in de milieumodellering?

(2) Welke soorten remote sensing-gegevens en analysegereedschappen zijn van belang om bossen te karteren in het studiegebied?

(3) n hoeverre kan de geo-informatie-verwerking geautomatiseerd worden?

(4) Kunnen kunstmatige intelligentie en multischaal-methoden verbeteringen opleveren ten opzicht van traditionele technieken?

Genoemde vragen werden op basis van de volgende doelstellingen gesteld:

(1) het definiëren van een strategie om de bossen in het studiegebied te karteren;

(2) het ontwikkelen van een waarschuwingssysteem voor ontbossing om het nemen van tijdige actie mogelijk te maken;

(3) het ontwikkelen van een strategie om lange tijdseries van Landsat-gegevens te bewerken en de relevante informatie te extraheren;

(4) het onderzoeken van methoden om spectraal-gelijkende bedekkingtypen te onderscheiden met gebruikmaking van andere informatiebronnen en/of alternatieve analysemethoden, en
(5) het ontwikkelen van een automatische benadering voor de detectie en kwantificering van veranderingen in landbedekking gebruikmakend van remote sensing-beelden.

2. *Een Gebied van Half-loofverliezende Atlantische Bossen*

Men veronderstelt dat de Atlantische bossen in Brazilië (groenblijvende, half-loofverliezende en Araucaria bossen) ooit een gebied van één miljoen vierkante kilometer bestreken. Geschatte cijfers geven aan dat dit nu gereduceerd is tot minder dan 5% van de oorspronkelijke bedekking. Het *half-loofverliezende Atlantische bos* is een belangrijke representant van het Atlantische bos, dat meer bedreigd wordt dan dat van de Amazone, minder bestudeerd is dan de groenblijvende tegenhanger en meer achteruitgegaan is dan beide. Het gebied dat als studiegebied voor dit proefschrift geselecteerd is om het half-loofverliezende Atlantische bos te bestuderen bevindt zich in het zogenaamde "*Vale do Alto Rio Grande*" gebied in het zuiden van de provincie Minas Gerais in het zuidoosten van Brazilië. Tegen het eind van de negentiende eeuw werd de verbouw van koffie in het gebied geïntroduceerd en het areaal groeide erg snel, hetgeen een van de belangrijkste oorzaken van ontbossing werd. Tegenwoordig zijn koffie- en melkproductie de belangrijkste economische activiteiten in het gebied, naast de toegenomen industrialisatie. Het gebied wordt gekarakteriseerd als glooiend, met hoogten variërend tussen 700 en 1000 m in het grootste deel van het gebied. Er komen echter ook hoogten tussen 1100 en 1400 m voor op de steilere bergkammen. Het klimaat is een gematigd tot subtropisch klimaat met een natte zomer en een droge winter. De belangrijkste rivier in het studiegebied is de "*Rio Grande*". Het gebied is bestudeerd met behulp van een lange tijdserie aan remote sensing-gegevens (28 beelden van 1981 tot 1999), afkomstig van het Landsat-aardobservatieprogramma. Hulpgegevens bestonden uit orthofoto's (1:10.000) en gedigitaliseerde contourlijnen met een verticale resolutie van 20 m.

3. *Geografische Informatieverwerking*

Remote sensing-waarnemingen zijn metingen van de reflectie of emissie van straling nadat deze in meer of mindere mate in wisselwerking is getreden met het aardoppervlak en met de atmosfeer. De metingen worden georganiseerd in de vorm van een beeld of als een beschrijving van een gebied op een bepaald moment in de tijd. Herhaalde waarnemingen van een bepaald gebied vormen een zogenaamde multitemporele gegevensset. Zo vormen waarnemingen van hetzelfde gebied op een bepaald moment in de tijd, maar in verschillende delen van het electromagnetische spectrum, een zogenaamde multispectrale gegevensset. Recent wordt veel aandacht besteed aan de eigenschappen van milieuverschijnselen op verschillende schaalniveaus en dientengevolge aan waarnemingen met behulp van remote sensing op verschillende schaalniveaus. Een zogenaamde "multischaal-waveletanalyse" scheidt de gezochte informatie naar gelang de overheersende schaal waarop het verschijnt, onafhankelijk van het domein (dat wil zeggen ruimtelijk, spectraal, temporeel, etc.). Wavelets worden berekend door iteratie van een signaal met een serie filters, zodat ze het signaal ontleden in informatie op verschillende resolutieniveaus. Als de beschouwde signalen remote sensing-beelden zijn, dan correspondeert de schaalparameter met de afmeting van objecten op het aardoppervlak. Deze kunnen effectief gemodelleerd worden met deze nieuwe multiresolutie-weergave. Wavelets kunnen zo patronen blootleggen die op de oorspronkelijke remote sensing-beelden niet duidelijk zijn. Computers en programma's met een zelflerend vermogen (machineleertechnieken) worden binnen het ruimere veld van de kunstmatige intelligentie al enkele decennia ontwikkeld. Neurale netwerken en regel-inductie, twee populaire voorbeelden uit het veld van de machineleertechnieken, zijn recentelijk met veelbelovende resultaten toegepast op het classificatieprobleem in de geo-informatie-wetenschappen.

4. Het Verwijderen van Wolken uit een Remote Sensing-tijdserie

In dit hoofdstuk worden nieuwe schema's gebaseerd op de multiresolutie-waveletanalyse geïntroduceerd om lange tijdseries van Landsat-gegevens voor te bewerken en om de toepasbaarheid in milieugerelateerde toepassingen te verbeteren. Met name het onderwerp van het verwijderen van wolken en hun schaduwen wordt behandeld. Het beschrijft het toepassen van de vermenigvuldiging van wavelet-schalen om binaire maskers van slechte waarnemingen te genereren. De robuuste effenende-opschonende waveletmethode wordt vervolgens toegepast op elk temporeel profiel waarin afwijkende waarden zijn ontdekt. De interpolatiestap is gebaseerd op niet-parametrische functieschattingen met toepassing van "wavelet-krimping" op de opgeschoonde tijdseries. Verontreiniging met wolken is in een wolkenvrije tijdserie gesimuleerd en de ontbrekende (slechte) waarden werden met behulp van vijf verschillende methoden geschat.

Verontreiniging met wolken is gesimuleerd voor 3715 pixels. Er werden 2508 pixels automatisch gedetecteerd door middel van toepassingen van de procedure gebaseerd op vermenigvuldiging van wavelet-schalen. De verontreinigde pixels, die niet gedetecteerd werden, vertegenwoordigden vage grenzen van wolken en schaduwen, bos in de schaduw met al een lage reflectie, en bewolkte delen met kale bodem die hoge reflectiewaarden in het referentiebeeld hadden. Bovendien werden andere afwijkingen, zoals een geometrisch onjuiste passing (misregistratie), ook automatisch gedetecteerd. De waveletgebaseerde methode was nauwkeuriger voor bewolkte gebieden met betrekking tot de interpolatie van ontbrekende waarden, terwijl de lineaire regressie methode het beter deed in beschaduwde gebieden. Multischaal-waveletproducten zouden effectief ingezet kunnen worden om automatisch slechte waarden in een beeld te vinden zodat deze vervolgens door middel van een of andere gewenste methode vervangen kunnen worden. De hier voorgestelde methode identificeerde niet alleen wolken en beschaduwde pixels, maar ook andere afwijkingen zoals misregistratie-effecten en kortdurende veranderingen (bijvoorbeeld de littekens van branden). De robuuste niet-lineaire waveletregressie kan tegelijkertijd zowel de detectie als ook de schatting uitvoeren en ruis-gereduceerde beelden op ieder punt in de tijdserie produceren. De waveletbenadering is dus veelbelovend als voorbewerkingsstap voor een effectieve tijdserie-analyse.

5. Het Classificatie van Bosrestanten

De noodzaak voor verbeterde karteringsmethoden wordt duidelijk uit onze nog matige kennis van basisinformatie over bosarealen en -condities. Gefragmenteerde ecosystemen, zoals het half-loofverliezende Atlantische bos, vragen om het gebruik van beelden met een hoge ruimtelijke resolutie. Het voorkomen van koffie- en eucalyptusplantages in het studiegebied levert beperkingen op voor een nauwkeurige classificatie van bosrestanten met de momenteel beschikbare hoge-resolutie gegevens ten gevolge van spectrale overlap tussen de betreffende klassen.

In dit hoofdstuk werden een voorbewerkte tijdserie (geproduceerd zoals beschreven in hoofdstuk 4) en andere informatie met betrekking tot spectrale en ruimtelijke eigenschappen gebruikt om bosgebieden te classificeren. Het experiment onderzocht de relaties tussen kenmerken afgeleid uit een digitaal hoogtemodel, ruwe remote sensing-gegevens en verschillende transformaties om begroeide gebieden, beeldtextuur en spectrale-temporele relaties te versterken. Gebaseerd op expert-kennis en zogenaamde "data mining" technieken werden series met kenmerken gedefinieerd om als invoer te dienen in traditionele en machineleer-algoritmes voor patroonherkenning, te weten de zogenaamde "maximum likelihood" classificatie, univariate en multivariate beslisbomen en neurale netwerken. De resultaten lieten zien dat de maximum likelihood classificatie met temporele textuurbeschrijvingen verkregen met wavelettransformaties het meest nauwkeurig was voor het classificeren van het half-loofverliezende Atlantische bos in het studiegebied. De maximum likelihood methode voldeed relatief goed voor alle series met invoerkenmerken, resulterend in een karteringsnauwkeurigheid voor bos tussen 34,5% en 51,3%. Hier staat tegenover dat neurale netwerken de grootste variatie vertoonden met een nauwkeurigheid variërend van 19,0% tot 45,2%. Zoals verwacht trad verwarring vooral op met koffie- en eucalyptusplantaties, maar neurale netwerken en univariate beslisbomen classificeerden ontboste gebieden, die nu als grasland in gebruik zijn, ook foutief. Univariate beslisbomen gaven de meest robuuste resultaten voor verschillende kenmerksets, met een classificatienauwkeurigheid voor bos tussen 39,6% en 46,7%. Temporele informatie van vegetatie-indices was belangrijker dan beeldtextuur, terreintopografie en ruwe spectrale informatie voor het onderscheiden van het half-loofverliezende Atlantische bos in het onderzochte studiegebied. Op basis van dit onderzoekwerd geconcludeerd dat het beter is om de maximum likelihood classificatie en temporele textuurbeschrijvingen van NDVI-tijdseries als invoergegevens te gebruiken indien men een nauwkeurige kartering van het half-loofverliezende Atlantische bos in het "*Vale do Alto Rio Grande*" studiegebied wil uitvoeren met de gegevensset die voor deze studie beschikbaar was en rekening houdend met de overige gegeven factoren.

6. Multischaal-analyse van Veranderingen

De huidige methoden om twee of meer remote sensing-beelden te vergelijken en om onderlinge verschillen te detecteren zijn afhankelijk van een nauwkeurige radiometrische normalisatie en geometrische rectificatie, welke in veel gevallen moeilijk te realiseren zijn ten gevolge van gebrekkige (radiometrische) ijkgegevens en problemen in het bepalen van (geometrische) paspunten. Het doel van de in dit hoofdstuk voorgestelde methode was om de gevoeligheid van een geautomatiseerde detectie van veranderingen voor de effecten van radiometrische en geometrische misregistratie te verkleinen door veranderingen te extraheren volgens grootteklassen gebruikmakend van een multischaal-benadering.

Een beeld met veranderingen, geproduceerd door een van de standaard radiometrische methoden voor de detectie van veranderingen (bijvoorbeeld het berekenen van het verschil in pixelwaarde tussen twee beelden), werd ontleed in verschillende hoge frequentiebanden met variabele resoluties en een lage frequentieband op de grofste resolutie door middel van een wavelettransformatie. De vermenigvuldiging van de wavelet-schalen werd vervolgens gebruikt om veranderde locaties te versterken en misregistratie-effecten te onderdrukken.

Visualisatie van veranderde locaties kan eenvoudig gerealiseerd worden door het multischaal-product als een simpele kleurcomposiet weer te geven. Deze simpele visualisatie kan erg nuttig zijn als grote gebieden geëvalueerd moeten worden. Misregistratie-effecten en veranderingen van kleine gebieden werden als fijne details geïsoleerd, terwijl verschillen in fenologische eigenschappen en atmosferische gesteldheid gevangen werden in de geëffende voorstellingen als algemene verschillen tussen de beelden. Verwijdering van vegetatie, herbeboste gebieden en nieuwe ontginningen van mineralen werden succesvol gelokaliseerd zonder voorafgaande radiometrische correctie of definitie van een drempelwaarde, terwijl verschillen die niet gerelateerd waren aan verandering in de bedekking vermeden werden.

7. *Automatische Detectie van Ontbossing*

Automatisering is een van de eerste doelen van de geo-informatie-verwerking geweest vanwege de mogelijkheid tot het uitvoeren van taken zonder direct menselijk ingrijpen met behulp van computer-ondersteunde analyses. De grootste beperkingen bij het bewerken van remote sensing-tijdseries zijn gerelateerd aan (1) geometrische vervormingen, (2) de kleinschaligheid van de waar te nemen veranderingen, (3) de temporele schalen waarop veranderingen plaatsvinden, (4) atmosferische condities, (5) de radiometrische respons van objecten op het aardoppervlak en (6) het geleidelijke karakter van sommige typen van veranderingen. Het doel van deze studie was om een geautomatiseerde, eenvoudige en flexibele procedure voor raster-gebaseerde GIS-actualisatie te ontwikkelen.

De in dit hoofdstuk voorgestelde en geïllustreerde procedure gebruikt twee remote sensing-beelden, die op verschillende momenten in de tijd opgenomen zijn, GIS-lagen die de te onderzoeken typen landbedekking vertegenwoordigen en veldgegevens voor het huidige patroon van landbedekking en voor de veranderde locaties. Het meest recente beeld wordt gebruikt voor de actualisatie van de GIS-lagen gebaseerd op radiometrische verschillen met het oudste beeld. De procedure bestaat uit vier modules die elk een verschillende taak uitvoeren: (1) lokalisering van de veranderde locaties, (2) kwantificering van het veranderde gebied, (3) classificatie van het nieuwe type landbedekking en (4) actualisatie van de database. Allereerst wordt het verschilbeeld ontleed met een wavelettransformatie en de maxima van de multischaal-producten worden geëxtraheerd voor de veranderde locaties volgens de methodologie ontwikkeld in hoofdstuk 6. Vervolgens wordt een segmentatie op het verschilbeeld toegepast volgens een bepaalde beslisregel om te controleren of de buurpixels van ieder gedetecteerd maximum spectraal overeenkomstig zijn. Ten derde wordt iedere veranderde pixel of gesegmenteerd gebied aan die landbedekkingklasse toegekend waarvoor de kans op lidmaatschap het grootst is. Tenslotte wordt het resultaat gebruikt om alle GIS-lagen waar veranderingen optraden te actualiseren. Deze procedure is vergeleken met twee andere benaderingen om veranderingen te detecteren en te identificeren, namelijk de zogenaamde post-classificatie vergelijking en de directe multitemporele classificatie.

De nauwkeurigheid van de detectie en identificatie van veranderingen met gebruikmaking van de hier voorgestelde procedure was vergelijkbaar met die van een directe multitemporele classificatie gebaseerd op neurale netwerken, maar aanzienlijk beter dan post-classificatie vergelijking. Dit resultaat bevestigt de verwachte foutenvoortplanting indien men dit vergelijkt met de resultaten van afzonderlijke classificaties. De voorgestelde methode detecteerde veranderingen met TM band 3, welke de band binnen de beschikbare set (TM band 3, 4 en 5) is die het meest beïnvloed wordt door atmosferische effecten. Temporele beelden werden in verschillende seizoenen van het jaar verkregen en ze vertoonden een aanzienlijke misregistratie ten opzichte van elkaar. Toch voldeed de procedure goed en bleek ongevoelig voor deze problemen.

De in dit hoofdstuk beschreven procedure was minder gevoelig voor geometrische en radiometrische misregistraties vanwege de multiresolutie-benadering die in de zoekmodule opgenomen is. Tenslotte konden gesegmenteerde gebieden als individuele objecten beschouwd worden en ook als zodanig geclassificeerd worden waarbij foutieve classificaties van geïsoleerde pixels vermeden werden en de nauwkeurigheid van de classificatie verbeterd werd.

8. Conclusies

In overeenstemming met de belangrijkste doelstellingen van dit proefschrift is een strategie op basis van remote sensing-informatie ontwikkeld om bosrestanten in sterk gefragmenteerde terreinen voor het "*Vale do Alto Rio Grande*" gebied te karteren en te monitoren. Er is een procedure ontwikkeld voor het snel bepalen van locaties met ontbossing over een groot gebied die eenvoudig geïmplementeerd kan worden door leken op het terrein van de beeldbewerking. Het heeft de mogelijkheid om locale overheden en overheidsinstituten een ontbossings-waarschuwingssysteem voor de overblijfselen van de half-loofverliezende Atlantische bossen te bieden.

De in hoofdstuk 3 beschreven regressietechniek gebaseerd op wavelets verwijderde wolken en corrigeerde tegelijkertijd en automatisch misregistraties terwijl betrouwbare schattingen voor de vervangen waarden werden verkregen. De multischaal-benadering leverde een effectief gereedschap op voor het bestuderen van remote sensing-beelden, die willekeurig in de tijd ingewonnen zijn, verontreinigd met wolken en schaduwen zijn, verstoord zijn door misregistraties of willekeurige Gaussische ruis bevatten. Het raamwerk zoals beschreven in hoofdstuk 6 en geïmplementeerd in hoofdstuk 7 helpt bij het snel detecteren van veranderingen voor grote geografische gebieden. Temporele informatie blijkt van het grootste belang voor het karteren van het half-loofverliezende Atlantische bos en vooral NDVI-tijdseries bleken waardevolle kenmerken voor de classificatie te zijn. In hoofdstuk 4 voldeed het traditionele maximum likelihood algoritme duidelijk beter dan de algoritmen gebaseerd op machineleertechnieken indien temporele kenmerken voor de classificatie gebruikt werden. De multischaal-analyse moet men zien als een aanvulling op en niet als een vervanging voor traditionele geo-informatie-verwerkingstechnieken. Het levert een serie schaalafhankelijke representaties van het aardoppervlak op en isoleert landschapskenmerken naar gelang de dominante schaalniveaus waarop ze voorkomen.

Gebaseerd op de bevindingen uit dit proefschrift kunnen de stellingen uit hoofdstuk 1 als volgt geherformuleerd worden:

1) Bij het analyseren en bewerken van tijdseries van Landsat-beelden zijn niet-lineaire en niet-parametrische regressietechnieken effectiever in het minimaliseren van de effecten van verontreinigingen met wolken en afwijkingen veroorzaakt door misregistraties.

2) Lange tijdseries zijn bruikbaar bij het onderscheiden van spectraal-gelijkende objecten op het aardoppervlak. Deze kunnen vooral nuttig zijn bij het onderscheiden van natuurlijke en door de mens gemaakte landbedekkingtypen.

3) Geografische gegevens bevatten informatie op diverse ruimtelijke en temporele schalen. Automatisering kan verbeterd worden indien bij de bewerking met dit multischaal-karakter rekening wordt gehouden.

4) Multischaal-methoden kunnen toenemende hoeveelheden gegevens effectiever hanteren dan benaderingen op één vastliggende schaal. Traditionele patroonherkenningsmethoden leveren echter ook nog steeds belangrijke gereedschappen voor geografische informatiebewerking.

(Half)Automatische detectie van veranderingen en GIS-actualisatie zijn uitvoerbare taken die door locale bestuurders en planners geïmplementeerd zouden moeten worden, om de bosdynamiek in een bepaald gebied te monitoren en te begrijpen. Een significante verbetering in de automatische detectie van veranderingen volgens de voorgestelde methode omvat de ontwikkeling van algoritmen voor het automatisch selecteren van de schalen binnen de multischaal-benadering. Voor het karteren van andere bedekkingtypen dan bos moet onderzoek relevante kenmerken en geschikte classificatoren opleveren. Met betrekking tot het karteren van bossen in het studiegebied moet verder onderzoek zich richten op het classificeren van objecten binnen de bosklasse en op het definiëren van belangrijke kenmerken om dit uit te voeren. De in dit proefschrift beschreven technieken zijn uiteindelijk ontwikkeld om problemen in het temporele en ruimtelijke domein op te lossen. Dezelfde principes kunnen echter ook toegepast worden op het spectrale domein, bijvoorbeeld voor de identificatie en kwantificering van absorptiekenmerken in spectrale signaturen, voor gegevensreductie en voor het verwijderen van ruis in beelden.

SUMÁRIO

1. Introdução

Os líderes mundiais têm reconhecido em reuniões sem precedentes que os *ecossistemas florestais* desempenham um papel fundamental em processos vitais como ciclo de carbono, mudanças climáticas, degradação do solo e dinâmica da água. Uma exigência básica para quantificar e modelar estes processos é a disponibilidade de *mapas precisos* da cobertura florestal. Neste contexto, tecnologias de *sensoriamento remotos* e *sistemas de informações geográficas* representam ferramentas promissoras, onde a aquisição e a análise de dados em *escalas apropriadas* são fundamentais para o desenvolvimento e utilização de modelos ambientais confiáveis. A produção de dados de *alta-resolução* e a crescente *série temporal* coletada até agora apresentam um potencial para melhorar dramaticamente o nosso conhecimento acerca do meio ambiente. No entanto, *integração* e *análises apropriadas* de tal conjunto de dados constituem um desafio para a realização deste potencial. Assim, as seguintes perguntas foram consideradas neste estudo:

(1) Quais são as exigências de pré-processamento para a aplicação de séries temporais de sensoriamento remoto em modelagem ambiental?

(2) Que tipos de ferramentas analíticas e variáveis derivadas através de sensoriamento remoto são pertinentes para mapear florestas na área de estudo?

(3) Até que ponto o geoprocessamento pode ser automatizado?

(4) Inteligência artificial e métodos de análise em múltiplas escalas podem melhorar o geoprocessamento?

Estas perguntas foram baseadas nos objetivos listados abaixo:

(1) Definir uma estratégia para mapear florestas na área de estudo,

(2) Desenvolver um sistema para detecção de desmatamento para que ações oportunas sejam tomadas,

(3) Desenvolver uma estratégia de pré-processamento e extração de informação para ser aplicada em longas séries temporais de imagens Landsat,

(4) Investigar métodos para separar tipos de cobertura de terra que são espectralmente semelhantes usando outras fontes de informação e/ou métodos de análise de imagem alternativos, e

(5) Desenvolver um método automático para detecção e quantificação de mudanças na cobertura da terra usando imagens de sensoriamento remoto.

2. *Uma Área de Floresta Atlântica Semidecidual*

Acredita-se que a floresta Atlântica *sensu lato* chegou a cobrir aproximadamente um milhão de quilômetros quadrados, o que corresponde a quase 12% da área do país. Hoje em dia, este bioma está reduzido a menos que 5% da cobertura original. As florestas semidecíduas representam um subdomínio da floresta Atlântica que carece em estudos científicos quando comparado com o subdomínio das florestas costeiras, e que corre riscos mais eminentes do que as florestas amazônicas. A área escolhida para se estudar a floresta Atlântica semidecidual fica situada no "Vale do Alto Rio Grande" no sul de Minas Gerais. Ao final do século XIX, a cultura de café foi introduzida na região e aumentou rapidamente para se tornar uma das principais causas de desmatamento. Hoje em dia, além da crescente industrialização, a cultura do café e a produção de leite são as principais atividades econômicas da região. A área em estudo é delimitada pelas coordenadas 21° 05' - 21° 47' S and 44° 02' - 45° 04' O. A área foi estudada usando-se uma série temporal (28 imagens de 1981 a 1999) de dados provenientes do programa Landsat de observação da Terra via satélite. Dados auxiliares incluíram ortofotos na escala de 1:10.000 e curvas de nível com resolução vertical de 20 m, digitalizadas a partir de cartas topográficas da região.

3. *Processamento de informações geográficas*

Observações através de sensoriamento remoto são medições da energia refletida ou emitida após a radiação eletromagnética haver interagido com os objetos na superfície da Terra e com a atmosfera. As medições são organizadas como uma imagem de forma a retratar uma região da superfície da Terra em um dado momento. Repetindo-se observações de uma mesma área e/ou em diferentes porções do espectro eletromagnético, formamos um conjunto de dados multitemporal e/ou multispectral. Recentemente, muita atenção te sido dada às múltiplas escalas que caracterizam os fenômenos ambientais e consequentemente, de nossas observações com sensoriamento remoto. A análise com wavelets separa a informação de interesse de acordo com as escalas predominantes nas quais está se manifesta. Wavelets vêm da infinita repetição de um banco de filtros, e por causa das repetidas filtragens com filtros cada vez maiores, elas decompõem um sinal em detalhes que indicam a informação contida em diferentes escalas. Se os sinais em consideração são imagens de sensoriamento remoto, o termo "escala" em análise com wavelets corresponde ao tamanho dos objetos na superfície da Terra, que passam a ser modelados com mais facilidade usando-se esta nova representação em múltiplas escalas. Técnicas de aprendizado de máquina tem sido desenvolvida há algumas décadas dentro do campo de inteligência artificial. O objetivo da inteligência artificial é entender como os seres humanos reconhecem padrões e desenvolver sistemas computacionais inteligentes. Redes neuroniais e regras de indução, dois paradigmas populares em aprendizado de máquina, foram recentemente aplicados a problemas de classificação em geoprocessamento e mostram resultados promissores, principalmente na modelagem de fenômenos não-lineares e não-paramétricos.

4. Remoção de Nuvens em Séries Temporais de Sensoriamento Remoto

O uso de dados temporais é extensivamente explorado nesta tese. Neste capítulo, são apresentados esquemas baseado na análise em múltiplas resoluções, usando wavelets, para o pré-processamento de longas séries temporais de imagens Landsat e para melhorar sua aplicabilidade em avaliações ambientais. Particularmente, foram consideradas metodologias para remoção de nuvens e suas sombras. Este capítulo descreve a aplicação do produto entre escalas da transformação com wavelets para gerar máscaras binárias de observações corrompidas. O método "*robust smoother-cleaner wavelets*" foi aplicado em cada perfil temporal onde foram encontrados valores anômalos. A fase de interpolação foi baseada em estimação não-paramétrica usando-se "*wavelet shrinkage*". Contaminações por nuvens foram simuladas em uma série temporal livre de nuvens e os valores desconhecidos foram estimados usando-se cinco métodos: 1) valor médio, 2) valor mínimo, 3) valor máximo, 4) regressão linear, e 5) o procedimento baseado em regressão não-paramétrica com wavelets proposta neste capítulo. As comparações foram feitas com base na raiz do quadrado médio do erro (RMSE). Na interpolação dos valores desconhecidos, a regressão baseada em wavelets foi mais precisa para áreas com nuvens, enquanto que a regressão linear apresentou os melhores resultados em áreas sombreadas. O método proposto aqui identificou tanto pixels contaminados por nuvens e sombras, quanto outras anomalias como erros de registro de imagens e mudanças de curta duração. Já o método de regressão foi capaz de detectar e estimar os valores desconhecidos ao mesmo tempo. Assim, a análise com wavelets apresenta-se promissora para um efetivo pré-processamento de series temporais.

5. *Classificação dos Remanescentes Florestais*

A necessidade de melhores métodos de mapeamento se faz evidente pelo nosso pouco conhecimento sobre informações básicas, como por exemplo, extensão e condição das florestas em geral. Ecossistemas fragmentados como a floresta Atlântica semidecidual demandam o uso de imagens com alta resolução espacial. Não obstante, por causa de problemas relativos a similaridade espectral, a ocorrência de plantações de café e de eucalipto na região traz limitações para a classificação de remanescentes de florestas semidecíduas. O experimento descrito neste capítulo relacionou atributos derivados de um modelo de elevação digital, de dados de sensoriamento remoto, e várias transformações de imagens para realçar áreas de vegetação, textura de imagem e relações spectro-temporais. Conjuntos de atributos foram definidos usando-se o conhecimento de especialistas e técnicas de mineração de dados. Estes conjuntos foram usados em classificações tradicionais e em classificações baseadas em aprendizado de máquina, viz. máxima verossimilhança, redes neuroniais e árvores de decisão univariadas e multivariadas. Os resultados mostraram que a classificação por máxima verossimilhança usando medidas de textura temporal foi a melhor combinação para se classificar os remanescentes de floresta Atlântica na área de estudos. O classificador de máxima verossimilhança apresentou um desempenho relativamente razoável com todos os conjuntos de atributos, mostrando precisão de classificação de florestas variando entre 34,5% e 51,3%. Em contraste, redes neuroniais mostraram a maior variação, com precisão variando entre 19,0% e 45,2%. O pior precisão de classificação (19%) foi proveniente da combinação de redes neuroniais com o conjunto de atributos obtidos via mineração de dados, principalmente devido ao grande número de comissões. Como esperado, confusão na classificação aconteceu principalmente com plantações de café e de eucalipto, mas redes neuroniais e árvores univariadas também fizeram confusão com áreas desmatadas. Árvores univariadas proporcionaram os resultados mais robustos para os conjuntos de atributos, com precisão de mapeamento variando entre 39,6% to 46,7%.

6. *Análise de Mudanças em Múltiplas Escalas*

O objetivo do método proposto neste capítulo foi o de reduzir a sensibilidade de detecção digital de mudança aos efeitos de discrepância radiométrica e geométrica, através da extração de mudanças de acordo com classes de tamanho e usando métodos em múltiplas escalas. Uma imagem-mudança, produzida por qualquer método padrão de detecção de mudanças radiométricas (e.g., subtração de imagens), é decomposta com wavelets em seus componentes de alta freqüência e em uma representação aproximada relativa ao componente de baixa freqüência. O produto entre escalas de alta freqüência foi usado para realçar locais onde ocorreram mudanças na cobertura e para suprimir os efeitos derivados dos erros de registro. Usando-se o produto entre escalas de alta freqüência em uma simples composição colorida, a visualização de áreas onde ocorreram mudanças fica simples e rápida. Todas as mudanças detectadas por este procedimento de visualização foram verificadas na realidade, embora sua quantificação não tenha sido possível. Efeitos do registro impreciso e mudanças de pouca extensão foram isolados nas primeiras escalas de decomposição, enquanto que diferenças por causa de estágios fenológicos e condições atmosféricas foram isolados nas últimas escalas e na representação aproximada. Remoção de vegetação, áreas reflorestadas, bem como novas áreas de exploração de pedra foram efetivamente detectados sem a necessidade de prévia retificações radiométrica ou definição de valores de "threshold", enquanto que diferenças não relacionadas com mudanças na cobertura da superfície foram evitadas.

7. *Detecção Automática de Desmatamento*

Automatização tem sido uma das primeiras metas em geoprocessamento, devido ao potencial de executar tarefas não-supervisionadas proporcionada pelo uso de computadores. As dificuldades com detecção de mudanças em imagens de satélites são ainda maiores do que o mapeamento estático, impondo limites para a automação. As principais dificuldades estão relacionadas com: (1) as transformações geométricas, (2) o tamanho das mudanças que devem ser observadas, (3) a escala temporal em que as mudanças ocorrem, (4) as condições atmosféricas, (5) a resposta radiométrica dos objetos sobre a superfície da Terra, e (6) a natureza gradual de alguns tipos de mudanças. O objetivo deste estudo foi o de desenvolver um procedimento automático, simples e flexível para atualização de sistemas de informações geográficas (SIG) rasterizados. O procedimento proposto e ilustrado neste capítulo usa duas imagens de sensoriamento remoto adquiridas em diferentes datas, camadas do SIG representando as coberturas em estudo e um conjunto de verdades de campo para a cobertura atual e para áreas onde ocorreram mudança. A imagem mais recente é usada na atualização baseando-se em diferenças radiométricas com a imagem mais antiga. Quatro módulos compõe o procedimento de acordo com as principais tarefas executadas: (1) localização de áreas onde ocorreram mudanças, (2) quantificação da área modificada, (3) classificação das novas coberturas e (4) atualização da base de dados. O procedimento foi comparado com dois outros muito usados para detecção e quantificação de mudanças, viz. comparação pós-classificatória e classificação multitemporal direta. O procedimento foi menos sensível à erros de registro por causa da abordagem multiescala usada. Diferente de comparação pós-classificatória, o procedimento apresentado requer verdade de campo somente para a cobertura atual. Já em comparação com a classificação multitemporal direta, as classes de mudança não precisam ser definidas nem amostras precisam ser coletadas em locais que sofreram mudanças. Por fim, as áreas segmentadas podem ser consideradas objetos homogêneos e classificadas com tal, reduzindo o efeito de salpicamento nos resultados da classificação. Possíveis refinamentos incluem a determinação automática de limites de detecção e a possibilidade de se trabalhar com imagens multivariadas.

8. *Conclusões*

De acordo com os objetivos principais desta tese, uma estratégia baseada em sensoriamento remoto visando mapear e monitorar remanescentes florestais em áreas fragmentadas foi desenvolvida para a região do "Vale do Alto Rio Grande". Um procedimento que poderia ser facilmente implementado por não-peritos em processamento imagem para uma rápida avaliação de locais desmatados foi proposto. O método apresenta o potencial de proporcionar para autoridades locais e para institutos governamentais um sistema de controle de desmatamento para os remanescentes de floresta Atlântica semidecidual. A abordagem em múltiplas escalas mostrou-se uma ferramenta efetiva para estudar imagens de sensoriamento remoto que foram arbitrariamente amostradas na dimensão temporal, contaminadas por nuvens e sombras, e corrompidas por erros de registro. O procedimento descrito no capítulo 6 e implementado no capítulo 7 foi menos sensível ao barulho gerado durante o registro de imagens, pode ser combinado com qualquer técnica padrão de detecção de mudanças e pode proporcionar vantagens quando áreas muito extensas devem ser avaliadas. Dados temporais mostraram-se de extrema importância para mapear a floresta Atlântica semidecidual e, particularmente, séries temporais de NDVI provaram ser características úteis durante a classificação. Métodos de múltiplas escalas reduzem a quantia de informação para ser analisada ao executar tarefas automatizadas, mas, mesmo assim, deve existir um conhecimento prévio quanto as escalas importantes para uma dada aplicação. No capítulo 4, o classificador de máxima verossimilhança superou claramente os algoritmos baseado em aprendizado de máquina sempre que características temporais foram usadas para classificação. A análise em múltiplas escalas deveria ser vista como um complemento no geoprocessamento tradicional e não como um substituto para técnicas estabelecidas. Esta proporciona uma série de representações da superfície da Terra que isola características de paisagem de acordo com os níveis de escala dominantes nos quais as características se manifestam. Conclui-se que técnicas tradicionais poderiam, então, ser aplicadas à escalas selecionadas de acordo com os objetivos de um determinado projeto. Baseado nos achados apresentados nesta tese, postulados 1 à 3 foram confirmados, mas o postulado 4 foi parcialmente confirmado:

1) Técnicas de regressão não-linear e não-paramétrica são mais efetivas para se analisar e processar séries temporais de imagens Landsat com o intuito de minimizar os efeitos de contaminação de nuvem e distorções causadas por erros de registro.

2) Longas séries temporais são úteis para melhorar a separação de objetos espectralmente semelhantes na superfície da Terra. Estas podem ser particularmente importantes na distinção entre tipos de cobertura naturais e artificiais.

3) Dados geográficos apresentam informação em múltiplas escalas espaciais e temporais. A automatização pode ser melhorada se esta característica for levada em consideração durante o processamento.

4) Métodos em múltiplas escalas podem lidar com o crescente volume de dados disponíveis mais efetivamente que abordagens baseadas em escalas fixas. Métodos tradicionais de reconhecimento de padrão ainda proporcionam ferramentas importantes para processamento de informações geográficas.

No ambiente de processamento em múltiplas escalas que foi proposto nesta tese, cada conjunto de dados foi decomposto em uma representação em múltiplas escalas usando transformações com wavelets. Integração de dados, regressão, compressão e extração de informação foram realizadas no domínio transformado. Os resultados, transformados de volta (ou não) para os domínios espacial, temporal e espectral em qualquer resolução desejada, foram usados em sistemas de aprendizado de máquina que geraram conhecimento relativa à eventos e relações independentemente do tipo de dado. Neste contexto, eventos e relações foram então traduzidos em classificações, regressões, indicadores, predições etc. Detecção (semi)automática de mudanças e atualização de SIGs são tarefas plausíveis que deveriam ser implementadas por autoridades locais e planejadores para monitorar e entender a dinâmica de florestas na região. Melhorias significativas na detecção automática de mudanças incluem o desenvolvimento de algoritmos para seleção automática de escalas. A metodologia de pré-processamento apresentada no capítulo 3 pode ser usada para aumentar a disponibilidade temporal de imagens Landsat e séries temporais mais completas podem ser usadas para proporcionar perfis temporais com significado ecológico mais coerente. A efetiva classificação da floresta Atlântica semidecidual do Vale do Alto Rio Grande deveria sempre que possível levar em consideração dados temporais. No que diz respeito ao mapeamento de florestas da região, pesquisas futuras deveriam focar na classificação de sub-tipos florestais e na definição de características relevantes para esta tarefa. Por fim, as técnicas descritas neste estudo foram desenvolvidas para a solução de problemas relacionados com os domínios do espaço e do tempo. No entanto, os mesmos princípios podem ser aplicados ao domínio espectral para identificação e quantificação de bandas de absorção em assinaturas espectrais, para redução de dados e redução de barulho nos dados.

The Author

Biography

Luis Marcelo Tavares de Carvalho was born on February 7^{th}, 1971 in São José dos Campos, state of São Paulo, Brazil. He completed secondary school in 1987 at the *Instituto Pentágono de Ensino* in Santo André and studied forestry engineering from July 1989 till July 1995 at the *Universidade Federal de Lavras* (UFLA). In September 1995, he started a M.Sc. research project on environmental management at the *Departamento de Ciências Florestais* (DCF) of UFLA. He obtained the degree of master in 1997, with specialisation in community ecology, forest structure and canopy dynamics of montane and semideciduous Atlantic forests. He carried out an extensive part of the M.Sc. research at the *Parque Estadual de Ibitipoca* in Minas Gerais. In August 1996 he worked for the *Universidade Estadual de Minas Gerais* (UEMG) as a lecturer of ecology and evolutionary biology in a recycling course for teachers of the secondary schools of northern Minas Gerais. In September 1997, he presented a workshop on the utilisation of hemispherical photography in environmental studies for M.Sc. and Ph.D. students of the *Departamento de Biologia* of the *Universidade Estadual de Campinas* (UNICAMP). In November 1997, he started the Ph.D. research that is described in this thesis at the *Laboratory of Geo-information Sciences and Remote Sensing* of *Wageningen University*.

Publications

- Refereed journal papers:

CARVALHO L.M.T., Fontes M.A.L., & Oliveira-Filho A.T., 2000. Tree species distribution in canopy gaps and mature forest in an area of cloud forest of the Ibitipoca Range, south-eastern Brazil. *Plant Ecology* 149, 9-22.

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- Book chapter:

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The Landsat TM image on the back cover is one of the images used in this research. The colour representation is RGB with band 4 (R), band 5 (G), and band 3 (B). In this image, forests appear red.

The oblique aerial photography was taken during field campaigns in 1999. In this image, forests appear dark green.

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