Spatial modelling and monitoring of natural landscapes

Promotoren:

dr.ir. M. Molenaar,	Hoogleraar in de Geo-informatica en de Ruimtelijke Gegevensinwinning
dr. J. Sevink,	Hoogleraar in de Fysische Geografie, in het bijzonder de Bodemgeografie, de Landevaluatie en de Landschapsecologie

Spatial modelling and monitoring of natural landscapes

with cases in the Amsterdam Waterworks Dunes

Wim Droesen

Proefschrift
ter verkrijging van de graad van doctor
op gezag van de rector magnificus
van de Landbouwuniversiteit Wageningen,
Dr. M.C. Karssen,
in het openbaar te verdedigen
op woensdag 19 mei 1999
om 13.30 uur in de Aula.

This research was funded by the Amsterdam Water Supply:
Gemeentewaterleidingen Amsterdam
PObox 1005
1005 AD Amsterdam
the Netherlands

Cover: Jaap van der Wel

Droesen, Wim J.

Spatial modelling and monitoring of natural landscapes;
with cases in the Amsterdam Waterworks Dunes / Wim Droesen.
Thesis Wageningen Agricultural University
with summary in Dutch
ISBN 90-5808-054-4

Printed by: Ponsen & Looijen bv, Wageningen

STELLINGEN

1. Componenten van natuurlijke landschappen kunnen realistisch worden gemodelleerd als een mozaïek van scherp begrensde ruimtelijke objecten met gradueel variërende interne velden.

   dit proefschrift

2. De semi-automatische interpretatie van hoge resolutie kleur-infrarood beelden van een duinlandschap levert een gedetailleerd en nauwkeurig mozaïek van vegetatiestructuurobjecten.

   dit proefschrift

3. De toepasbaarheid van een beeldinterpretatiemethode dient primair getoetst te worden aan de patroonkenmerken in een beeld in relatie tot de terreinkenmerken. Abusievelijk worden vaak statistische randvoorwaarden als uitgangspunt genomen.

   dit proefschrift

4. Vegetatietypen - in de duinen - hebben een fuzzy karakter in ruimte en tijd.

   D.W. Roberts (1989) Fuzzy systems vegetation theory (Vegetatio 83: 71-80)
   dit proefschrift

5. Expertkennis van complexe ecologische systemen, zoals vochtige duinvalleien, kan adequaat worden geformaliseerd met behulp van fuzzy logica.

   dit proefschrift

6. In de discussie over de bruikbaarheid en betrouwbaarheid van landelijke ecologische modellering op basis van expert-modellen - zoals DEMNAT - en meer procesmatige modellen - zoals SMART en MOVE - kunnen fuzzy modelconcepten de balans doen doorslaan in het voordeel van de eerste.

7. Gezien het feit dat de dynamiek in de duinen vooral uit vegetatiesuccessie bestaat, getuigt een ecosysteemvisie onder de titel ''Duinen voor de wind'' van een eenzijdige blik.

   M. Janssen en A. Salman (1992) Duinen voor de wind: een toekomst visie op het gebruik van de Nederlandse duinen als natuurgebied van internationale betekenis (Stichting Duinbehoud, Leiden)

8. Digitale orthofoto's zijn een kosten-effectieve informatiebron voor landschapsecologische en aanverwante karteringen. Het gebruik van deze beelden verdient dan ook aanbeveling.

9. De klassieke tweedeling in veld- en bureauwerk tijdens karteringen vervaagt door ontwikkelingen in de informatietechnologie. Relevanter wordt het onderscheid tussen het observeren en vastleggen van gegevens in het terrein of in de virtuele werkelijkheid.

10. Het poldermodel werkt nivellerend; ook op de ruimtelijke inrichting van Nederland. Bestaande kwaliteiten nemen af, terwijl er onvoldoende ruimte is voor offensieve planning, gericht op werkelijke kwaliteitsverbeteringen in stad en land.

    C.A. Louws (1999) Persoonlijke communicatie

11. Het onderbrengen van 'GIS' op de tekenkamer van een organisatie doet geen recht aan de aard van het werk en leidt tot een beperkt gebruik van de functionaliteit.

12. De informele - doorgaans vage - organisatiecultuur van een kennisintensieve organisatie is belangrijker dan de formele structuur.

    M. Weggeman (1996) Kennismanagement, inrichting en besturing van kennisintensieve organisaties (Scriptum)

13. Goede typevaardigheden dragen bij aan een vlotte interactie tussen mens en computer. Het instellen van typeles in het basisonderwijs verdient daarom aanbeveling.

14. Het heffen van statiegeld op blikjes is een eenvoudige en effectieve manier om van wegwerpers zoekers te maken.

Stellingen behorende bij het proefschrift "Spatial modelling and monitoring of natural landscapes with cases in the Amsterdam Waterworks Dunes" van Wim Droesen.

Roosendaal, 21 april 1999.

to Hannie, Jan and Susan

Preface

The Amsterdam Water Supply is an innovative company. Consequently, the Amsterdam Water Supply was in the late 1980's one of the first companies in the sector taking geographic information systems and remote sensing applications into operation. Geographic information systems were employed to facilitate the acquisition, analysis and storage of massive amounts of spatio-temporal data regarding its extensive water catchment area. Aerial surveys were employed over the Amsterdam Waterworks Dunes to obtain spatial information on landscape dynamics.

However the utilisation of these new tools and techniques gave rise to many research questions for which consultancy was obtained from the Department of Land Surveying and Remote Sensing of the Wageningen Agricultural University and the Department of Physical Geography of the University of Amsterdam. In due course the co-operation between these three organisations led to the definition of a PhD project of which the results are presented in this thesis. I gratefully acknowledge the Amsterdam Water Supply for their initiative and funding.

Many people contributed to this thesis. Firstly, I want to thank my promoters. Martien Molenaar for his encouraging attitude as the work went along. His power of abstraction helped me organise seemingly complex matters. Pim Jungerius introduced me to the geomorphology and pedology of the dunes. He was succeeded by Jan Sevink who thoroughly read and commented on drafts of the thesis.

Next I gratefully acknowledge the colleagues of the Amsterdam Water Supply I co-operated with most intensively. The chapters 3, 4 and 5 could not have been written without the field data collected by Mark van Til. I also heavily profited from his expertise on dune vegetation. Luc Geelen co-ordinated the ecohydrological modelling of the Amsterdam Waterworks Dunes, the results of which are partly presented in chapter 7. Fortunately, my fuzzy view on this matter appeared quite evident to him. In addition Gert Baeyens, Ton Graveland, Theo Olsthoorn and Jacob Steinmetz supervised my work on behalf of the Amsterdam Water Supply. The commitment of their skills resulted in an fully utilised working environment and helped me to improve the quality of this thesis.

Special thanks I owe to Dan Assendorp at the University of Amsterdam. Many of the concepts presented in this thesis were formed during lengthy mutual discussions. Next I thank Nanna Suryana Warsitakusumah, Jan Hein Loedeman, René van der Schans and Henk Schok at the Wageningen Agricultural University, Frank van der Meulen and Victor Witter at the University of Amsterdam, Harrie van der Hagen of the South Holland Dune Waterworks and all others who contributed to this thesis.

Riegart Moors and Susan Weightman are acknowledged for correcting the spelling and syntax of the manuscript.

I intended to write a thesis worthy of note by workers in the field of geographical information systems, remote sensing and landscape-ecology. I trust you will find it interesting reading matter and will be able to apply the presented concepts to your own benefit.

Roosendaal, 31 December 1998

Contents

1. Introduction

1.1 Monitoring natural landscapes

This thesis is concerned with the information supply for the manager of natural landscapes and in particular the role geographical information (GI) systems and remote sensing (RS) play in this process. *Landscape management* applies to those man-induced activities which aim to direct landscape development in accordance with certain objectives. Landscape management includes a range of activities from fundamental ecological research to the design and execution of practical management measures (Leser, 1991). Here we are interested in the production of the information necessary to embark upon the planning of management measures. The information flow during the different phases of planning, such as scenario studies and decision making, and plan execution is not dealt with. Before elucidating the information requirements of the landscape manager, the object under study will be specified.

A landscape is considered *natural* when the human effects, if present, are not ecologically significant to the landscape as a whole (Forman and Godron, 1986). As such a landscape does not have to be free from all human activity. Areas where the anthropogenic activities are limited to for instance extensive cattle breeding might still be considered natural, unlike agricultural and urban areas or areas used for forestry.

A landscape manager is confronted with a group of key questions (Holbrook et al., 1992, Davies et al., 1995). What are the features of interest and how significant are they? What is the relationship between these features in space and time and in terms of function and structure? How are the features changing and why? How do they relate to different management regimes, and, if some factor changes, what would be the implication for the resource and its future management?

Consider for example the management of the Amsterdam Waterworks Dunes. Apart from recreation, drinking water supply and sea defence, an important function of the Amsterdam Waterworks Dunes is nature conservation. The significance of the dune area as a nature reserve is caused by the amount and the intensity of different natural processes (sect. 1.5). These processes concern mainly groundwater, relief, soil, vegetation and animal life (Bakker et al., 1979). Gradual changes and sudden catastrophes resulted in a complex and finely grained landscape where both sharp contrasts and smooth transitions occur. For instance a blow out can occur next to shrubs but also be enclosed by a gradient of pioneer vegetation.

Unmistakably, vegetation succession in the area tends towards scrub formation. Moreover, herbaceous vegetation locally transforms into grass vegetation due to atmospheric deposition (Ten Harkel and Van der Meulen, 1996) and reduced grazing activities by rabbits (Geelen, 1990). Grass and scrub encroachment together with former sand reclamation by dune managers reduced the geomorphologic activity in the area and are likely to nullify the finely grained landscape pattern in the long run. Dune managers are now counteracting these undesirable developments by reintroducing dynamics in the area by means of large grazing mammals (sheep and cattle) and the stimulation of blow outs (Ehrenburg and Baeyens, 1992).

The managers of the Amsterdam Waterworks Dunes are in a constant need for up to date spatial information in order to lay out optimal management plans and to evaluate the effectiveness of the management measures. Landscape monitoring is the umbrella term for activities aiming at the generation of this information. The conceptual basis for landscape monitoring has to be provided by landscape ecological models, where *landscape ecology* is the study of the ecological structure, function, and change in a land area (Forman and Godron, 1986). Typically, landscape ecological models extend in space and time.

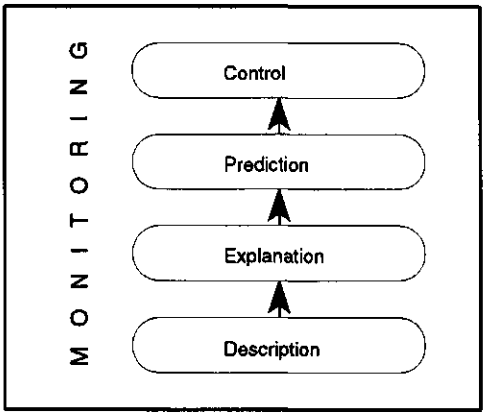


Figure 1.1 Four ordered objectives for landscape monitoring (the links symbolise a 'part-of' relationship).

Landscape ecological models can be classified with respect to criteria concerning conceptual and instrumental issues, e.g. the level of abstraction or the type of mathematics used (Baker, 1989). Corresponding to Chatfield (1989), the modelling objective is used to classify landscape ecological models into four categories (1) description, (2) explanation, (3) prediction and (4) control (fig. 1.1). These categories are ordered according to increasing capabilities.

Descriptive modelling aims at deriving a proper representation of landscape features of interest in the space-time continuum. Data acquisition and inventory are the two most important aspects (e.g. Hope et al., 1993; Miller and Morrice, 1993), although this modelling phase might involve some analysis such as cluster analysis, the characterisation of pattern and shape (LaGro, 1991; Pastor and Broschart, 1990) and trend estimation (Jakubauskas, 1989; Wildi, 1988).

Explanatory modelling goes beyond the level of description and intends to discover relationships between variables in order to explain their behaviour. Statistical techniques like multivariate analysis (Gurnell et al., 1993) and ordination (Jongman et al., 1987) can be helpful in this respect. Many techniques are available for the analysis of relationships between variables in the space-time domain (e.g. Cressie, 1991; Legendre and Fortin, 1989; Turner et al., 1990). Obviously, the established relationships depend upon the spatial entities of the underlying descriptive model (Fotheringham and Rogerson, 1993). Openshaw (1989) uses the term 'modifiable aerial unit problem' to indicate the difficulty of tuning the spatial entities to a certain analysis method. Tobler (1989) takes an opposite view on this problem and argues that artefacts can be minimised by choosing appropriate analysis methods indifferent to changes of spatial units.

Only when explanatory research yields a profound understanding of the relevant mechanisms determining landscape development, can the next phase in landscape modelling be undertaken, i.e. the forecasting of future events through *predictive modelling*. Consequently, models of this type are less numerous (e.g. Rastetter, 1990; Wissel, 1991; Albrecht, 1992; Van Deursen, 1995).

Finally, landscape modelling can help to *control* landscape development. Hereto, various actual and/or future aspects of the landscape are evaluated with respect to certain criteria. When a critical level is exceeded a management measure is induced. Obviously, the decision for a specific management measure depends on its predicted impact. As pointed out before, this thesis will not deal with the actual control or management of the landscape. In this thesis examples will be provided of the first three modelling types.

Monitoring is the umbrella term for the modelling activities introduced in the previous section (fig. 1.1). Consequently, monitoring can involve elements of four model types in any combination. The data flow in a monitoring process is handled by a monitoring system. A monitoring system is a set of hard- and software for the measurement, storage, processing and presentation of spatial and temporal data. Usually, a GI system and remote sensing applications form prominent parts of such a system (Haefner, 1987; Welch et al., 1992).

1.2 Landscape ecological modelling using GI systems and remote sensing

In the last decade, GI systems have become a standard instrument in landscape ecological research (e.g. Turner and Gardner, 1990; Haines-Young et al., 1993; Johnson, 1990). A GI system is a set of hard and software for the storage, processing and presentation of spatial information. Some relevant topics dominating last years GIS-related research are the object-oriented approach (Oxborrow and Kemp, 1989; Molenaar, 1998), handling uncertainty (Heuvelink, 1993; Lodwick et al., 1990; Veregin, 1989), aggregation and generalisation (Richardson, 1993) and temporal aspects (Langran, 1989). Recently the graphic visualisation of spatio-temporal data has become a new area of study.

Remote sensing data have been used for a longer period. These data have been recognised to be an indispensable source of information for the landscape modeller. Initially, aerial photographs were used in an analogue form. Nowadays scanned aerial photographs and other digital remote sensing data such as satellite images are frequently used (Quattrochi and Pelletier, 1990). Consequently, landscape modellers also become acquainted with digital image processing techniques. These developments benefit from the ongoing integration of image processing techniques in GI systems.

The availability of GI systems for a structured processing of environmental data, and digital image processing as a tool for spatial data acquisition opens new possibilities for the modelling of natural landscapes. However, the application of these techniques not only facilitates the construction process of a digital landscape model, but also brings about the need to reconsider the concepts underlying the modelling process (Haines-Young et al., 1993). While working with GI systems ecologists often adhere to old concepts and working methods, whereby the digital environment is utilised but not fully exploited.

A landscape is conventionally represented by chloropleth maps, which resulted from a manual photo interpretation. Although nowadays these maps are digitally stored in a GI system, their information content equals an analogue representation. A proper application of GI systems and remote sensing, however, should aim at improving the digital representation of a landscape, such that the analysis of these landscape data yield more accurate and relevant information. Digital landscape models should improve with respect to:

- the degree of reality and the level of detail. Generally, a natural landscape shows a mosaic of continuous an discrete patterns making a representation in discrete spatial units only, e.g. patches and land units, rather poor.
- the degree of subjectivity. By formalising the input of expert knowledge and image interpretation issues, the construction of landscape models becomes less subjective and repeatable.

In order to turn these potential improvements into practice new concepts and methods for landscape monitoring need to be developed. The concept of a landscape (i.e. structure, function and change) can be subdivided into several levels of abstraction (fig. 1.2). Grelot cited by Kemp (1993), terms the models on the first level *geographic models*. Geographic models are conceptual models used by modellers 'as they evolve an understanding of the phenomenon being studied and extract its salient features from the background of infinite complexity in nature'. Because the studies in this report have a landscape-ecological character, it is more appropriate to term these types of conceptual models *landscape-ecological (LE) models*. Note, that in doing so the meaning of a LE-model is curtailed to conceptual modelling only.

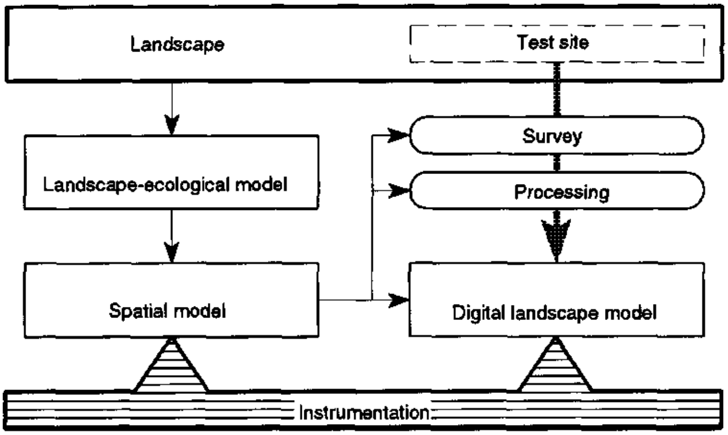


Figure 1.2 Process of conceptual and concrete landscape modelling.

The second level of abstraction is represented by *spatial models*. Conceptual spatial models are formally defined sets of entities and relationships used to discretize the complexity of landscape-ecological reality (Goodchild et al., 1992). The entities in these models can be measured and the models completely specified. On the next level data structures describe details of specific implementations of spatial data models (Molenaar, 1994). Data structures and lower data layers are considered to be part of the instrumentation. Here we are primarily concerned with landscape-ecological models, spatial models and the relationship between them.

It was argued that the spatial model has to follow from the specifications in the landscape-ecological model. However, in practise one works usually the other way around, starting from the spatial models readily implemented in commercial GI systems. In general these spatial models do not provide sufficient functionality to represent complex landscape-ecological systems satisfactorily. Moreover the creativity of the modeller is confined. In an ideal situation landscape modellers in search of appropriate analytical tools and spatial modellers lacking an ecological background interact to produce a seamless coupling between the two modelling steps. The latter situation is pursued in this thesis.

So far only conceptual models have been dealt with. The next step is the construction of a concrete or *digital landscape model* according to the specifications originating from the conceptual spatial model (fig. 1.2). These specifications concern the implementation of the spatial model with some data structure, and the surveying and processing of the actual data.

1.3 Thesis objectives

The general objective of this thesis is to develop methods for:

1. monitoring landscape-ecological aspects of natural landscapes
2. a by employing tailored spatial models, and
   b using digital remote sensing data.

The first part of the general objective deals with the intended activities and the object under study. By monitoring is meant all those activities related to spatio-temporal modelling introduced in section 1.1. The intended landscape-ecological aspects of natural landscapes are geomorphology, hydrology, soil and vegetation and their mutual interaction.

The second part of the objective specifies two conditions by which the monitoring process is steered in order to obtain a close resemblance between the landscape under study and its digital representation. The first condition concerns the definition of a spatial model capable of representing the complex spatio-temporal variation characteristic for natural landscapes. By the second condition, it is recognised that remote sensing provides the best practical means to derive landscape covering data on earth surface characteristics. Clearly, the significance of monitoring largely depends on the tuning of the spatial model with the information content of the remote sensing data. Practical limitations in data acquisition and data processing set restrictions to the digital landscape model and therefore have to be faced during the specification of the objectives and the definition of the conceptual models. This iterative search for optimal attunement, results in methods that are partly grafted upon the instruments. The importance of remote sensing data, however, justifies this procedure.

The general objective of the thesis is given a concrete form in three more specific objectives proceeding from the management practice in the Amsterdam Waterworks Dunes. For a proper nature and hydrological management of the area the following models are needed:

3.a Spatial and temporal descriptive model of the vegetation structure and areas of wind activity using high resolution digital CIR-photographs.

3.b Explanatory model of the spatial distribution of plant communities using vegetation structural and other environmental data.

3.c Predictive model of ecotopes in dune slacks using vegetation structural and environmental data and a quantitative hydrological model.

CIR-photographs reveal details of the dune landscape concerning vegetation structure and wind and water erosion (Jungerius and van der Meulen, 1988). Hence, these features can be interpreted and captured by a descriptive model extending in space and time (3a). Generally, these photographs do not provide detailed information on the vegetation composition. Consequently, spatial information on the species composition (3b) has to be explained from available information on the structure of the vegetation and other environmental data, like water table and relief.

While the proposed models 3a and 3b relate to the whole dune area, the predictive ecohydrological model (3c) applies to dune slacks only. The central issue in the construction of the ecohydrological model was the formalisation of knowledge in an expert system.

1.4 Thesis organisation

The thesis starts with the introduction of some conceptual aspects of landscape modelling (chapt. 2). Emphasis is put on the relationship between spatial and landscape ecological modelling. In the subsequent four chapters these concepts are applied and tested. Chapter 3 and 4 deal with objective 3a of the thesis. Chapter 3 considers the classification of the vegetation structure with digital CIR photographs resulting in state descriptions of the vegetation structure. Subsequently, a spatio-temporal analysis is performed on these state descriptions to quantify landscape dynamics (chapt. 4).

The estimation of the species composition using vegetation structural and environmental data is dealt with in chapter 5 (objective 3b). Chapter 6 deals with objective 3c, i.e. the construction of a predictive ecohydrological model for dune slacks. The thesis concludes with some remarks on the applied methods and gives some future perspectives for digital landscape monitoring (chapt. 7).

1.5 Description of the test area

The Amsterdam Waterworks Dunes border the North Sea to the west of Amsterdam (fig. 1.3). The area measures about 3300 ha and stretches 8 km along the coast. A variety of highly complex patterns express a great wealth of natural beauty in the area. Bakker et al. (1979) performed a hierarchical system analysis of the Dutch dunes, which resulted in a landscape ecological model consisting of 7 hierarchical levels (fig. 1.4). At the top of the hierarchy each level or *landscape component* is primarily governed by processes in higher components resulting in top-down constraints, while the feed-back mechanisms are weak. Going down the hierarchy, the strengths of the top-down and bottom-up relationships become more and more equivalent. In this thesis emphasis is put on geomorphology, vegetation and hydrology. Therefore, these three landscape components are briefly described.

The dune landscape has been formed over the last five millennia during periods of eolian drift. During these periods the dunes expanded in the direction of the sea and existing dunes moved again. This process of periodic large-scale geomorphologic activity resulted in a series of landscape zones parallel to the coastline. After fixation of the sand by pioneer species, different vegetation types will succeed eachother.

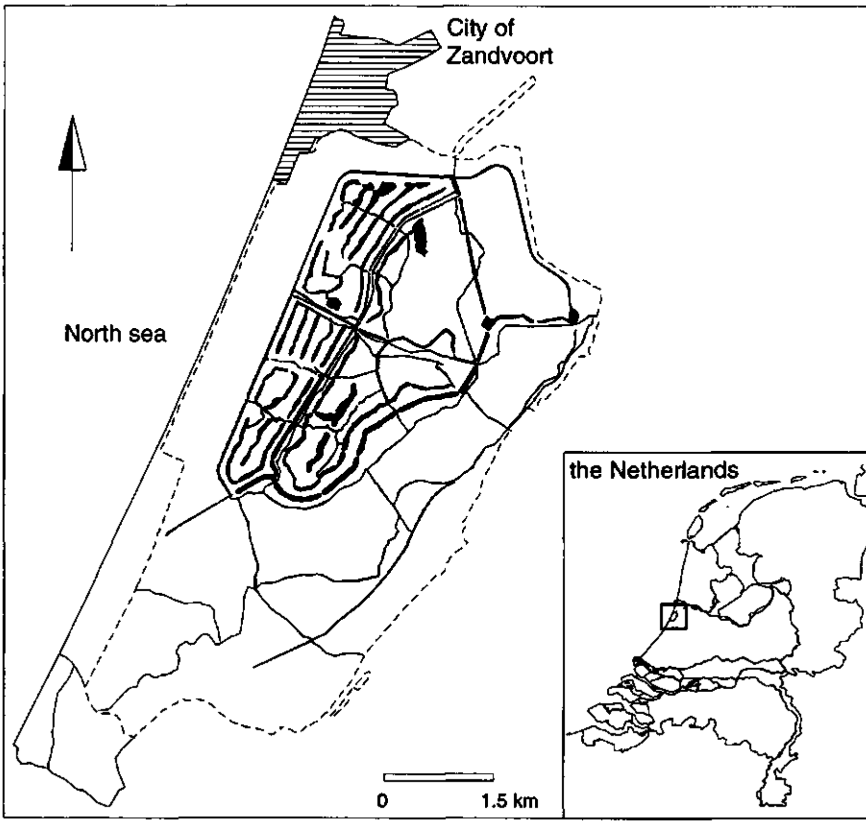


Figure 1.3 Topography and location of the Amsterdam Waterworks Dunes.

The first major zone encountered starting from the coast and a foredune vegetated by *Ammophila arenaria*, is a landscape characterised by parabolic dunes. *Ligustrum vulgare*, *Salix repens* and low herbaceous vegetation are the main types of vegetation here. The next, older dune landscape can be typified by wide dune slacks and dune ridges with a height up to 25 m. The vegetation of this zone is dominated by *Hippophae rhamnoides*. Further inland are the oldest, more decalcified inner dunes, mostly vegetated by a mosaic of short grasses, dwarf scrub, *Quercus robur* and *Populus spp* woodland (Ehrenburg and Baeyens, 1992). Nowadays, most of the area is covered with vegetation. However, throughout the area spots of active wind erosion

occur. These blow outs come into being on places where the vegetation is degraded. In turn less active blow outs are fixed by vegetation (Jungerius and Van der Meulen, 1988).
Besides natural processes, man has also played a major role in transforming the landscape. By the seventeenth century, part of the area was used for agriculture (Geelen, 1990). Arable farming and cattle breeding continued until about 1945. Until recently, sand-drifts were reclaimed by planting *Ammophila arenaria*. The largest impact of man, however, concerns the hydrology of the area.

The hydrological system is strongly affected by activities related to the production of drinking-water (Olsthoorn et al., 1998). In 1853, the Amsterdam Water Supply started to discharge groundwater from this area. Until the year 1957, the groundwater table dropped several meters because the amount of discharge exceeded the input through precipitation. From then on, prepurified river water was infiltrated and artificially recharged in part of the area. These man-induced changes in water quantity and quality had a major effect on vegetation in dune slacks which is associated to the phreatic surface.

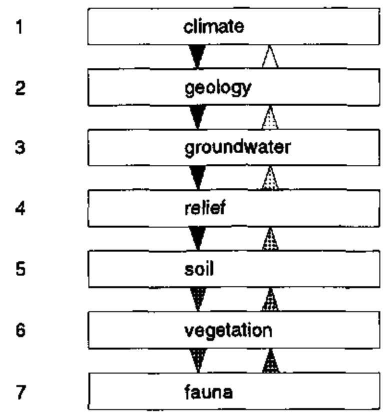


Figure 1.4 Hierarchical model of a dune system consisting of seven related landscape components, the darker the link the stronger the relationship (after Bakker et al., 1979).

2. Conceptual aspects of landscape monitoring

The relationship between spatial modelling and landscape-ecological concepts was mentioned in section 1.2. It was argued that the spatial model has to follow from the specifications derived from the landscape ecological model. Therefore, this chapter starts with a short introduction of some basic landscape-ecological concepts relevant to spatial modelling (sect. 2.1). The subsequent sections elucidate three approaches to spatial modelling; fields (sect. 2.2), objects (sect. 2.3) and objects with nested fields (sect. 2.4). Along with the description of these three spatial models their possible application in modelling natural landscapes is evaluated.

2.1 Pattern and process

Landscapes are systems operating in the four dimensional spatio-temporal continuum at the earth' surface (Leser, 1991). Generally, the starting point for a system analysis is to distinguish between pattern and process. Accordingly, a *system* is defined as a complex unit in space and time operating systematically in a way that the integral configuration of *pattern* and *process* can be restored after non-destructive disturbances (Mueller, 1992). Forman and Godron (1986) specify the interaction between landscape structure (pattern) and functioning (process) as an endless feedback loop:

> 'Past functioning has produced today's structure;
> today's structure produces today's functioning;
> today's functioning will produce future structure.'

As any system, natural landscapes have some fundamental characteristics like self-regulation, self-organisation and an inherent hierarchical structure (Mueller, 1992). Because the hierarchical structure of landscapes provides some major clues for specifying a proper spatial model, it is dealt with in more detail.

Landscapes have an organisational structure ranging from low to high levels. Take as an example the following range of subsystems each operating as part of the landscape system: leaf, tree and woodland. These subsystems are ordered according to increasing size, life time and complexity. Obviously, a leaf is a subsystem of a tree and in turn a tree is a subsystem of woodland. The paradigm for handling the organisation underlying such systems is *hierarchy theory* (Urban et al., 1987; O'Neill et al., 1989; Kotliar and Wiens, 1990; Dikau, 1990).

Hierarchically organised systems can be divided or decomposed into discrete functional components (holons) operating at different scales. The hierarchical paradigm provides guidelines for defining these functional components of a system, and defines ways to relate components at different levels to one another, e.g. lower-level units interact to generate higher-level behaviours and higher-level units control those at lower levels. Events at a given level have a characteristic frequency and a corresponding spatial extent. In general, low-level events are comparatively small and fast. Higher-level behaviours are larger and slower.

A subsystem at a given hierarchical level experiences only the dynamics of other subsystems operating on that level. By comparison the dynamics of higher-level subsystems are too slow to be experienced as variable, while the dynamics of lower-level subsystems are to fast to be individually experienced. Hence, a system merely experiences the aggregated dynamics of all its subsystems. For instance the grazing of rabbits on a dune grassland is more easily described by the aggregated activities of all rabbits, than by describing the activities of each individual rabbit. When these notions are incorporated in a model, effectively non-equilibrium dynamics or spatial heterogeneity at one level can be translated to equilibrium or constancy at a higher level (Urban et al., 1987). In summary a hierarchical perspective brings about three strategic concerns in the description of a landscape (O'Neill et al., 1989):

- detect patterns at multiple hierarchical levels and define the spatial units functioning on each level,
- relate a pattern to adjacent levels, and
- infer which processes generate the pattern.

In spatial information processing two major approaches exist for the conceptual representation of hierarchical systems, the field and object respectively (Molenaar, 1998; Baker, 1989; Piwowar et al., 1990):

- A (physical) *field* is a feature which is contiguously distributed over space and time. In a field the strength of the interacting forces is a function of the position within the field and the resulting pattern can also be expressed in terms of position dependent field values. Examples of terrain features with a field characteristic are the ground water system and the electromagnetic radiation emitted or reflected by the earth surface and detected by human vision and remote sensing techniques.
- Contrarily the *object* approach assumes that the earth's surface is populated with spatially interacting discrete units. Each unit or object has its own behaviour. The pattern resulting from these processes can be expressed by the spatial distribution and the state of the objects. Evident objects are individual plants or animals, but also less tangible spatial units like plant communities and blow outs can be considered as objects.

Both the field and object approach enable the combined modelling of pattern and process. In order to quantify the patterns and processes of a specific landscape within the framework of one of the two terrain descriptions two main research strategies can be distinguished. Firstly, one can start from a hypothetical process description and test the hypothesis on gathered data. A second strategy is to gather data on the landscape structure and recover the underlying processes from an analysis of the data in an explorative research. The emphasis in this thesis is put on pattern as starting point for empirical explorative research on landscape development. A correct representation of a landscape in a pattern is therefore of primary concern.

Spatio-temporal pattern

The components of data on the real world are attribute, space and time. Consider a vector of attributes Å and a spatial and temporal domain of interest, D_s and D_t respectively. Then Å(**x**,**t**) is the value of Å in the domain of interest, where **x** represents a variable taking values in D_s and **t** represents a variable taking values in D_t. Å(x,t) is a full *spatio-temporal pattern*, when Å is known for every location $x_i \in D_s$ and every moment $t_j \in D_t$. A *spatial pattern* Å(x|t_j) provides attribute values at every location within D_s but only for one moment t_j. Accordingly, a *temporal pattern* Å(t|x_i) holds attribute values at every time within D_t for only one position x_i. Any sufficiently large set of points Å(x_i|t_j) or Å(t_j|x_i) provides a point pattern, i.e. a partial pattern description.

The spatial domain D_s is a subarea of a metric space R_n. The distance in this space can be defined in absolute or relative measures (e.g. Holly, 1978; Meentemeyer, 1989; Turner et al., 1989). In this thesis D_s is a subarea of a two dimensional euclidian space R^2 resulting from the projection of a segment of the curved real world surface. Relative space is created when distance is related to some functional relationship. The distance between two points can for instance be expressed in the effort required by an organism to travel between them, i.e. a non-linear transformation of euclidian space. Time adds the third dimension to the model space. Here chronotime is used. Time can be relative too, for instance when the functioning of plants is specified along the seasonal cycle.

Unfortunately, the value of Å in model space is unknown and has to be estimated. The approximation of Å(x,t) by an estimation method M(x,t) is denoted as A(x,t). A(x,t) is the spatio-temporal pattern one deals with in practice. A pattern is thus created through an estimation method, e.g. measurement, interpolation or process modelling. Yet depending on this method different patterns can be derived for one attribute from a single landscape. Consequently, pattern is no inherent property of a landscape but a product of the interaction between landscape and applied methods (Wiegleb, 1989; Perez-Trejo, 1993).

Spatio-temporal patterns A(x,t) are frequently produced by spatio-dynamic models in the field of meteorology and hydrology. Examples of spatio-temporal patterns in landscape-ecology are few (Turner and Gardner, 1990). This can be attributed to a lack of theory to build spatio-temporal models and practical limitations to the collection of the vast amount of input data usually needed (Baker, 1989). Until now, landscape-ecological modellers have put most effort in a proper quantification of spatial pattern A(x|t_j), simplifying the problem of spatio-temporal modelling to the quantification of a number of spatial patterns in time. Hence, a spatio-temporal pattern becomes a collection of spatial patterns in time $\{A(x|t_1), A(x|t_2), ...A(x|t_n)\}$, where each spatial pattern represents a slice of the spatio-temporal continuum, comparable to a temporal sequence of remote sensing images. In the next paragraphs the representation of spatial patterns by the field and object approach will be elucidated.

2.2 Fields

A field takes attribute values A at any position in the spatial domain D_s as a function of its position:

$$A = f(x) \quad x \in D_s \tag{2.1}$$

Usually, the spatial variability of A is considerable and the representation of a field by an analytical function becomes practically impossible (Kemp, 1993). Consequently, a field is represented by a finite collection of discrete data captured in a data structure. For the representation of fields several data structures are available retaining a contiguous character, e.g. triangular irregular networks (TIN), contour models and rasters. Subsequently, the raster structure is used to represent fields, because it is the most comprehensive structure and remote sensing data are structured accordingly.

2.2.1 Spatial field represented in cell-raster

In a raster the thematic data are directly linked to position. A raster is a collection of points or cells which cover the terrain in a regular grid. In a point raster each raster element contains thematic data that refer to a point position. In a cell raster the thematic information refers to an area segment represented by each element, i.e. attribute values are aggregated over the cell. For practical reasons these cells or segments are usually square, although a hexagonal shape might be more appropriate to represent curved-shaped natural features. When a third dimension (Z or time) is added the cells become volumes, named voxells.

It depends on the data acquisition technique and the processing of the data whether data in a raster represent a point or a cell. Digital images usually have a cell structure, where a cell is called pixel. Figure 2.1 shows the geometric definition of a cell-raster (Molenaar, 1998):

- The origin of the axes along which the rows and columns will be counted. The origin has the coordinates (X_0, Y_0).
- The orientation of the two orthogonal axes.
- The choice of the stepsizes dX and dY specifies the geometric resolution of the raster.
- The extent of the raster is determined by the lower left corner of the lower left cell and upper right corner of the upper right cell, respectively (X_l, Y_l) and (X_h, Y_h).

Topology is the final geometrical aspect of a raster to be dealt with. The topology of a raster is based on the topologic relationships among the elements, i.e. the adjacency of the raster cells. Each cell has two types of neighbours. Adjacent elements in the same row and in the same column are called full neighbours. Cells having a common corner point with the central element are diagonal neighbours. From these basic topological links any neighbourhood can be defined. A neighbourhood can also be defined by distance and/or direction from a central cell, e.g. circle, rectangle and doughnut. Note that topological relationships refer to spatial relationships, unlike the common ecological term chorological (Zonneveld, 1989). Ecologists are used to term relationships that exist on a specific point, topological.

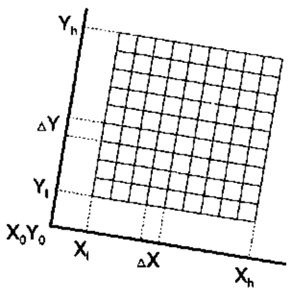


Figure 2.1 Geometric definition of cell rasters (see text for explanation).

The thematic characteristics of a raster are determined by its attributes, where each attribute is defined by a name, scale type and domain. A single valued raster contains values of only one attribute. If a raster describes two or more attributes the raster is called multi-valued (fig. 2.2).

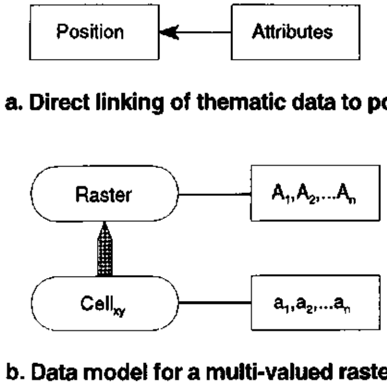


Figure 2.2 Spatial field represented by a cell raster.

Firstly, cell values of a raster can be obtained through systematic sampling. Although not completely correct, i.e. the support of the measurement is not equal to a specific grid cell (Lillesand and Kiefer, 1994), remote sensing imaging instruments perform a systematic area sampling. Systematic sampling in the terrain is very laborious and therefore rarely applied (Legendre and Fortin, 1989).

Secondly, cell values can be obtained through the interpolation of a set of irregularly distributed sample values. Some current spatial interpolation methods are inverse distance weighting, triangular irregular networking (Ebner and Eder, 1992; Gold, 1989), kriging (Delhomme, 1978; Oliver and Webster, 1990) and co-kriging (Atkinson et al., 1992; Dancy et al., 1986). Cressie (1991) provides methods for temporal and spatio-temporal interpolation.

2.2.2 Spatial resolution and terrain features

The spatial resolution of the cells determines the geometric precision of a raster. In ecology the finest level of detail in a data set is usually termed grain (Kolasa and Rollo, 1991). Note that the precision of a spatial data set is not specified by scale. The term (cartographic) scale is exclusively used for the ratio of the distance on a map to the distance in the terrain (Carlile et al., 1989; Milne and O'Neill, 1990; Ver Hoef et al., 1989). In studies of landscape patterns, data may be available at a variety of resolutions and extents. Obviously, this variation has an effect on the characteristics of a pattern (Turner et al., 1989; Cushnie, 1987). Subsequently, the relationship between raster data and terrain features as a function of resolution is elucidated.

The spatial resolution of digital remote sensing images divides the features in the terrain into two groups (Strahler et al., 1986). Features greater than a cell will appear in one or more cells or pixels and might thus be individually detectable. These features are named *high resolution* features. Contrarily, the features smaller than the resolution are not individually detectable, and termed *low resolution*. In the latter case a cell contains aggregated data from more than one feature. Ranging from coarse to fine spatial resolutions, i.e. changing towards smaller cell sizes, more features will turn from low to high resolution. When, for example, a herbaceous vegetation is observed with a spatial resolution of 1 metre, individual herbs and mosses are not detected. Consequently, the interpretation of these plants has to be performed on the community level. This also counts for individual tree seedlings with a crown diameter about less than one metre. Further growth of the tree will result in the coverage of more cells, by which it becomes a high resolution object and thus detectable.

Gradual spatial variation in the composition of low resolution objects generally results in more or less continuously varying patterns, which are best represented as a field. High resolution terrain features bringing on different attribute values in a field, e.g. a solitary tree in a digital image, can be detected and delineated and might therefore be represented as an object (sect. 2.3).

2.2.3 Fuzzy classification

A field is suitable to represent more or less continuously varying terrain features. By using a raster continuous fields become, however, discrete in the spatial domain. In the thematic domain continuity means that attributes take continuous values. Because *crisp classification* yields discrete attribute values this technique is not applicable to all features in natural landscapes. Nevertheless, landscape-ecologists frequently apply classification, because it is acknowledged to be a powerful technique to extract essential information from the background of infinite complexity. In agricultural areas where each plot is cropped with a single species, crisp classification is appropriate (Huising, 1993; Janssen, 1994). In natural landscapes a continuous type of classification has to be applied to accommodate the quantification of gradients. A proper representation of gradients is of ecological importance, because these situations often possesses high natural values (Van Leeuwen, 1966). The notion of continuous classification can be expressed with the mathematical concept of *fuzzy classification.*

Classification is concerned with statements like $x \in S$, i.e. does spatial element x belong to thematic class S. In order to solve this decision problem the class has to be defined first of all. A class is defined by the properties that are characteristic for its members. These properties can be operationalised by a membership function. Consider for convenience a one dimensional membership function M defined on a continuous attribute **a** (fig. 2.3). In the classical Boolean set theory, a class is defined by a membership function, which takes as values only 1 or 0:

$$M_B(a) = 1 \qquad \text{if } b_1 \leq a \leq b_2 \qquad 2.2$$
$$M_B(a) = 0 \qquad \text{if } a < b_1 \text{ or } a > b_2$$

where b_1 and b_2 are thresholds (fig. 2.3a). A membership value of 1 means 'belongs to' the set or class, while a value of 0 means that it does not. As it is defined by precise boundaries, a crisp class applies to discrete features in the terrain.

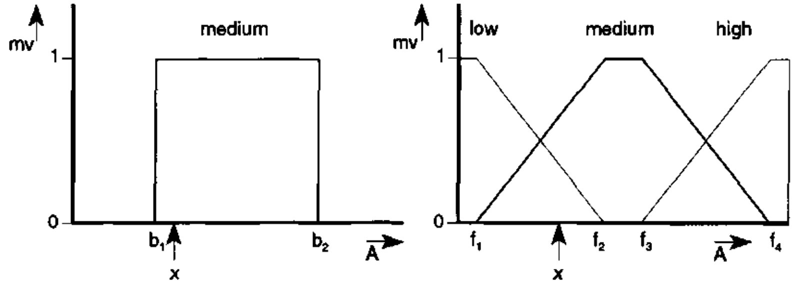


Figure 2.3 Specification of a crisp (left) and fuzzy class 'medium' (right) by a membership function.

Alternatively, fuzzy sets or fuzzy classes apply to those situations where no sharp distinctions in the real world can be made. This type of uncertainty with respect to class boundaries is called vagueness. Vagueness of a class can be expressed by allowing the membership function to take any value in the range of 0 to 1. Figure 2.3b shows the membership function of the fuzzy set 'medium' defined by a piece wise linear function:

$$\begin{aligned}
M_F(a) &= 1/(f_2-f_1) \bullet (f_2-a) && \text{if } f_1 \leq a \leq f_2 \\
M_F(a) &= 1 && \text{if } f_2 < a \leq f_3 \\
M_F(a) &= -1/(f_3-f_2) \bullet (f_3-a) && \text{if } f_3 < a \leq f_4 \\
M_F(a) &= 0 && \text{if } a < f_1 \text{ or } a > f_4
\end{aligned} \qquad 2.3$$

When the relevant attribute value is known for a spatial element, the membership value can be calculated which indicates the degree of membership or compatibility of this spatial element with a class. A membership value of 1 means full compatibility, while a value of 0 means no resemblance. Membership values between 0 and 1 express partial compatibility. It is important to realise that membership values are not probabilities. One apparent difference with probabilities is that the summation of membership values over the classes not necessarily equals 1, although this is not apparent from figure 2.3b (Zimmerman, 1985).

The fuzziness of the class medium (eq. 2.3) is governed by the range between f_1 and f_2 and f_3 and f_4 respectively. Obviously, the fuzziness decreases with decreasing ranges. Note that the class becomes crisp when the two ranges become zero. Consequently, crisp classification is considered to be a special case of fuzzy classification.

Admitting partial membership implies that an element x can be compatible with more than one fuzzy class. Consider for example the three fuzzy ordinal classes in figure 2.3 to be moisture content classes defined along the variable 'depth of water table'. For spatial element x the fuzzy classification results in a vector of three membership values (0.4,0.6,0.0) for the classes low, medium and high moisture content respectively. Apparently, this element has nearly equal compatibility with classes low and medium moisture content. In the crisp case the turn over between classes is very arbitrarily modelled at a single depth of the water table. In the crisp case element x is classified as (0.0, 1.0, 0.0) indicating full compatibility with one class only. The example shows that fuzzy classification enables the modelling of ecological gradients through the vague turn over between classes. Although seemingly less precise than crisp data, fuzzy data are often a more adequate representation of reality (Klir and Folger, 1988).

2.3 Spatial objects

As opposed to the field approach, the object-structured approach applies to discrete terrain features (Oxborrow and Kemp, 1989). Many landscape-ecological concepts use discrete spatial units to structure a landscape pattern. Kotliar and Wiens (1990) term their elementary units patch and define it as 'a non-linear surface area differing in appearance from its surroundings'. Accordingly, a patch can be delineated apart from the underlying processes. In case of a vegetated area patches are defined by differences in plant communities. In non-vegetated areas patches result from differences in environmental variables, e.g. lake, bare sand or stony area.

Zonneveld (1989) introduces the term 'land unit' for 'an ecological homogeneous tract of land at the scale of issue'. The land unit can be considered as a subsystem with dynamic properties and relationships to neighbouring land units. All methods guiding the landscape ecologist in determining appropriate objects for the landscape under study have in common that the object has to be internally homogeneous in some respect and externally heterogeneous. Consequently, in the object approach spatial variation is modelled at the objects' boundary (Suryana, 1997).

The fact that an object differs from its surroundings does not imply, however, that an object has no internal variability. Even more so, homogeneous objects are rarely observed in nature (Kotliar and Wiens, 1990). Objects homogeneous in one respect can be inhomogeneous in another. The internal variability or heterogeneity of an object can be described, though. For example tree species near the fringe of a wood might differ from the inner species.

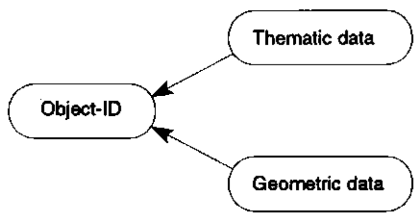
Different survey methods applied to a single landscape result in objects ranging in complexity and tangibility. Apparently, more or less sharp transitions in the terrain are a prerequisite for meaningful locating object boundaries, i.e. the sharper the transitions the less uncertainty is involved. The uncertainty related to the objects' boundary will increase when the changes in the terrain become more gradual.

The ease of constructing terrain objects largely depends, therefore, on the type of landscape. In agricultural areas the identification of lots and the subsequent labelling with a single crop is a straight forward process (Janssen, 1994). Contrarily, natural landscapes often show a range in more or less continuous and discrete transitions causing a varying tangibility of the terrain objects. Under these circumstances the recognition of objects can be less evident, generally resulting in less accurate and inconsistent object boundaries (Middelkoop, 1990; Janssen, 1996).

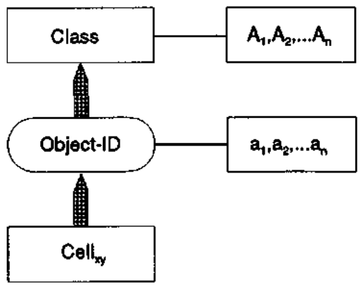
2.3.1 Spatial objects represented in cell raster

In the object-structured approach the thematic and spatial data are handled separately and linked through an object identifier (fig. 2.4a). The object geometry can be defined either in a vector or raster structure (Piwowar et al., 1990). In this thesis, objects are obtained by applying discretisation processes to remote sensing imagery, i.e. fields represented in a raster structure (sect. 2.2.1). For convenience objects are represented in a raster structure too, preventing raster-vector conversion vice versa.

In a cell raster the geometry of objects is defined by linking one or more adjacent cells (or pixels in an image) with some characteristic in common to an object-id (fig. 2.4b) (Molenaar, 1994). Note, that one cell can form an object too, which means that the smallest object is equal to the resolution of the raster. The link between objects O and the geometry is made through the 'Part of' function: PARTO[cell, O]. If a $cell_{x,y}$ is part of an object O_j this is represented by PARTO[$cell_{x,y}$, O_j] = 1 and PARTO[$cell_{x,y}$, O_j] = 0 if not. If objects are fuzzy in their spatial extent, this can be expressed by allowing the 'part of' function not only to take the values 0 or 1, but to take any value $0 \leq$ PARTO[$cell_{x,y}$, O_j] ≤ 1. In this thesis the object approach is only applied to discrete terrain features. Hence the concept of fuzzy objects is not applied.



a. Linking of thematic and geometric data through an object identifier.



b. Data model for a spatial object.

Figure 2.4 Spatial object represented by a cell raster.

The geometry of a spatially crisp object consists of a collection of one or more adjacent cells, i.e. a *segment*. A segment has an outer boundary and may contain one or more holes. Obviously, segments obtained from natural patterns usually have an irregular shape. The precision of the segment's boundary is determined by the spatial resolution of the raster.

In figure 2.4 the relationship between cells and objects is specified as many to one (n : 1). This relationship results in mutually exclusive objects. Alternatively, a many to many relationship (n : m) allows cells to belong to two or more objects. For instance a cell might simultaneously belong to a river and road where both objects cross or to a soil and vegetation unit. In a many to one relationship between cells and objects these situations have to be modelled in separate data layers of objects.

Objects are defined within the framework of a classification system. Generally, an area is populated with sets of objects that are different, so that each set should have its own description structure, i.e. each set should have its own list of attributes and process characteristics. These sets of objects are called *object classes* or short *classes*. Hence, the classes are typified by the fact that the objects belonging to the same class share the same descriptive structure. Examples of object classes are woodland, build-up area and road.

The relationship between an object O and a class C is made through the membership function M[C,O]. If an object O_j belongs to a class C_k this is represented by $M[C_k,O_j] = 1$, and $M[C_k,O_i] = 0$ if not (Molenaar, 1998). Uncertainty in the relationship between object and class is expressed by allowing the membership function to take any value $0 \leq M[C_k,O_j] \leq 1$. In this thesis objects are not allowed to be uncertain with respect to their object class. Hence, the relationship between object and class is of the type many to one (n:1) (fig. 2.4). Again it is asserted that in uncertain situations a field description is more appropriate.

By assigning an object to a class the attribute structure of the class is inherited, $LIST(C_k) = \{A_1,A_2,...A_r\}$. Each attribute is specified by a name, scale type and domain defining the set of attribute values. By storing an attribute value for each attribute, an object is fully defined. Note that although the class of an object is crisp, the state description of an object can be made fuzzy by its attributes and attribute values.

Object construction

In this thesis, objects are constructed by applying discretisation processes to remote sensing images, i.e. spatial fields. This process can be divided in four phases, which largely follow from the definition of objects provided in the previous section:

Object isolation by segmentation

In this phase, an object is spatially defined and its field data are isolated. The delineation of an object is performed by segmentation techniques. A simple segmentation technique is density slicing. More advanced segmentation techniques aim to locate the boundaries of segments on relatively strong changes in a field. These techniques can be categorised in edge detection and region growing.

Characterisation of segments by features

In this phase, relevant features are selected, measured and stored as attribute values for each segment. Any feature contributing to the characterisation of a segment is valid. Usually, the features consider aspects of the spatial field coinciding with the segment, like average field values (e.g. tone in case of images) or features indicating the internal variability of the field, such as variance and texture.

Assigning of object to object class

By classification each object is assigned to a predefined object class. This can be done by expert judgement, for instance during visual image interpretation, or by quantitative classifiers, e.g. a maximum likelihood classifier.

Estimation of attribute values

By assigning an object to a class the attribute structure of the class is inherited. Consequently a value should be stored for each attribute.

Object dynamics

Objects representing natural phenomena change during their life-time. Here the dynamics of terrain elements is represented by a sequence of state descriptions. Obviously, this is only meaningful when the life-time of the objects extends over several temporal resolution steps of the state descriptions, i.e. high resolution objects in time (sect. 2.2.2).

The dynamics of objects is governed by four basic processes (fig. 2.5) (Forman and Godron, 1986; Huising, 1993; Janssen, 1994). An object comes into existence and will finally cease to exist. Given an observation system, the birth of an object occurs when a feature turns from low to a high resolution or when continuous or discrete processes alter a field. For instance a continuous change results from the increase in abundance of specific species, while fire and landslides are discrete events. Obviously, the same processes can cause objects to cease to exist.

During the objects' life-time both the geometric and thematic characteristics might change. Thematically, an object changes with altering attribute values. For instance when the attribute height of a shrub is updated. A more drastic object change occurs when the object class is altered. For instance when a shrub exceeds a certain height and becomes a tree.

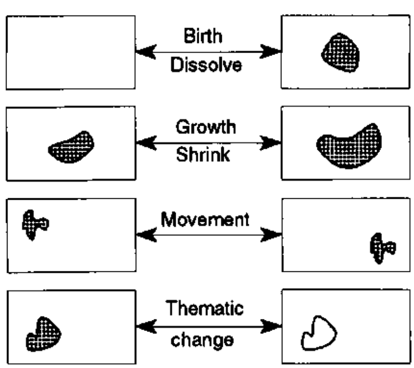


Figure 2.5 Basic processes of object dynamics.

In the spatial domain the object changes either by birth, dissolve, growth, shrink and/or movement (fig. 2.5). These processes can result in a change of position, orientation, size or shape, or any combination of these, which may lead to topological changes as well (fig. 2.6). In a lattice of dynamic objects mutual influences bring on composite processes like object splitting and merging. Object movement applies particularly to non sessile features like animals of which the dynamics is far below the temporal resolution. Therefore, landscape modelling is usually restricted to sessile terrain features (Aspinal, 1992).

2.3.2 Aggregation hierarchy

Generally, a landscape description should consist of multiple levels of abstraction in order to handle its organisational complexity and hierarchic structure (sect. 2.1). In literature on data modelling three types of object hierarchies occur; *classification*, *aggregation* and *association*. In a classification hierarchy objects are related by 'is a' links. For instance a birch is a tree is a woody species. Classification operates only on thematic aspects of objects enabling object generalisation. Alternatively, aggregation operators act on both thematic and geometric aspects of objects. By aggregation, objects are related in up-ward direction by 'part of' links. For instance a tree is part of a woodland.

Finally, different levels of objects can be linked by association. Objects can be associated on any common ground, like all blow outs in a certain area. Although not necessary, topology can be used to define object associations. For example all parcels adjacent to parcel x are associated with parcel x. Usually, object associations can be obtained through queries and are therefore not explicitly embedded in a data model. For digital landscape modelling aggregation appears the most powerful operation to link multiple levels of abstraction. For this reason, aggregation hierarchies are studied here in more detail.

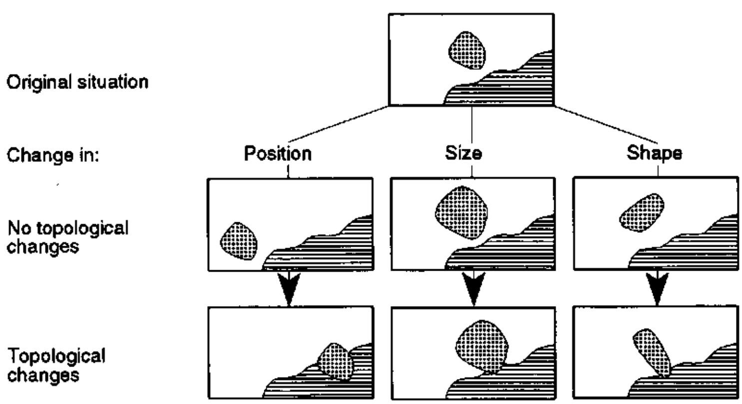


Figure 2.6 The effect of object dynamics in a lattice (after Janssen, 1994).

Objects on a specific hierarchical level, can be aggregated to form new composite objects on a next higher hierarchical level. An aggregation hierarchy shows how composite objects can be build from elementary objects and how these objects can be put together to build more complex objects and so on, i.e. a composite object can be an elementary object for a next higher hierarchical level.

An aggregation hierarchy has a bottom-up character in the sense that starting from the elementary objects composite objects of increasing complexity are constructed in an upward direction. As stated the upward relationship in an aggregation hierarchy is called a 'part of' link. Because aggregation operators work both on the thematic and geometrical aspect of the elementary objects, the definition of an aggregation should consist of (Molenaar, 1998):

- rules specifying the classes of the elementary objects building an aggregated object. These thematic rules can be refined by imposing conditions on attribute values.
- rules specifying the geometric and topologic relationships among these objects. These geometric rules are often based on topological relationships between objects.

One common geometric condition usually made is containment, i.e. the spatial extent of an elementary object fully falls within a composite object. Aggregations performed under this condition are nested (fig. 2.7). The link between an elementary object O_i and a composite object CO_j is given by a PARTCO[O_i,CO_j] function. This function takes the value 1 when the object is member of a composite object and 0 if not, bringing on a many to one (m : 1) relationship, i.e. composite objects are disjunct.

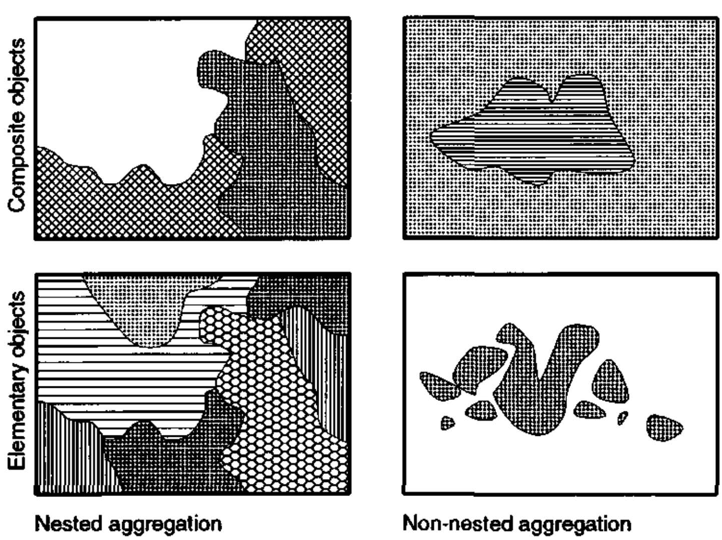


Figure 2.7 Nested and non-nested object aggregation.

Uncertainty in the relationship between object and composite object is expressed by allowing the membership function take any value $0 \leq$ PARTCO[CO_j,O_i] ≤ 1. This enables the definition of fuzzy composite objects, i.e. composite objects become not disjunct and can be overlapping. For instance a shrub at the border of a woodland and herbaceous vegetation might belong a little bit to both. In this thesis only disjunct composite objects are defined.

Now, consider the situation that the condition of containment is dropped. By dropping this condition, object aggregations of a more loose character can be created and the PARTCO function is not applicable any more. Non-nested aggregation or amalgamation allows different parts of an elementary object to fall within different composite objects. Figure 2.7 might show for instance the amalgamation of the composite object woodland from clusters of trees. In ecology amalgamation is often used, especially as a step in object construction during manual image interpretation (Geelen, 1990).

If elementary objects are combined to form a composite object, their attribute values are often aggregated as well. The compound objects inherit the attribute values from the objects of which they are composed. The desaggregation of such values is usually quite difficult because it can only be done if information is added in the operation, affirming again its bottom-up character. Therefore top-down relationships in an aggregation hierarchy usually do not aim at desaggregation but more at specification, originating from the notion that a composite object provides the context of an elementary object. Hence, in terms of the modelling objectives presented in section 1.1, an aggregation hierarchy enables both the construction of a descriptive and explanatory model through the definition of bottom-up and top-down relationships, respectively.

2.3.3 Spatial objects with nested fields

Two opposite approaches for the spatial modelling of natural landscapes have been introduced, the field and object respectively. Because natural landscapes often show both continuous and discrete variation in space and time, they are not properly represented in only one of the two alternatives. Consider for example a major landscape type in the test site, where shrubs and blow outs are distributed over a continuously varying herbaceous vegetation. Obviously, the shrubs and blow outs are best represented by objects, while the continuous character of the herbaceous vegetation should be modelled as a field. In order to be able to describe continuous and discrete variation simultaneously, a hybrid terrain description allowing the nesting of fields in spatial objects is suggested.

Spatial object with nested field represented in cell raster

Consider again the example vegetation of shrubs and blow outs scattered over a herbaceous vegetation. Obviously, three object types can be defined and constructed, i.e. shrub, blow out and herbaceous respectively (fig. 2.8a). By assigning an object to a class the attribute structure of the class is inherited. In case of internally homogeneous object types it is sufficient to store a single attribute value for each attribute. In case of heterogeneous object types the internal variation can be explicitly quantified by storing attribute values for each cell constituting the object (fig. 2.8b). By doing so a field is constructed within an object. In the example a single attribute value is stored for the objects belonging to the class shrub and blow out, while an attribute value is assigned to all individual cells belonging to the herbaceous objects.

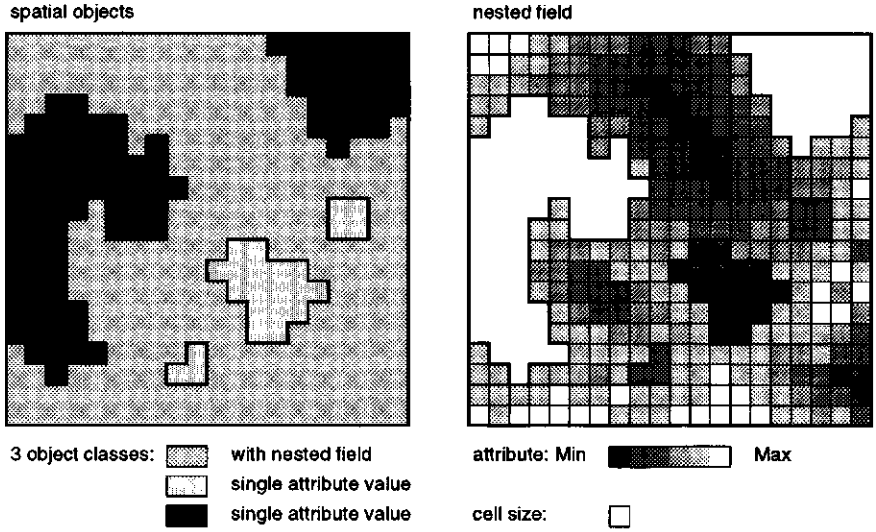


Figure 2.8 The concept of 'Spatial object with nested field' (see text for explanation).

The concept of '*spatial objects with nested field*' is an extension of the classical object approach. Besides an attribute list an object class is further specified by a flag taking the values 'OBJECT' or 'FIELD'. The flag 'OBJECT' indicates that the attribute values have to be stored as a single value on the object level, while the flag 'FIELD' effectuates that the attribute values are stored at the cell level (fig. 2.9).

There is no practical application of this hybrid approach known to the author, which is surprising, because many landscape-ecologists recognise the existence of both discrete and gradual transitions (Whittaker, 1967). Moreover there is a strong analogy between the approach of spatial objects with nested fields and the landscape-ecological concept of patches in a matrix (Forman and Godron, 1986). In this concept non-patch areas are called matrix when the following three criteria are met:

- relative to the patchy area the non-patch area is more extensive,
- the non-patch area is highly interconnected, and
- controls many of the dynamics in the landscape.

Consider again the example vegetation, where shrubs and blow outs form patches. Due to the criterium of more or less sharp boundaries around patches obviously not the whole landscape has to be patch covered. In the example the rest-area or non-patch covers the herbaceous vegetation. This non-patch typically meets the criteria for a matrix, because it covers most of the area and constitutes a single area. Moreover the omnipresence of the herbaceous vegetation determines the conditions for the germination and growth of shrubs and as such controls landscape development. Obviously, the patches are best represented by objects, while the continuous character of the matrix should be modelled as a field.

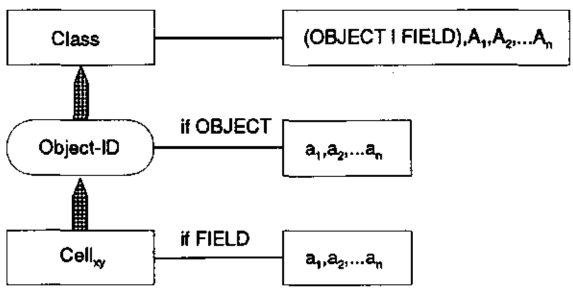


Figure 2.9 Data model for the representation of a spatial object with nested field by a cell raster.

3. Classification of vegetation structure from CIR-images

3.1 Introduction

In a monitoring system, the set of remotely sensed data should be multi-temporal. When the spectral data are obtained within one seasonal cycle, signature migration can be used to study crop growth (Van Leeuwen, 1996), to improve the accuracy of land-cover interpretation or to distinguish between more land-cover types (Girard, 1986). When the multi-temporal data extend over a time frame of several years vegetation structural processes can be monitored. Two broad strategies exist for the detection of land-cover change in multi-temporal data:

- direct interpretation of spectral migration patterns, and
- classification of separate dates followed by an analysis of the changes in interpretation results.

The interpretation of spectral migration patterns, optionally enhanced with techniques like image differencing or ratioing, might yield acceptable results only if a limited number of dates is analysed (Mouat et al., 1993). Due to the increasing complexity of the spectral patterns and changes of sensor characteristics the method becomes unpractical for more dates, especially when meteorological conditions are different during the growing seasons (Milne and O'Neill, 1990). Here the more current second strategy is adopted where remote sensing data of different dates are separately interpreted.

Manual aerial photo interpretation

Initially, the Amsterdam Water Supply obtained information on vegetation and soil through the manual interpretation of a temporal sequence of large scale false-colour photographs (Ehrenburg et al., 1988; Appelman et al., 1990; Geelen, 1990). Generally, *manual image interpretation* concerns the identification and delineation of objects by hand. Of the four steps in object construction (sect. 2.3.1) usually only the first and third step are performed, i.e. the delineation and subsequent classification of more or less homogeneous areas given a predefined interpretation key.

When the interpretation key is based on vegetation structural characteristics only, the interpretation can be performed with limited amount of fieldwork. Contrarily, manual image interpretation based on keys using vegetation compositional characteristics generally involves a considerable amount of fieldwork in order to assign the delineated segments to vegetation classes (Van Dorp et al., 1985).

Manual photo interpretation is based on the visual perception by a human interpreter sensitive to several interpretation features, like tone/colour, parallax, size/shape, texture, shadow and context. An experienced interpreter is able to use combinations of these characteristics to perform the job in mono or stereo view. This makes manual interpretation a very robust interpretation method which can deal with highly complex spectral patterns and performs even well if the image quality varies (Lillesand and Kiefer, 1994; Schwabe, 1991). Despite these advantages, the manual construction of objects in a spectral field suffers from some major disadvantages:

- Objects only represent discrete terrain features properly (sect. 2.4).
- Due to the subjectivity of the method the consistency of the objects' geometry and classification is limited, especially when objects are amalgamated from lower order features in the image (sect. 2.3.2).
- The spatial and thematic accuracy of the objects is generally not specified.
- The interpretation process is not formally defined, i.e. many decisions in the process are performed implicitly and can not be recovered to perform the interpretation on new images.

These disadvantages are emphatically manifest in temporal analysis, where many transitions appear to be artificial (Van Dorp et al., 1985).

Alternatively, to area-covering image interpretation, manual photo interpretation can be confined to the classification of samples with a fixed support and randomly or systematically distributed over the image. In this approach image interpretation becomes a matter of designing an appropriate sampling scheme followed by a classification of the samples. The subjective and time consuming task of object delineation is omitted. Although the analysis of point samples can provide valuable information, this method is not often applied (Werth and Work, 1992; Kolbl and Trachsler, 1980). Obviously, an area-covering model of terrain features is often preferred over a representation of a landscape by a set of sample points.

Digital image interpretation

Digitally stored RS data enable *digital image interpretation*, which is based on the application of pattern recognition techniques (Rosenfeld and Kak, 1982). Digital techniques have the potential to score better on the points listed in the previous section:

- Both objects and fields can be constructed.
- The interpretation rules are consistently applied over the area.
- There are many methods to quantify the geometric and thematic accuracy of the interpretation results.
- The procedure is largely formalised, although some steps might still be subject to subjectivity, like the selection of training areas.
- In case of stereo images automatic elevation measurements can be performed.

Digital image interpretation also has some disadvantages, especially its sensitivity to varying image quality. Radiometric distortions resulting from shadowing effects or changing recording conditions usually hamper digital interpretation (Lillesand and Kiefer, 1994). Moreover the limited number of interpretation keys generally applied, merely tone and texture, causes the failure of digital interpretation in situations where manual interpretation still yields proper results (Musick and Grover, 1991).

Nonetheless, the monitoring system under construction applies digital interpretation techniques when possible. Therefore the analogue false colour aerial photographs need to be converted in a digital format. The production of a digital orthophoto free from radiometric and geometric distortions is described in appendix I.

Digital images can be interpreted by regressing spectral data with quantitative variables measured in the field like biomass (Atkinson et al., 1992; Dancy et al. 1986) and vegetation cover (Dymond et al., 1992). Because the spectral patterns obtained from natural scenes and dunes in particular are very complex, classification seems a more robust interpretation technique.

Unfortunately, remotely sensed data have tended to be crisply classified regardless of whether the vegetation exists as a well defined mosaic or as a series of continua (Wood and Foody, 1989). Consequently, many classification errors can be attributed to artificial boundaries in an image which has gradients in reality. Crisp classification has to be treated with some caution in patterns of natural landscapes. Crisp classification is particularly suited to construct objects of different object classes, while fuzzy classification should be used to quantify continuous patterns, i.e. fields (Wood and Foody, 1989; Blonda et al., 1991).

Subsequently, the methods of interpreting high resolution CIR-orthophoto-mosaics by a combination of crisp and fuzzy classification techniques will be dealt with.

3.2 Methods

Two radiometrically corrected colour infra-red orthophotos with a resolution of 0.25m are available from the test site. The images were taken in the summer of 1990 and 1995 and have a geometric accuracy of approximately 1.5 times the pixel size. The production of orthophoto-mosaics is elucidated in appendix I (fig. 3.1).

The image interpretation starts with the definition of an object hierarchy. The objects in the hierarchy and their ordering result from tuning the information need on the one hand and practical limitations in deriving spatial information from high resolution digital CIR-orthophotos on the other hand.

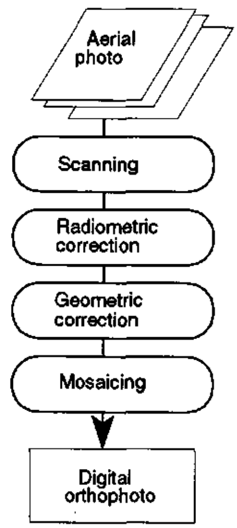


Figure 3.1 Transformation of analogue aerial photographs to digital radiometrically corrected orthophoto mosaics.

3.2.1 Specification of object hierarchy

The construction of objects and fields demand different classification techniques, i.e. crisp and fuzzy classification respectively. In turn objects of different object classes might urge for a specific crisp classification. For instance a texture feature enables the subclassification of woody vegetation up to the species level, while the use of a texture feature in the subclassification of herbaceous vegetation is ineffective (Bijlsma, 1993). Consequently, Ton et al. (1991) suggest that the construction of objects and fields from complex images demands a step-by-step approach, conveniently ordered in a hierarchy. In a hierarchical interpretation an optimal discrimination between land cover classes is achieved by adapting the interpretation techniques to the specific demands of the classes on each node or fork in the hierarchy. Ton et al. (1991) list three more reasons to build a spectral land-cover recognition system on hierarchical premises:

- Natural land-cover types have an implicit hierarchical structure. For example land cover is evidently subdivided in vegetated and non-vegetated cover types. In turn vegetated areas can be split up in wood and non-wood areas, and so on.
- A hierarchical classification system can classify a sub-area to a certain hierarchical level depending on the quality of the spectral data. Due to meteorological differences between the recording dates the separability of classes varies. For instance the subclassification of non-wood in grasses and herbs can not always be performed.
- Hierarchical classification offers computational advantages resulting from hierarchical pruning. If a land-cover type is ruled out, then no specification of that type need be considered.

Figure 3.2 depicts the land-cover hierarchy for the test site, containing 4 levels and 17 classes. The land-cover types up to level 2 appear as discrete high resolution features (sect. 2.2.2) in the orthophoto, like individuals or clusters of woody plants, patches of herbaceous vegetation, patches of blond sand, water bodies and roads. 'Blond sand' is defined as non-vegetated sand with negligible organic matter content. Each of these discrete land-cover types belong to a different object class.

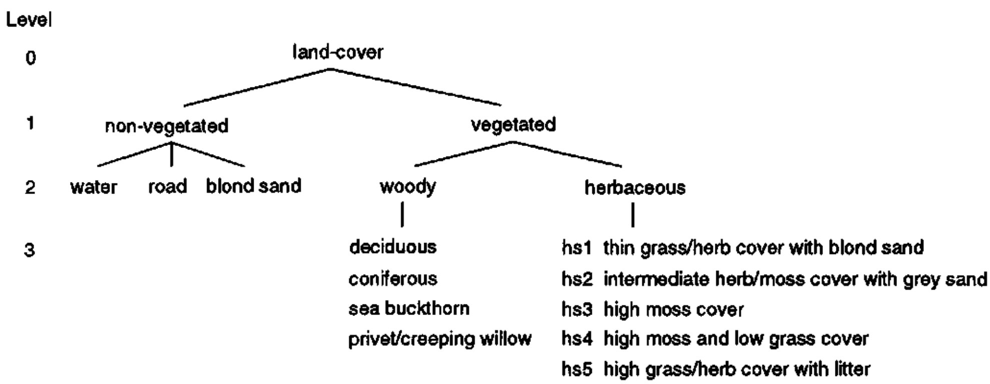


Figure 3.2 Land-cover hierarchy for the test site.

The internal variability of two object classes is explicitly modelled, i.e. 'woody' and 'herbaceous' respectively. The composite woody objects are desaggregated to elementary objects belonging to a specific species group. Four species groups are distinguished: deciduous, coniferous, sea buckthorn and privet/creeping willow. These groups had to be defined because not all different species could be distinguished by image interpretation. The deciduous tree species like *Betula pendula, Betula pubescens* and *Quercus robur* constitute one class 'deciduous', while *Ligustrum vulgare* and *Salix repens* had to be grouped in a single class too, i.e. privet/creeping willow.

The variation in herbaceous vegetation is modelled as a field. The herbaceous vegetation in the test site consists of the following abiotic and biotic elements: blond and grey sand, ectorganic material, annual, biennial, perennial and clonal herbs, solitary, clonal and tussock forming grasses, mosses, lichens and woody plants at the low resolution level. These sub-pixel features occur in any possible cover combination throughout the area. Mostly, the composition changes continuously, although sharp boundaries occur too. In this continuum of herbaceous vegetation five typical cover types or prototypes **hs** are distinguished and typified by a concise description (table 3.1).

In the terrain some sites will show a high resemblance with only one class, while others have properties belonging to two or more of these classes. Typically, these partial memberships can be quantified in a fuzzy classification, where the resemblance of a site with a class is indicated by a membership value $MV_{hs} \in [0,1]$.

Hence a site is characterised by a vector of five membership values (MV_{hs1}, MV_{hs2}, MV_{hs3}, MV_{hs4}, MV_{hs5}). For instance the vector (0.0, 0.6, 0,4, 0.0, 0.0) indicates that the site has nearly equal resemblance with hs_2 and hs_3 and no similarity with hs_1, hs_4 and hs_5.

Table 3.1 Description of the herbaceous structural classes (hs) (after Assendorp and van der Meulen, 1994).

hs1 Thin grass/herb cover with blond sand

Blond sand, i.e. sand with negligible amount of organic matter, has, by far, the largest contribution in this coverage type. It is however accompanied by pioneer plant types. Herbs are annual as well as biennial. Grass types are mainly solitary and clonal which react more or less positive to wind activity. Tussock forming grass types can be present.

hs2 Intermediate herb/moss cover with grey sand

Largest contribution to the overall coverage is by mosses who react more or less positive to or can sustain some geomorphologic activity. Bare grey sand, i.e. sand with organic matter content, has a substantial contribution to the overall coverage. Herbaceous plant types are annual and biennial with locally some perennials. Some woody plants at the sub-pixel level can occur, grasses are solitary and tussock forming.

hs3 High moss cover

A total coverage of the soil with mosses and lichens, very locally with annual and biennial herbs. Grasses are nearly absent.

hs4 High moss and low grass cover

The soil is totally covered with mosses combined with a low herbaceous vegetation. Herbs and grasses are mainly small though larger woody plants at the sub-resolution level can occur.

hs5 High grass/herb cover with litter

Mainly grasses and perennial or clonal herbs cover the soil completely. The herbs are partly woody plants at the sub pixel level. Dead ectorganic matter determines partly the nature of this type.

3.2.2 Relating vegetation structural classes with spectral data

In this thesis, classification techniques are applied to establish a relationship between vegetation structural classes and spectral data. Consider, firstly, the estimation of membership values in a fuzzy classification procedure.

A geometrically corrected image is a field of spectral data in model space, denoted as S(x,y) where S is a vector of spectral bands. These remotely sensed data can be presented in a feature space S as well, where each spectral band (s_i) defines an axis of this space. When the image contains m bands, $s = (s_1, s_2, ...s_m)$ represents a particular point in S, and $S = \{s\text{: } s=(s_1, s_2, ...s_m)\}$ represents the set of all possible points in the feature space. Because pixels take a position in S too, the feature space can be employed to estimate generalised vectors of membership values. The generalised membership values in S establish a quantitative definition of a structural class which was previously described in a qualitative sense only (table 3.1). Such a quantitative class definition is called class extension. For a given cover type **hs**, the class extension c_{hs} is given by all points having a membership value greater than 0 (fig. 3.3):

$$c_{hs} = \{s\colon MV > 0\} \qquad 3.1$$

Indeed c_{hs} is a fuzzy set defined by membership values on a collection of points, rather than a parametric membership function, because the parameters of the latter function are usually hard to estimate, if an analytical model exists at all. Due to varying recording and meteorological conditions during the growing season, the class extensions only count for the spectral data in a specific image.

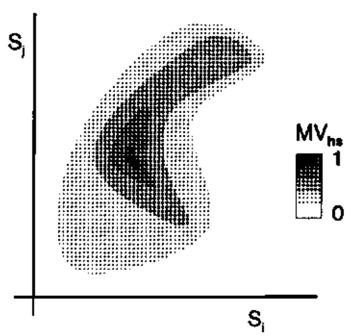


Figure 3.3 Example of a two dimensional fuzzy set quantifying the extension of a land cover class in spectral space.

Alternatively, to eq 3.1 representing c_{hs} as a collection of points, this two dimensional fuzzy set can be expressed as a field of membership values in the feature space $MV_{hs}(s_1,s_2,...s_m)$. The latter field can be used to lookup MV_{hs} for each pixel in the image S(x,y), resulting in a fuzzy classified image MV_{hs}(x,y). Note that continuous gradients between fuzzy herbaceous structural types in the terrain are presumed to result in continuous transitions between those types in the image and the feature space as well. This overlap between clusters of fuzzy vegetation classes in the feature space has ecological significance and is explicitly quantified.

Now consider, secondly, the problem of discriminating between woody and herbaceous vegetation in a crisp classification procedure. Although the classes woody and herbaceous vegetation are mutually exclusive in the image -except for the mixed pixels- the clusters of both classes intent to overlap in spectral feature space. The uncertainty of assigning pixels on point s=(s_1, s_2, ...s_m) in the feature space to wood is expressed by a probability p_w. The probabilities on each point s in S constitute a probability field $p_w(s_1, s_2, ...s_m)$ providing a generalised relationship between spectral data and the presence of woody vegetation. The estimated field can be used to look up p_w for each pixel in the image S(x,y) resulting in a probability field in image space $p_w(x,y)$. This field provides the probability for each pixel to be wood. By labelling all pixels having $p_w > 0.5$ segments of woody vegetation are obtained.

Crucial in crisp and fuzzy classification are the fields of probabilities and membership values in the feature space, $p_w(s_1, s_2, ...s_m)$ and $MV_{hs}(s_1, s_2, ...s_m)$ respectively. Generally, these fields are unknown and have to be estimated, i.e. $p^e_w(s_1,s_2,...s_m)$ and $MV^e_{hs}(s_1,s_2,...s_m)$. In the next section an estimation procedure is described.

Estimation of class extensions in spectral feature space

The estimation procedure consists of the following phases: selection of image samples, interpretation of image samples and generalisation of the samples in the feature space.

Selection of image samples

Consider the image S(x,y) and a corresponding two dimensional feature space $S(s_1,s_2)$ (fig. 3.4). First step in the selection of image samples is the selection of samples in the feature space. N samples are stratified randomly obtained from the feature space. The samples have a circular support with a radius of 5 DN and a point of gravity $s_i=(s_1,s_2)_i$.

Subsequently, each image pixel is assigned to none, one or more samples, i.e. not the whole subarea of the feature space is sampled and samples might overlap. In the image space a single sample from the feature space consists of many single pixels and clusters of pixels distributed over the image (fig. 3.4). Note that in this way spectrally homogeneous samples in the image space are obtained. By averaging the s_1-values and s_2-values of the pixels belonging to a sample, the mean sample characteristics $s_i=(s^m{}_1,s^m{}_2)_i$ are obtained. The latter point not necessarily coincides with the original sample centre in the feature space $s_i=(s_1,s_2)_i$.

Interpretation of image samples

In random order each sample is successively presented to an experienced interpreter by overlaying the image S(x,y) with a sample. Through alternately switching on and off the overlay-plane the interpreter is able to perform an observation. Depending on the type of estimation made by the interpreter, each observation yields either a membership value $MV^o{}_{hs}(s_1,s_2)_i$ or a probability $p^o(s_1,s_2)_i$. Note that the subjectivity in the observations concerns thematic aspects only, because sample selection is performed algorithmically.

The fact that a single sample in the feature space relates to many clusters of pixels in the image assures that the interpreter has several spatial contexts for each sample, which is an indispensable condition to reduce the subjectivity of an individual observation (Rosenfeld and Kak, 1982).

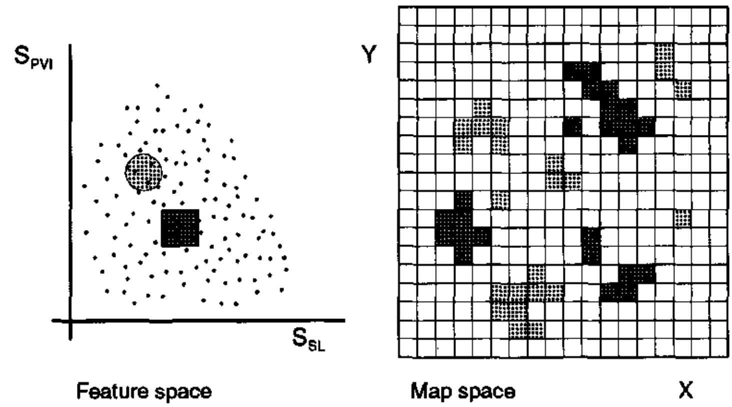


Figure 3.4 Relationship between feature space and image space; one area sample taken from the feature space relates to many spectrally homogenous clusters of pixels in the image.

Generalisation of samples in feature space

Next phase is the generalisation of the observations to a field of membership values $MV^e_{hs}(s_1,s_2)$ or a probability field $p^e_w(s_1,s_2)$. Take for example the generalisation of membership values. When the process of fuzzy observation by an expert is considered stochastic, an observed membership value MV^o_{hs} consists of a deterministic term MV^d_{hs} and an error term MV^ε_{hs}:

$$MV^o_{hs}(s_1,s_2)_i = MV^d_{hs}(s_1,s_2)_i + MV^\varepsilon_{hs}(s_1,s_2)_i \qquad 3.2$$

Obviously we are interested in estimating the deterministic component. This is possible when the error term meets the following criteria:

$$\begin{aligned} &E[MV^\varepsilon_{hs}(s_1,s_2)] = 0 \\ &\mathrm{var}[MV^\varepsilon_{hs}(s_1,s_2)] = c(s_1,s_2) \\ &\mathrm{cov}[MV^\varepsilon_{hs}(s_1,s_2)_l, MV^\varepsilon_{hs}(s_1,s_2)_k] = 0 \end{aligned} \qquad 3.3$$

The first condition asserts that the error is on average zero. Secondly, the variance is assumed to be position dependant in the feature space. Thirdly, it is presumed that the covariance is zero, which means there is no relationship between the error on two feature space points $(s_1,s_2)_l$ and $(s_1,s_2)_k$. Presuming that these conditions are met, the deterministic trend in the fuzzy observations can be estimated at a series of points on a grid by means of a moving average operation.

Remember that the sample support in the feature space is about a circle with radius 5 DN. Hence it is reasonable to calculate the membership value on a specific position in the feature space as a weighted mean from all observed membership values within a distance of 5 DN:

$$MV^{e}_{hs}(s_1,s_2)_0 = \sum_{i=1}^{n} \omega_i . MV^{o}_{hs}(s_1,s_2)_i \, / \sum_{i=1}^{n} \omega_i \qquad 3.4$$

where weight ω_i is proportional to the aerial overlap of the sample support and a circular area with radius 5 DN from the point to estimate. The aerial overlap between two equal sized circles is maximal when the circle centres coincide and decreases to zero when the circle centres are two times the radius apart (fig. 3.5). The variance of the membership values is calculated as:

$$MV^{var}_{hs}(s_1,s_2)_0 = \sum_{i=1}^{n} \omega_i . (MV^{o}_{hs}(s_1,s_2)_i - MV^{e}_{hs}(s_1,s_2)_i)^2 \; / \sum_{i=1}^{n} \omega_i \qquad 3.5$$

The variance of the membership values quantifies the uncertainty of the expert in estimating membership values.

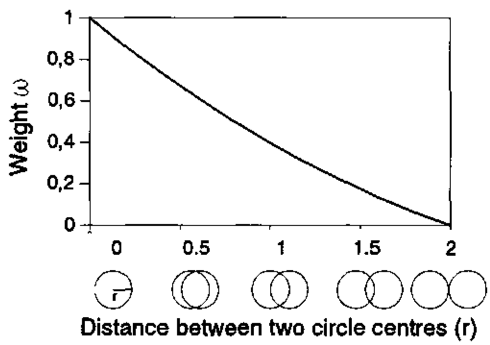


Figure 3.5 Interpolation weight ω in eqs. 3.4 and 3.5 as a function of the distance between two circle centres.

3.2.3 Crisp classification of blond sand, herbaceous vegetation and wood

In the next section the introduced classification procedure will be specified for the classification of the vegetation structure in the test site.

PVI transformation

The image classification is preceded by an image transformation. CIR-orthophotos $S(x,y)$ enable the construction of a three dimensional feature space $S(s_{ir}, s_r, s_g)$. However, spectral data obtained from vegetation in the red and green band are strongly correlated (R_{1990}=0.94 and R_{1995}=0.93). Dropping the green band from the feature space will therefore not result in a significant loss of information, while classification becomes easier in a two dimensional feature space.

The spectral data in the infra-red and red band obtained from a vegetated scene result from the combined radiation of vegetation and soil (Knipling, 1970). These spectral features can be transformed in two features more directly related to either vegetation or soil characteristics, i.e. the perpendicular vegetation index s_{PVI} and the soil line s_{SL} respectively (Lillesand and Kiefer, 1987). Generally, s_{PVI} values increase with increasing biomass of the vegetation while s_{SL} values indicate the brightness of the soil and therefore increase with decreasing soil moisture content and organic matter content (Baumgardner et al., 1985). Because these features have a physical meaning the interpretation of relationships in the feature space is simplified. Moreover, by the transformation the data of different dates become more compatible. The PVI-transformation consists of a rotation and an offset correction (after Clevers and Buiten, 1991):

$$s_{PVI} = 1/(1 + C^2)^2 \,.\, (s_{ir} - s^o_{ir} - C.(s_r - s^o_r)) \qquad 3.6$$
$$s_{SL} = C^2/(C + 1)^2 \,.\, (s_{ir} - s^o_{ir} + (s_r - s^o_r)/C) \qquad 3.7$$

where C is tg(α) of the soil line and s^o_{ir} and s^o_r represent the offset in infra-red and red respectively (fig. 3.6UL). Usually, these are the values off the darkest pixel in the image. However, under-exposure of the photograph results in negative offset values. Originally, equations 3.6 and 3.7 were inferred for radiance values and therefore only apply to density values as well, if density values are linearly related to radiance values. This condition holds for the major part of the range in density values and is only blurred for very low and high density values (Philipson, 1997). The PVI-transformation of the image S(x,y) yields a second image $S^{PVI}(x,y)$, where S^{PVI} is a vector of the two features s_{SL} and s_{PVI} and a corresponding feature space $S^{PVI}(s_{SL}, s_{PVI})$ (fig. 3.6UR).

The introduced methods for the interpretation of images (sect. 3.2.2) are applied to PVI-transformed images. The process of image interpretation holds a number of hierarchically ordered classification steps following from the land-cover hierarchy depicted in figure 3.2. On the first level vegetated and non-vegetated areas are distinguished. Because the cover types road and water can be easily derived from topographic maps, the only non-vegetated class to be isolated in the image is 'blond sand'. Hence, the isolation of blond sand is subject of the first interpretation step. The second step involves the subdivision of the vegetated area in woody and herbaceous vegetation. The third phase deals with the subclassification of wood into several species or species groups. The interpretation steps are summarised in table 3.2.

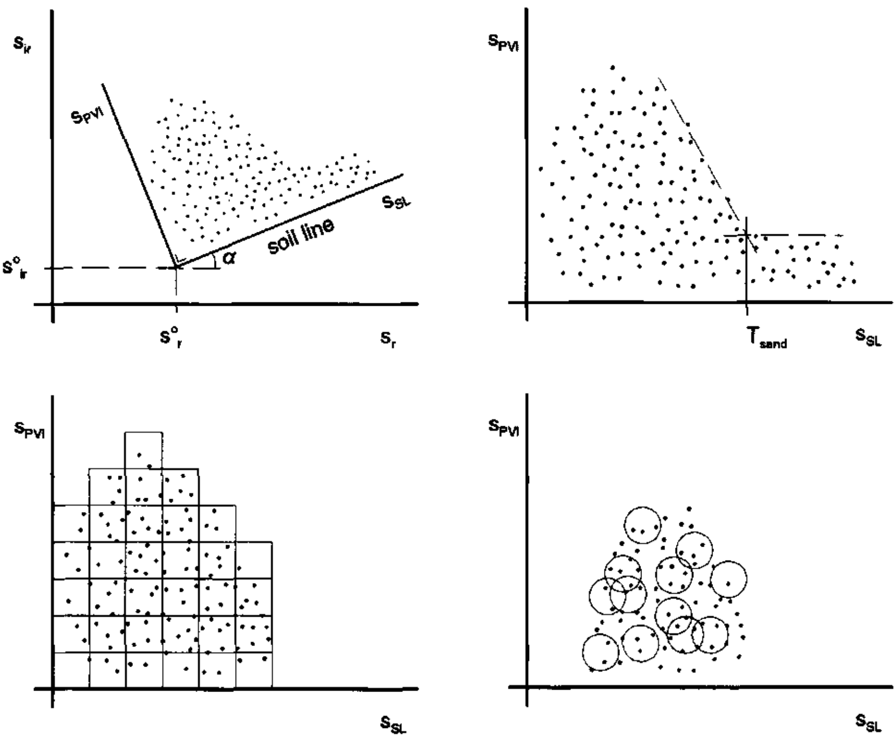


Figure 3.6 Phases in the interpretation of land cover; UL PVI-transformation of CIR-image; UR Threshold classification of blond sand; LL Systematic sampling of a subarea of the feature space occupied by woody and herbaceous vegetation; LR Random sampling of a subarea of the feature space occupied by herbaceous vegetation.

Step 1 Construction of 'blond sand' objects

The first classification step holds the isolation of pixels covered with 'blond sand'. Consider all image pixels in the feature space (fig. 3.6UR). This cluster has a typical vermiform fold occupied by pixels having high values on the soil line and low PVI-values. Indeed these pixels are covered with blond sand. Consequently 'blond sand' pixels are conveniently isolated from vegetated pixels by identifying a threshold value on the soil line.

Step 1.1 The threshold T_{sand} is located at the soil line value where the vermiform fold starts to widen due to the occurrence of pixels with higher s_{PVI} values (fig. 3.6UR).
Step 1.2 All image pixels with s_{SL}-values greater than T_{sand} are labelled 'blond sand'. Segments of blond sand are subsequently obtained by grouping neighbouring cells of blond sand.

Table 3.2 Steps in the classification of the vegetation structure.

1	**Threshold classification of blond sand**
1.1	Estimation of threshold value on soil line
1.2	Segmentation by pixel classification
2	**Construction of woody objects**
2.1	Estimation of probability for wood in feature space
2.2	Look-up wood probability for each image pixel
2.3	Smoothing of probabilities in the image
2.4	Segmentation by contextual pixel classification
2.5	Manual subclassification to species types
2.6	Accuracy assessment
3	**Fuzzy sub-classification of herbaceous vegetation**
3.1	Estimation of fuzzy sets in feature space
3.2	Look-up membership values for each image pixel
3.3	Aggregation of membership values to fuzzy measure values
3.4	Validation with reference data

Step 2 Construction of woody objects

The second interpretation step involves the construction of woody objects from the vegetated pixels in the image, i.e. the pixels not classified as water, road or 'blond sand' (fig. 3.2). Pixels covered with woody or herbaceous vegetation are discriminated in a crisp classification procedure consisting of 6 steps:
Step 2.1 Establish a generalised relationship between spectral data in the image and the presence of woody vegetation through the estimation of the probability field $p^e_w(s_{SL},s_{PVI})$ conform the procedure described in section 3.2.2. Systematically, 100 samples with a square support (10*10DN) were obtained from the feature space (fig. 3.6LL).
Step 2.2 By looking up p^e_w for each image pixel, the probability field $p^e_w(x,y)$ is obtained providing the probability for each pixel to be woody.
Step 2.3 In order to reduce any noise effects in the probability field $p^e_w(x,y)$ a contextual probability $p^e_{w,c}$ is calculated over a circular neighbourhood:

$$p^e_{w,c}(x,y) = (1-\omega).p^e_w(x,y) + \omega.\sum_{i \in circle_r} p^e_w(x_i,y_i)/n \qquad 3.8$$

where $p^e_w(x_i,y_i)$ is the probability of a cell having its point of gravity within a circular neighbourhood with radius r and n is the number of cells within the circle. $\omega \in [0,1]$ is a weight, where ω=0 causes $P^e_{w,c}$ to be equal to P^e_w, while ω=1 results in a pure contextual probability. The optimal value for ω is to be determined by a sensitivity analysis.

Step 2.4 The probability field $p^e_{w,c}(x,y)$ is classified by assigning all cells with $p^e_{w,c}$ greater than 0.5 to woody. Segments of woody vegetation are obtained by grouping neighbouring woody cells.

Step 2.5 The woody objects are manually subclassified into species or species groups.

Step 2.6 The accuracy of the classification and its dependence on weight ω and neighbourhood size is tested by a set of 1500 random reference pixels selected in the images of both dates. Each pixel is individually classified by visual interpretation. In order to quantify the intersubjectivity of the visual interpretation the reference pixels in the 1995 image are classified by two interpreters independently.

3.2.4 Fuzzy sub-classification of herbaceous vegetation structure

The third interpretation phase involves the fuzzy sub-classification of the herbaceous vegetation structure in 5 subclasses h1, h2, ...hs5 (table 3.1). This interpretation phase consists of 4 steps including validation with field samples.

Step 3.1 Establish a generalised relationship between spectral data in the image and the presence of herbaceous classes through the estimation of 5 membership fields $MV^e_{hs1...hs5}(s_{SL},s_{PVI})$ conform the procedure described in section 3.2.2. 250 samples with a circular support with radius 5DN were obtained from the subarea of the feature space populated with herbaceous pixels (fig. 3.6LR).

A fuzzy observation consists of a vector of 5 membership values $(MV^o_{hs1}, MV^o_{hs2}, MV^o_{hs3}, MV^o_{hs4}, MV^o_{hs5})_i$. The membership values of a single observation sum to one. The latter condition yields complementary membership values and forces the interpreter to quantify the turnover between classes.

Step 3.2 By looking up the membership values for each image pixel covered with herbaceous vegetation in $MV^e_{hs1...hs5}(s_{SL},s_{PVI})$, the fields $MV^e_{hs1...hs5}(x,y)$ in image space are obtained. The pixels with a spectral mixture of woody and herbaceous vegetation as well as pixels in shadow are not classified.

Step 3.3 In order to reduce noise and the number of unclassified pixels, the membership fields in image space are smoothed. Smoothing is achieved by a moving aggregation operator described in appendix II. Before smoothing the presence of herbaceous structural classes is expressed by a membership value. After the smoothing the resemblance of a pixel with a class **hs** is expressed by a fuzzy measure, i.e. pseudo-probability $P^e_{hs}(s_{SL},s_{PVI})$ or a possibility $\mathcal{P}^e_{hs}(s_{SL},s_{PVI})$.

Step 3.4 Fuzzy classification results of 1995 are validated with a set of reference data. The reference data consist of a set of 310 fuzzy observations obtained in the field close to the recording date. Each observation has a circular support with radius of 1 metre. The location of the sample centre was measured with differential GPS.

3.3 Results and discussion

Blond sand classification

Plate 1 shows objects of the class 'blond sand' in a subarea of the test site obtained after a threshold classification of the image. A visual check revealed only some minor classification errors caused by shadowing effects. The estimation of the threshold value by different interpreters yielded a maximum deviation of 6 DN. The latter deviation resulted in less than 1 percent change in the area blond sand, i.e. the choice of the threshold value is not very critical.

Construction of woody objects

Plate 1 shows the results of the construction of woody objects. The classification of woody vegetation started with the estimation of the probability for wood in the feature space $P^e_w(s_{SL},s_{PVI})$ for 1990 and 1995. The latter field shows a relative small curved transition zone between the wood and herbaceous cluster, suggesting that the two classes can be more accurately classified in the 1995 image compared to the 1990 image. The accuracy assessment confirms this (table 3.3). The classification accuracy in the 1990 image is over 90 percent while this is 93 percent in the 1995 image. The difference in accuracy between the two dates can be explained from different meteorological conditions during the growing season. The 1995 image is taken after a dry period causing water stress for the herbaceous vegetation, while woody plants are less sensitive in this respect. Contrarily, the 1990 photos were taken after a period of sufficient rainfall and show a herbaceous vegetation, which spectrally interferes more with scrubs and trees.

Table 3.3 Accuracy of wood classification as a function of neighbourhood weight (ω) and circular neighbourhood size in pixels (r) (eq. 3.8; N=1500 pixels).

year	1990		1995	
ω / r	**3**	**5**	**3**	**5**
0.00	91.3	91.3	93.0	93.0
0.25	91.0	91.0	93.3	93.4
0.50	90.4	90.0	93.9	93.5
0.75	88.8	87.7	93.0	92.0
1.00	86.3	84.9	90.8	82.9

The accuracy assessment shows further that the use of contextual information worsens the classification accuracy in 1990 and only increases the classification result in 1995 when the weight ω for neighbourhood cells not exceeds 0.5. Moreover, the smallest neighbourhood yields the best results. Differences in weight and the size of the neighbourhood not only influence the classification accuracy, but also affect the segmentation, i.e. the clustering of pixels classified as wood. Higher weights and greater sizes of the neighbourhood result on average in greater segments with smoother boundaries. The classification obtained with a circular neighbourhood of 0.75m and ω = 0.5 is presented in plate 1. These parameters provide a balance between the classification accuracy and a satisfactory segmentation of the test site.

The intersubjective classification accuracy of two interpreters was tested and ascertained on 94 percent. The 6 percent of the reference pixels differently classified by two experts mainly consist of mixed pixels on boundaries between wood and herbaceous vegetation. Obviously, the classification of these pixels is arbitrary in any classification procedure.

The classification method, presented here, out performed a supervised maximum likelihood classification with more than 5 percent. A proper training of a maximum likelihood classifier or any other classifier by the on screen selection of image samples is seriously hampered by the spectral variability of the cover class wood in the image space. Consequently, many usually small training samples have to be obtained to achieve acceptable classification results. Moreover, these samples often do not meet the statistical properties required by the classifier (Jeon and Landgrebe, 1992). Hence in the presence of high spectral variability in an image a classification procedure based on the generalisation of randomly selected homogeneous image samples seems more appropriate.

Fuzzy sub-classification of herbaceous vegetation

Plate 1 shows the fuzzy classification of the herbaceous vegetation for a subarea of the test site. The 5 herbaceous subclasses are modelled as fields within the object covered with herbaceous vegetation. The presence of a class is quantified by a pseudo-probability value. Conform the terrain situation the fuzzy representation of the herbaceous vegetation shows transitions between classes ranging from sharp boundaries to smooth gradients.

The fuzzy classification of the herbaceous vegetation in 5 subclasses started with the estimation of an equal number of fuzzy sets in the feature space through the generalisation of fuzzy observations. Figure 3.7 shows these two dimensional fuzzy sets or fields of estimated membership values $MV^{e}_{hs1...5}(s_{SL},s_{PVI})$ for 1990 and 1995 as well as their standard deviations $MV^{\sigma}_{hs1...5}(s_{SL},s_{PVI})$. Note that the membership values of the 5 classes added up should result in one, for a specific point in the feature space. The fuzzy observations were performed by a single expert.

Each class occurs with a single cluster and more or less gradually passes into a neighbouring class. The classes hs1, hs2 and hs3 clearly have a fixed relative position in the feature space. Apparently different meteorological circumstances during the growing season does not influence the arrangement of these clusters, unlike their size and shape. The cluster positions can be explained from physiognomic characteristics of the cover types they represent. The classes 'thin grass/herb cover with blond sand' hs1 and 'intermediate herb/moss cover with grey sand' hs2 both have high values on the soil line. These classes differ in respect to their volume of green vegetation. Consequently, hs1 has higher PVI-values. The class 'high moss cover' hs3 covers the soil to a large extent but has low green matter and is therefore characterised by both low PVI- and SL-values.

Notably, the position and size of the clusters of hs4 and hs5 interchange between the dates. The clusters of 1995 take a position in accordance with their cover characteristics. The class 'high moss and low grass cover' has low SL-values and intermediate PVI-values, while the class 'high grass and herb cover with litter' is expected to have high PVI-values. Apparently, the deviative cluster positions in 1990 result from spectral migration due to different meteorological conditions during the growing season.

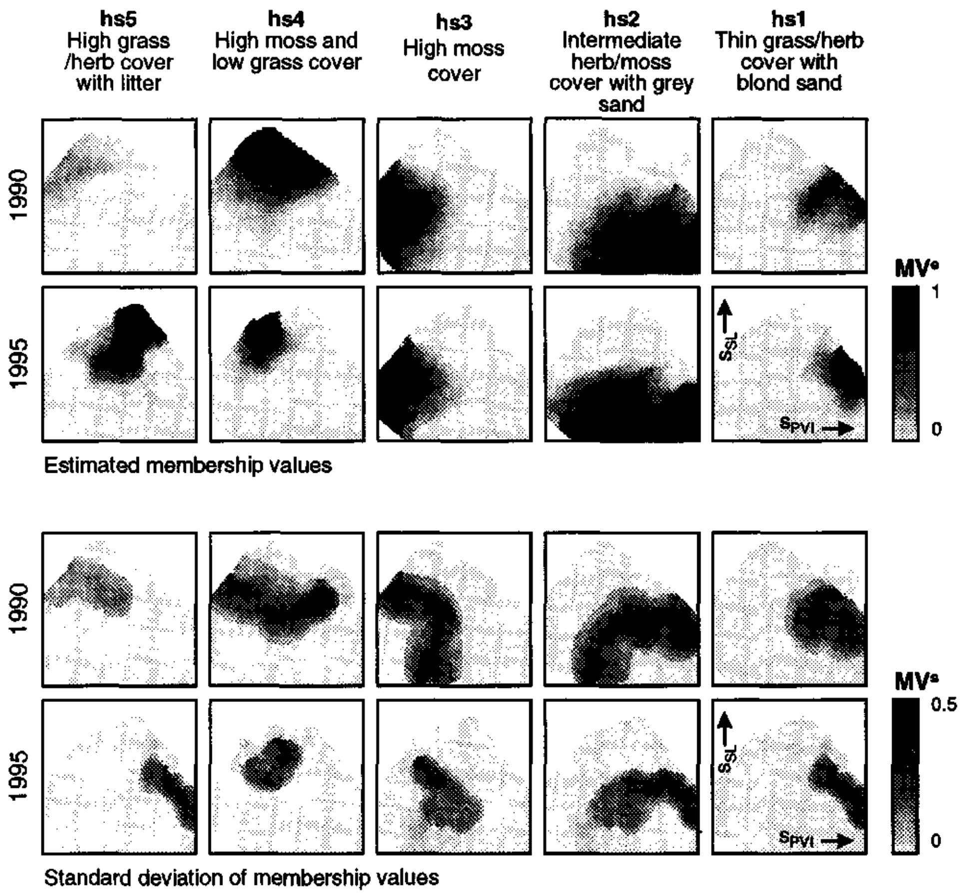


Figure 3.7 Fuzzy sets of the herbaceous classes in the feature spaces of 1990 and 1995; the estimated membership values $MV^e_{hs1..5}(s_{SL},s_{PVI})$ and standard deviation $MV^\sigma_{hs1..5}(s_{SL},s_{PVI})$.

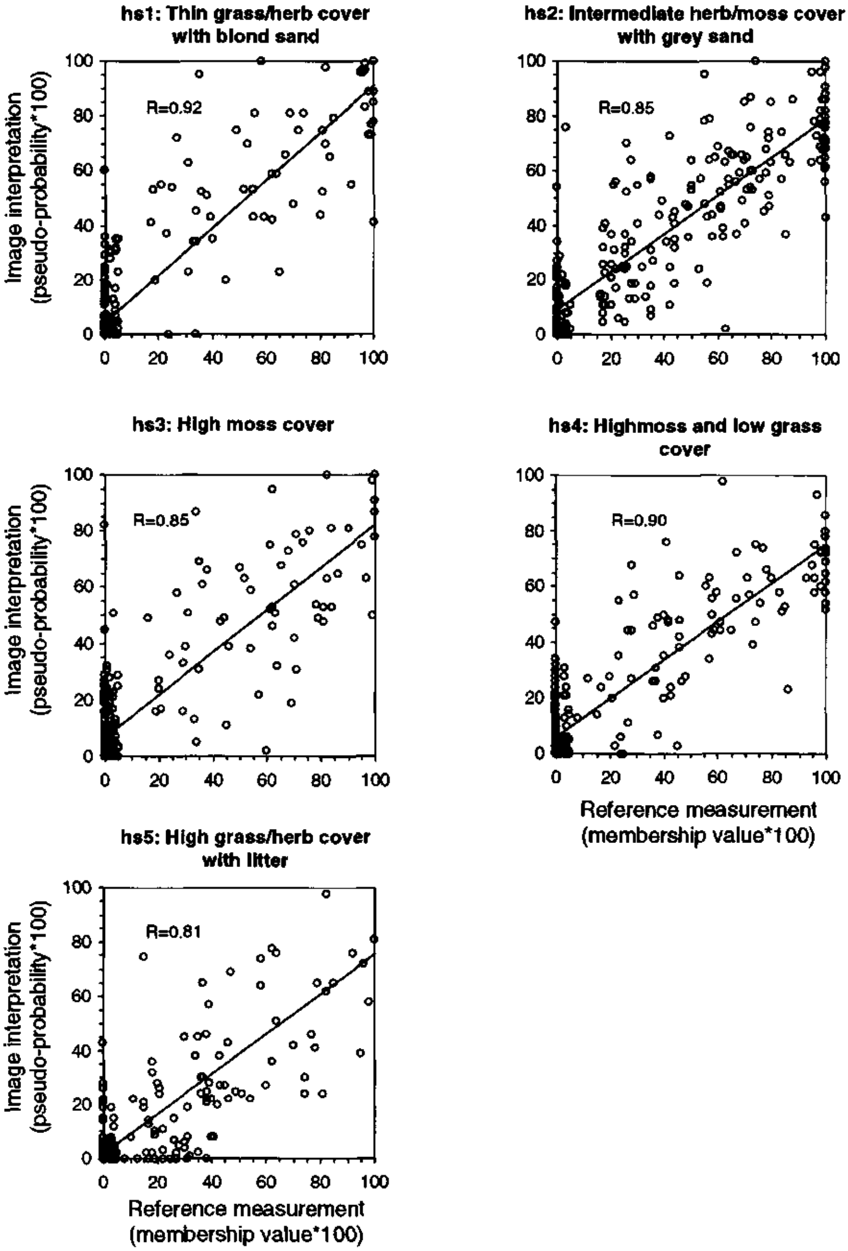


Figure 3.8 Validation of the fuzzy image classification of herbaceous structural types by 310 fuzzy observations in the terrain.

The uncertainty in fuzzy observations is restricted to the transition zones between the herbaceous cover types, as can be concluded from the standard deviation of the estimated membership values $MV^{\sigma}_{hs1...5}(s_{SL}, s_{PVI})$. Apparently the fuzzy observations have been consistently performed by the interpreter within the experimental set up for the observations, i.e. the fuzzy observation channel. The parameter setting of an observation channel aims at repelling subjectivity. Tests were conducted to determine the sensitivity of the method to 1) image sample characteristics and 2) the colour setting of the image.

The perception of colour by a human interpreter is known to be strongly affected by the context of the observation (Rosenfeld and Kak, 1982). Tests revealed that a single image sample should consist of at least 3 but preferably many more separated subsamples distributed over the image. Only then an interpreter is able to generate fairly consistent output. The second important aspect of the observation channel is the colour setting of the image. It appeared, that small changes in the image colour setting did not result in different observations. Apparently, the observations are merely related to relative differences in colour rather than absolute colours, when the scene is known to the interpreter.

A comparison of the fuzzy classification with reference data obtained in the field shows the validity of the image interpretation (fig. 3.8). The correlation coefficients between the field data and the interpretation results vary between 0.81 and 0.92. Ideally, the incidence of the regression lines equals one and the lines cross the origin. The validation graphs show that this is not the case, which is caused by 1) spectral confusion between the classes and 2) the higher variability of the reference data compared to the variation in the digital landscape model. The reduced variability in the digital landscape model results from generalisation processes during the interpretation of the image.

3.4 Conclusions

Two sets of analogue false colour aerial photographs from 1990 and 1995 were transformed into radiometrically corrected digital orthophoto-mosaics. The radiometric correction was necessary to undo the orthophoto mosaic from radiometric distortions that do not relate to variations in the terrain. For the interpretation of these images a supervised hierarchical classification method was presented. The step-by-step approach following from a predefined land cover hierarchy appeared suitable to deal with the complex spectral patterns in the images.

Discrete landscape patterns were interpreted by crisp classification techniques which enable the construction of spatial objects representing vegetation and geomorphologic phenomena. The continuous internal variation of herbaceous vegetation was quantified by fuzzy classification techniques yielding a field description of the variability. Fuzzy classification appeared a robust and valid technique to model ecological gradients.

A comparison of the chloropleth map obtained by the manual photo interpretation and the digital landscape model constructed in this chapter reveals that the latter approach yields a

- more realistic,
- more detailed, and
- less subjective

representation of the complex landscape in the test site. Although the application of digital interpretation techniques implies a minimum input of expert knowledge, the interpretation results remain to some extent subjective. This holds especially true for the fuzzy classification results. The fuzzy classifier is trained by a set of fuzzy observations obtained by expert-judgement in the field or on screen. Obviously, field observations obtained close to the recording data should be preferred over on screen observations. The quality of these observations largely depends on the

- experts' notion of the land cover classes, and
- experts' knowledge of the scene

Further objectivation of the method should be achieved by describing the fuzzy land cover classes by specimen in order to make the notion of classes exchangeable between experts.

The accuracy of the fuzzy grassland mapping largely depends on the spectral discrimination between the classes. Consequently, the CIR-image has to be acquired at the time the discrimination between the classes is optimal. In order to select the optimal acquisition date, the process of spectral migration of classes during the growing season, which is related to meteorological conditions, has to be determined. It is recommended to perform a multi-year experiments with a field spectrometer to study this phenomenon.

4. Quantification of vegetation structural dynamics

4.1 Introduction

The previous chapter dealt with the specification of a measurement system for the mapping of vegetation structural and geomorphologic features from digital colour infra-red orthophotos. A multi-temporal landscape model was produced of the test site quantifying these terrain features. This chapter deals with the exploration of vegetation structural and geomorphologic dynamics from these multi-temporal data. Information on spatio-temporal changes provides insight into the landscape ecological processes, which is a prerequisite to set out an optimal nature management plan (Piotrowska, 1988; Ehrenburg et al, 1988; van Leeuwen and van der Maarel, 1971).

Numerous types of analysis have been proposed to explore temporal and spatial landscape dynamics (Baker, 1989; Baker and Cai, 1992; Dunn et al., 1990; Johnson, 1990; O'Neill et al., 1989; Turner, 1990; Webster and Oliver, 1990). These methods apply to a set of spatial objects or fields relevant for a specific organisational level of the landscape, i.e. level of aggregation. The choice for a specific level of aggregation not only determines the ecological meaning of the objects and their level of detail, but also affects the accuracy of the analysis applied to these objects. The analysis should not necessarily be performed on the level of aggregation provided by the measurement system. Thematic and/or geometric inaccuracies in the data model can necessitate the aggregation of objects and fields provided by the measurement system to composite objects. Provided that an appropriate aggregation operation is applied, the temporal analysis on composite objects will yield more reliable results.

The objective of this chapter is to show the potential of the multi-temporal data set produced in the previous chapter with respect to landscape ecological analysis. Hereto, two primary issues originating from the practice of any nature manager will be further elaborated upon:

- Is the aerial extent of the land cover types changing and what is the turnover between the cover types, and
- Is the spatial structure of the landscape changing, i.e. are the patches of discrete land cover types changing and to what extent does this alterthe spatial variation of continuous terrain elements.

Subsequently, the methods will be presented to answer these questions. After the presentation and discussion of the results, the chapter ends with some conclusions.

4.2 Material and methods

Starting point for the analysis of landscape dynamics is the selection of an appropriate level of aggregation and the specification of the objects populating this organisational level of the landscape. The multi-temporal data set constitutes of the dates 1990 and 1995 (plate 1) and will be analysed on a composite level rather than on the level of the elementary objects detected by the measurement system. These elementary objects have a vegetation structural or geomorphologic nature, such as individual or clustered occasions of trees and shrubs, structural aspects of the herbaceous vegetation and sandy patches (table 4.1). As noticed in the introduction, geometric and/or thematic inaccuracies cause that not all elementary objects are suitable for temporal analysis. Therefore the elementary landscape structures are aggregated to composite objects, i.e. complex landscape structures.

Table 4.1 The objects and fields in the spatial model.

level of object aggregation	class	*attributes modelled as field*
elementary	blond sand	
	herbaceous	*thin grass/herb cover with blond sand (hs1)*
		intermediate herb/moss cover with grey sand (hs2)
		high moss cover (hs3)
		high moss and low grass cover (hs4)
		high grass/herb cover with litter (hs5)
	sea buckthorn	
	low scrub	
	high scrub/trees	
	reed	
	water	
composite	sandy area	
	matrix	*blond sand*
		thin grass/herb cover with blond sand (hs1)
		intermediate herb/moss cover with grey sand (hs2)
		high moss cover (hs3)
		high moss and low grass cover (hs4)
		high grass/herb cover with litter (hs5)
		sea buckthorn
		other scrub
	woodland	
	reed	
	water	

Composite objects are generally more abstract and consequently less tangible compared to elementary objects. Five major classes of composite objects are distinguished, sandy area, matrix, woodland, reed and water (table 4.1). All object classes are motivated by the information need on behalf of the nature management in the test site. A 'sandy area' constitutes of one or more deflation and accumulation zones forming patches of active wind erosion. Due to the spatial extent of sandy areas islands of herbaceous vegetation or even shrubs might occur in sand-areas. Woodlands are predominantly covered with high shrubs and trees. Again a woodland might enclose minor patches covered with a herbaceous vegetation or sand. The rest-area, not covered with sandy area, woodland, reed and water, constitutes the matrix. Consequently, the matrix ranges from fully shrub covered to fully grass or sand covered.

Subsequent to the description of the aggregation from elementary to composite objects (sect. 4.2.1), the calculation of temporal transitions between composite objects is elucidated in sect. 4.2.2. These transitions enable the answering of the first question raised in the introduction. The second question relates to spatial variation and dynamics. In order to study these landscape characteristics the concept of variography is introduced (sect. 4.2.3).

4.2.1 Amalgamation of composite objects

The applied rules to construct composite objects concern a special case of aggregation, i.e. non-nested aggregation. In a process of non-nested aggregation or amalgamation parts of elementary objects can belong to different composite objects. Consequently, a composite object can contain parts of one or more elementary objects (sect. 2.3.2; fig. 2.7).

The structure of the amalgamation rules is the same for the object classes woodland and sandy area, although the parameter settings differ. The elementary water and reed objects usually appear as major spatial units and need no aggregation. The process of amalgamation consists of seven steps:

- The coverage of high shrubs and blond sand is aggregated by a moving average calculation over a circular neighbourhood with radius r_n.
- Threshold classification of high shrubs or blond sand coverage; IF cover in cell > T_c THEN cell belongs to segment, where T_c is the minimum percentage cover.
- Segments are constructed by grouping adjacent cell with the same cover class.
- The resulting segments are selected on size; IF segment area > A_{min} THEN segment is selected.
- Subsequently, small holes in a segment are dissolved; IF hole area < A_h THEN hole is dissolved.
- Segments are selected on shape; IF maximum internal segment diameter > D_{min} THEN segment is selected.
- Finally, a segment is assigned to an object class.

The parameters for the construction of woodlands and sandy areas are established from general ecological practice and listed in table 4.2. The resolution of the grid with composite objects remains 0.25 metre.

After the construction of the matrix its internal variability is modelled as a field. The presence of 8 cover types, i.e. sand, hs1, hs2, ..hs5, sea buckthorn and other shrubs, is expressed by a probability value and calculated by a moving average operation over a circular neighbourhood with a radius of 1.50 meter. This results in a probability vector $(p_{sand}, p_{hs1}, p_{hs2}, p_{hs3}, p_{hs4}, p_{hs5}, p_{buckthorn}, p_{other\_scrub})_{(i,j)}$ for each cell (i,j).

Table 4.2 Parameters for aggregating woodland and sandy area objects from vegetation elements (see text for explanation).

Object class	r_n (m)	T_c (%)	A_{min} (m^2)	A_h (m^2)	D_{min} (m)
woodland	50	65	500	125	25
sandy area	5	65	50	12.5	2.5

4.2.2 Calculation of temporal transitions

The composite objects are used to analyse the vegetation structural and geomorphologic dynamics in the test-site. Firstly, the interaction between the objects is quantified. Because the object classes are crisp, the transitions are described in a *discrete state space*. Secondly, the internal dynamics of the matrix, quantified by a multi-valued field, is explored in a multivariate *continuous state space* (Baker, 1989).

Discrete state space

The transition of cells in univariate discrete state space can be generalised by a transition probability distribution or transition matrix. The term *transition probability distribution* is preferred over transition matrix in order to avoid confusion with the term matrix introduced for a specific object class. A transition probability distribution provides the transition probabilities $p(cc_{k,t0}.cc_{l,t1})$ between the five composite classes $cc \in$ {sandy area, matrix, woodland, reed, water} over a discrete time interval between t_0 and t_1. When the transition probability $p(cc_{k,t0}.cc_{l,t1})$ is divided by the marginal probability $p(cc_{k,t0})$, the conditional probability $p(cc_{l,t1}|cc_{k,t0})$ is obtained, providing the probability for cc_l on t_1 given the presence of cc_k on t_0. This approach is commonly applied in order to describe the dynamics of objects and changes between chloropleth maps of two or more dates (Lippe et al., 1985; Van Dorp et al., 1985; Jacobs and Sties, 1995).

Continuous state space

The internal variability of the matrix is quantified by 8 probability values, indicating the presence of an equal number of vegetation structural cover types. These matrix data can be presented in continuous state space, where each axis is defined by a cover type and measured in probability values. Each point or cell in the matrix takes a position in this space $\mathbf{p} = (p_{sand}, p_{hs1}, p_{hs2}, p_{hs3}, p_{hs4}, p_{hs5}, p_{buckthorn}, p_{other\_scrub})$ on t_0 and t_1. A change in site characteristics between the two dates results in a translation of the cell in the feature space (fig. 4.1). For each point **p** on t_0 and t_1 the general translation probability $P(\mathbf{p}_{t1}|\mathbf{p}_{t0})$ can be calculated from the data set. The set of all transitions having a probability value greater than O, provide the succession $s_\mathbf{p}$ for that point (fig. 4.1):

$$s_p = \{p: P > 0\} \qquad 4.1$$

The succession s_p (eq. 4.1) is conveniently parameterised with a centroid and standard deviation in all dimensions.

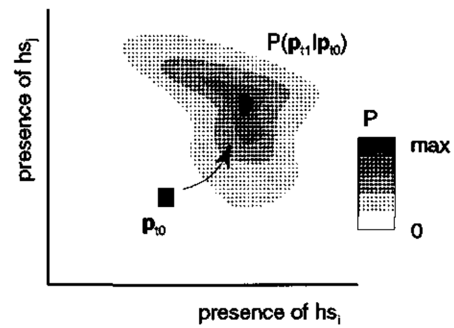


Figure 4.1 Example of vegetation succession in 2-dimensional feature space (see text for explanation).

4.2.3 Description of spatial variability by variography

The spatial variability of objects can be quantified by their size and shape, as well as their topological relationships. The spatial structure of fields can be explored by texture features (Nellis and Briggs, 1989; Haralick, 1979), pattern indices (O'Neill et al., 1988) and various tests for the presence of spatial autocorrelation (Legendre and Fortin, 1989; Webster and Oliver, 1990). The central tool in geostatistics is the semi-variogram, which is a graphical representation of the spatial variability in a set of data (Lacaze et al., 1994). Here the semi-variogram is used to describe the internal variability of the matrix and the variation in the herbaceous vegetation in particular.

Compared to autocorrelation the analysis of spatial dependence with a semi-variogram can be made using weaker conditions of stationarity (Oliver and Webster, 1986; Curran, 1988; Woodcock et al., 1988). The basic assumption is that the difference in value of a variable observed at two positions only depends on the distance between sampled points and their orientation.

The semi-variance $\gamma(h)$ is defined as half the expected squared difference between sample values p_{hs} separated by a given lag or distance h,

$$2\gamma(h) = E[p_{hs}(x_i) - p_{hs}(x_i+h)]^2 \tag{4.2}$$

where p_{hs} is the probability for a specific herbaceous type **hs** $\in$ HS. The semi-variance at a given lag h is estimated as the average of the squared differences between all observations, i.e. cells in case of grid data, separated by the lag,

$$\gamma(h) = 1/2N(h) \sum_{i=1}^{N(h)} [p_{hs}(x_i) - p_{hs}(x_i+h)]^2 \tag{4.3}$$

where N(h) is the number of pairs of observations at lag h. Only the cells having p_{hs} greater than 0.1 are involved in order to eliminate differences in semi-variance between the herbaceous structural classes originating from differences in aerial presence.

When the semi-variance is plotted against the distance, the experimental semi-variogram is obtained (fig. 4.2). The shape of a semi-variogram may take many forms, which can be related to a theoretical model, e.g. linear, spherical or exponential. Here the exponential model is applied to calculate the theoretical semi-variance,

$$\gamma(h) = c[1 - e^{(-h/r)}] \tag{4.4}$$

where c is the asymptote, and r is the distance parameter controlling the spatial extent of the function. The model parameters are estimated by least square regression.

A semi-variogram applies to the univariate case. Hence, the overall structural variation of the 5 herbaceous cover types needs to be reduced to a single variable, in order to enable the calculation of the semi-variance. Therefore, equation 4.3 is adapted to

$$\gamma(h) = 1/2N(h) \sum_{i=1}^{N(h)} [\sum_{\mathbf{hs} \in HS} abs(p_{hs}(x_i) - p_{hs}(x_i+h))/2]^2 \tag{4.5}$$

In eq. 4.5 the variation in the herbaceous vegetation ranges between 0 for two identical points at distance h to 1 for two points that show no similarity at all.

4.3 Results and discussion

Construction of composite objects

Plate 2 shows both the elementary and deduced composite objects in a subarea of the test site. Woodland consists predominantly of high shrubs. In the test site wooded areas usually occur on moist or wet locations in valleys and on the north slopes of dunes. Mostly these locations have relatively sharp boundaries justifying woodlands to be represented as discrete objects. This does not always apply to sandy areas. Sandy areas form major areas of active wind erosion and consist of deflation and accumulation zones. While the deflation zone generally shows clear boundaries this is not necessarily the case for accumulation zones. Because accumulation zones have a more or less gradual boundary, one might argue that occasionally the representation of sandy areas as spatially fuzzy objects or field is more appropriate.

The composite object type matrix occupies most of the remaining area. The matrix ranges from almost fully scrub covered to purely herbaceous vegetation or sand, although small patches of high shrubs and trees might belong to the matrix too. The internal spatial variability of matrix objects is modelled as a field. Plate 2 shows the probability fields of the matrix subtypes. Note, that the presence of shrubs in these probability fields is a smooth representation of the elementary scrub objects (plate 1).

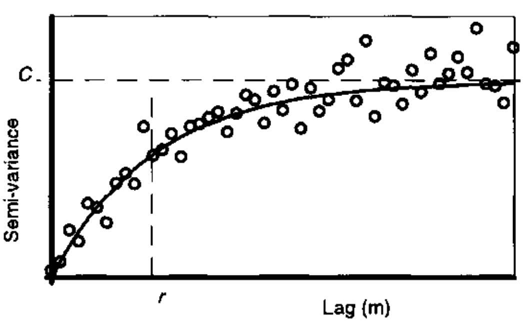


Figure 4.2 Experimental (.:.) and theoretical exponential (—) semi-variogram, where *C* is the assymptote and *r* measures the spatial extent of the function (eq. 4.4).

The amalgamation of composite objects from the measured elementary objects was primarily motivated to increase the stability and accuracy of objects on a level of aggregation relevant for ecological analysis in space and time. Consider a landscape consisting of a well-defined mosaic of patches. If the size of these patches is well over the spatial resolution of the measurement system and the patch characteristics can be easily distinguished by the system, there is no need for aggregation (Puech, 1994). The necessity grows with increasing complexity of the landscape considering the size of the landscape elements as well as their characteristics in relation to the geometric characteristics and discriminative capabilities of the measurement system. Buckthorn scrubs in the test site provide a typical example of elementary objects that need to be aggregated before a temporal analysis is performed, as will be shown in the next section.

Besides considerations regarding the accuracy of the digital landscape model, the necessity to mark off different levels of aggregation should be motivated by landscape ecological perspectives as well (Pickett et al., 1989; Kotliar and Wiens, 1990). With a measurement system based on the semi-automatic interpretation of high resolution colour infra-red imagery (chapter 3), a dune landscape can be described in rather small elements. Consequently, one has much flexibility to construct complex elements on a higher level of landscape organisation. Digital landscape models obtained by the manual interpretation of the same colour infra-red photographs do not provide this flexibility.

For practical reasons manual image interpretation yields a less detailed terrain description, because amalgamation is an implicit aspect of the mapping process. For example areas with a certain minimum shrub cover are delineated and labelled scrub while the areas with low shrub cover are called 'open vegetation' (Geelen, 1990). Unfortunately the process of amalgamation during manual image interpretation is primarily guided by practical constraints, while it should be directed by ecological perspectives. High resolution mapping systems provide the possibility to create an infinite number of views on the data model for analysis. Indeed, the presented composite objects in this section is only one possible view. Many other views are possible and although the applied rules of amalgamation have a subjective nature, the rules are formalised and therefore systematically employed over the whole test site and repeatable.

Dynamics of discrete landscape features

In a subarea of the test site a grazing experiment was conducted. Table 4.3 summarises the changes in aerial extent of the cover types that have occurred since the introduction of cattle. The main trends are the reduction of buckthorn shrubs and a decrease of the area grassland, i.e. herbaceous vegetation, in favour of the cover type sand. Ecologists are quite familiar with the quantification of vegetation dynamics by means of transition matrices between chloropleth maps (van Dorp et al., 1985). With the help of a GI system these statistics are easily obtained as well as aerial estimates of land cover changes.

However, thematic and/or geometric inaccuracies in the data model can yield erroneous analysis results. Consider for example the transitions calculated from the elementary objects in the data model (table 4.3a). The transition between buckthorn and grassland is improbably high, i.e. P=0.50. Buckthorn scrub frequently occurs in the test-site and ranges from dense to very open. In the digital landscape model the latter type appears as a minority of buckthorn cells scattered over a herbaceous vegetation (plate 1). Primarily the geometric accuracy of 1.5 times the cell size contributes to the erroneous turnover between buckthorn and grassland. In this case a temporal analysis should clearly not be applied on the level of aggregation provided by the measurement system, but on a higher level of aggregation at which the geometric accuracy plays a lesser role.

Table 4.3 Transition matrices of the elementary and composite objects in 1990 and 1995 of a subarea with cattle grazing, where p(hs90,hs95) is the joint probability and p(hs95|hs90) indicates the conditional probability.

A. Elementary objects

p(hs90,hs95) hs90	hs95 sand	grass-land	buck-thorn	low shrubs	high shrubs	reed	water	p(hs90)
sand	**0.031**	**0.009**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.040
grassland	**0.027**	**0.447**	**0.020**	**0.006**	**0.024**	**0.000**	**0.000**	0.524
buckthorn	**0.000**	**0.025**	**0.020**	**0.000**	**0.004**	**0.000**	**0.000**	0.050
low shrubs	**0.000**	**0.004**	**0.001**	**0.015**	**0.001**	**0.000**	**0.000**	0.021
high shrubs	**0.000**	**0.016**	**0.000**	**0.000**	**0.314**	**0.000**	**0.000**	0.331
reed	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.004**	**0.003**	0.008
water	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.026**	0.027
p(hs95)	0.058	0.502	0.041	0.022	0.344	0.005	0.028	1.000

p(hs95|hs90) hs90	hs95 sand	grass-land	buck-thorn	low shrubs	high shrubs	reed	water
sand	**0.78**	**0.21**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
grassland	**0.05**	**0.85**	**0.04**	**0.01**	**0.05**	**0.00**	**0.00**
buckthorn	**0.00**	**0.50**	**0.41**	**0.01**	**0.09**	**0.00**	**0.00**
low shrubs	**0.00**	**0.21**	**0.03**	**0.71**	**0.05**	**0.00**	**0.00**
high shrubs	**0.00**	**0.05**	**0.00**	**0.00**	**0.95**	**0.00**	**0.00**
reed	**0.00**	**0.00**	**0.00**	**0.00**	**0.08**	**0.58**	**0.34**
water	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.03**	**0.97**

B. Composite objects

p(hs90,hs95) hs90	hs95 sandy area	matrix	wood-land	reed	water	p(hs90)
sandy area	**0.030**	**0.009**	**0.000**	**0.000**	**0.000**	0.039
matrix	**0.028**	**0.540**	**0.028**	**0.000**	**0.000**	0.596
woodland	**0.000**	**0.016**	**0.315**	**0.000**	**0.000**	0.330
reed	**0.000**	**0.000**	**0.001**	**0.004**	**0.003**	0.008
water	**0.000**	**0.000**	**0.000**	**0.001**	**0.026**	0.027
p(hs95)	0.058	0.565	0.343	0.005	0.028	1.000

p(hs95|hs90) hs90	hs95 sandy area	matrix	wood-land	reed	water
sandy area	**0.77**	**0.23**	**0.00**	**0.00**	**0.00**
matrix	**0.05**	**0.91**	**0.05**	**0.00**	**0.00**
woodland	**0.00**	**0.05**	**0.95**	**0.00**	**0.00**
reed	**0.00**	**0.00**	**0.08**	**0.58**	**0.34**
water	**0.00**	**0.00**	**0.00**	**0.03**	**0.97**

Now consider the transition matrix calculated over the composite objects (table 4.3b) Although the composite object types provide less specific information, the aggregated data yield more accurate transition probabilities, which is reflected by a low percentage of unlikely transitions between cover types. The distinguished transition of reed into water and vice versa is caused by varying water levels in the water pans occurring throughout the test site and cattle grazing.

The conditional probabilities in table 4.3 can be used to predict a future state cc_2 on t_2, when it can be assumed that $p(cc_{1,t1}|cc_{0,t0})$ equals $p(cc_{2,t2}|cc_{1,t1})$. This assumptions asserts that when a system is in a certain state, there exists a fixed probability that it will be in some certain state at the next time step. If the transition probabilities are constant through time, a system is called homogeneous or stationary, and the transition probability distribution is qualified as a Markov model (Davis, 1986).

Most natural systems are, however, constantly changing and do not meet the condition of stationarity. Even the number of states might vary, i.e. new system states can arise and present states might evåde. An other objection against the application of Markov models are spatial dependencies in the functioning of a landscape. The Markovian assumption implies that changes at a certain point are independent of the changes at neighbouring points. Again this is a rather unrealistic assumption. Consequently, the application of a transition probability distribution is valid to describe transitions in the past and should be carefully applied to predict future states (Lippe et al., 1985, Usher, 1981; Turner, 1987).

Apart from the turnover between cover types, vegetation dynamics affect the spatial configuration of the landscape. The spatial variability of discrete spatial units is governed by the change in size and shape of the objects as well as their mutual topological relationships (sect. 2.3). A simple and robust indicator of changes in fragmentation and whimsicality of objects is the total boundary length in an area of interest. The length of the boundary between composite objects increased with 12 percent in five years. Apparently the number of transition zones and gradient situations has increased within the analysed time window

The development of buckthorn shrubs also shows a remarkable trend. Figure 4.3 shows the change in occurrence of this shrub type as a function of the density of the scrub. The presence of open buckthorn scrub, i.e. density less than 60 percent, is reduced by 20 percent, while the extent of dense buckthorn scrub increased with 5 percent. The latter trend might be attributed to the fact that cattle hardly accesses buckthorn scrub when the density is over 70 percent. The latter example clearly shows the wealth of detail captured by the landscape model. Many other types of spatial analysis can be performed to reveal this information.

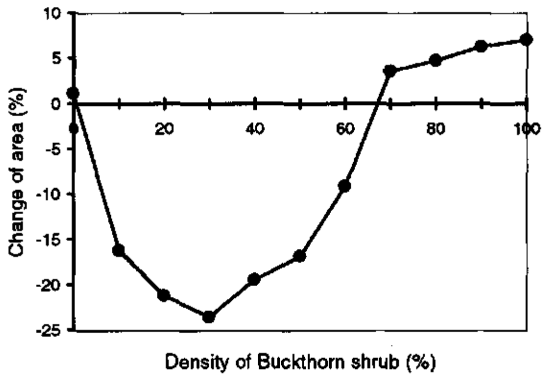


Figure 4.3 Change of aerial extent of buckthorn shrubs between 1990 and 1995 in relationship with shrub density.

Dynamics of herbaceous vegetation in matrix

This section focusses on the spatio-temporal dynamics of the herbaceous structural cover types within the matrix. The presence of herbaceous structural types, also indicated with grassland types, is quantified for each grid cell in the matrix by a vector of five pseudo-probability values (p_{hs1}, p_{hs2}, ... p_{hs5}). Consider the presence of herbaceous structural types in the test site ordered by pseudo-probability values, where each cell with a certain pseudo-probability value adds 0.0625 m^2 (=0.25*0.25m^2) to the cumulated area (fig. 4.4). All herbaceous types occupy relatively big areas with low pseudo-probability values. The presence of a grassland decreases sharply with increasing pseudo-probability values. The closer the pseudo-probability value is to one, the more typical is the appearance of a cover type. A cell is typically assigned to a class when the pseudo-probability is greater than 0.75. The grassland types hs2, hs3 and hs5 cover considerable areas in their typical appearance. The typical cover of the types hs1 and hs4 is rare in the test site. Consequently, these cover types mostly appear in combination with other grassland types.

By multiplying the pseudo-probability value with the cell size, the substantial area of a herbaceous cover type within a cell is obtained. Accumulation of the latter variable over the test site results in a curve shaped line crossing the origin of the graphs in figure 4.4. The area below the curve quantifies the total presence of a class in the test site. Although low pseudo-probability values occur very frequently, their contribution to the total presence of a herbaceous type is small. The contribution of typical grasslands to the total area is modest as well, because the area with high probability values is relatively small.

During the five years of grazing by cattle the presence of three grassland types has reduced (fig. 4.4LR). Reduction of the presence of cover type hs5 was one of the objectives of the grazing experiment. The area of two herbaceous types has increased. Grassland type hs1 shows the biggest increase. This cover type profits from the increase of active wind erosion in the test site. Also the total area of grassland type hs2 has increased,

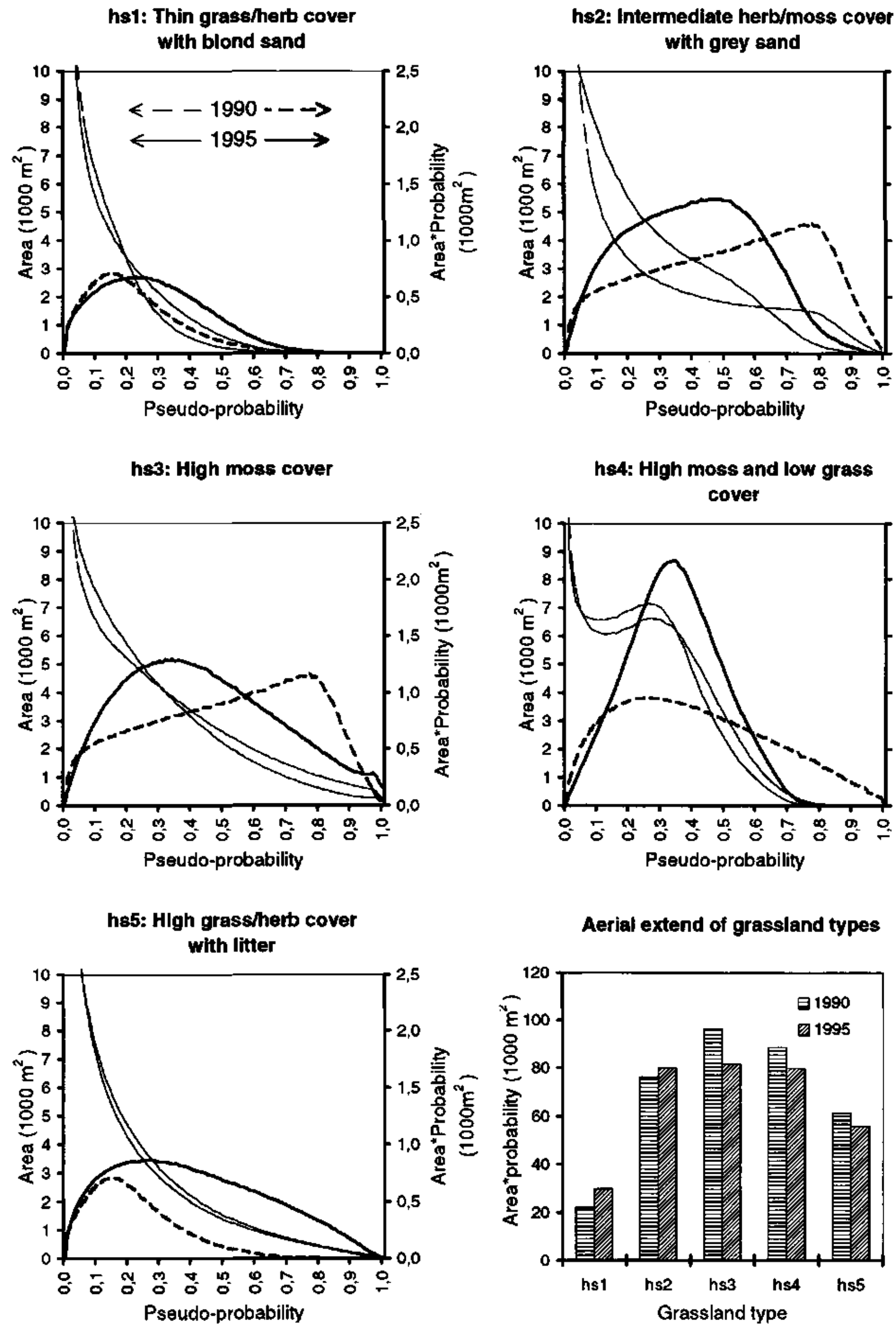


Figure 4.4 The distribution of the pseudo-probabilities of each grassland type in the test site in 1990 and 1995.

although the typical appearance of hs2 decreased strongly. Except for hs1, all cover types show a decrease of area covered with their typical appearance. Apparently the variation in the herbaceous vegetation structure is reduced. The down-shift of pseudo-probability values might be caused by grazing and trampling by cattle. Conclusions on the effect of cattle on the landscape dynamics can not be drawn because data on a reference site without cattle are lacking.

Turnover between cover types

Now the turnover between the classes is considered. As the grassland in the matrix is quantified by a quintuple valued field of pseudo-probabilities ($p_{hs1}, p_{hs2}, \ldots p_{hs5}$), each cell takes a position in a five dimensional feature space where the axes are measured by pseudo-probability values. Temporal changes in composition are best quantified by a translation in this feature space. The translation or migration of several grassland compositions is presented in table 4.4. Note that in this section the term migration relates to changes in the presence of vegetation classes and not to a spatial process.

Firstly the migration of typical grasslands between 1990 and 1995 is calculated. As stated before a grid cell is considered to be typically assigned to a grassland type when the pseudo-probability value is higher than 0.75. Cells meeting this condition in 1990 are selected and a generalised vector of pseudo-probability values is derived for 1990 and 1995 respectively. For instance typical cover type hs3 migrated from (0.04, 0.08, 0.87, 0.01, 0,00) in 1990 to (0.04, 0.32, 0.46, 0.15, 0.03) in 1995. The difference between the vectors provides the translation vector (0.00, 0.24, -0.41, 0.14, 0.03) indicating a major shift towards hs2 and a smaller shift to hs4 at the expense of hs3. In the scheme of vegetation succession, the turnover between hs3 and hs2 is a process of regression, while the shift of hs3 to hs4 is a progressive change. The translation distances in table 4.4, i.e. the Euclidean distances in the continuous state space, show that the typical grassland cover of the types hs2, hs3 and hs4 have changed twice as much compared to the cover types hs1 and hs5.

Also the dynamics of some grassland combinations is analysed. Four intermediate grassland types are considered. An intermediate cover type is located between two typical grassland types and therefore takes a position in the features space half way the two classes. The intermediate types are characterised by cells having a pseudo-probability values greater than 0.35 for two types simultaneously. For instance the intermediate grassland type of cover types hs4 and hs5 is generalised to (0.00, 0.04, 0.05, 0.46, 0.45). Within a time interval of 5 years this intermediate type migrated over a distance of 0.30 to (0.05, 0.22, 0.12, 0.29, 0.32), which means a regression of hs4 and hs5 primarily towards hs2.

All calculated translations seem plausible and therefore confirm the validity of the data model. The temporal changes have been analysed in a prospective view from 1990. Obviously it is also possible to perform a retrospective analysis starting from 1995. In a retrospective analysis the history of a certain cover type can be explored.

Table 4.4 Turnover of herbaceous structural cover types between 1990 and 1995 (see text for explanation).

Selection of cells in 1990 having probability values		$P^{hs1} > 0,75$		$P^{hs2} > 0,75$		$P^{hs3} > 0,75$		$P^{hs4} > 0,75$		$P^{hs5} > 0,75$		$P^{hs1} > 0,35$ $P^{hs2} > 0,35$		$P^{hs2} > 0,35$ $P^{hs3} > 0,35$		$P^{hs3} > 0,35$ $P^{hs4} > 0,35$		$P^{hs4} > 0,35$ $P^{hs5} > 0,35$	
Number of cells (*1000)		5,8		236,5		127,3		205,6		38,7		61,7		5,6		7,0		195,7	
		m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev
Generalised	hs1	**0,82**	0,05	0,04	0,02	0,04	0,03	0,00	0,00	0,00	0,00	**0,44**	0,07	0,11	0,07	0,00	0,01	0,00	0,01
vector of	hs2	0,09	0,03	**0,87**	0,07	0,08	0,04	0,02	0,01	0,05	0,02	**0,51**	0,09	**0,39**	0,03	0,00	0,02	0,04	0,05
probability	hs3	0,04	0,02	0,05	0,03	**0,87**	0,07	0,05	0,02	0,05	0,01	0,02	0,04	**0,39**	0,04	**0,42**	0,05	0,05	0,06
values	hs4	0,04	0,01	0,04	0,02	0,01	0,01	**0,88**	0,08	0,09	0,04	0,01	0,02	0,01	0,03	**0,41**	0,05	**0,46**	0,08
in 1990	hs5	0,01	0,00	0,00	0,00	0,00	0,00	0,05	0,03	**0,81**	0,04	0,02	0,03	0,09	0,06	0,17	0,06	**0,45**	0,07
		m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev	m	stdev
Generalised	hs1	**0,61**	0,22	0,31	0,14	0,04	0,08	0,02	0,06	0,03	0,08	**0,31**	0,25	0,19	0,17	0,01	0,05	0,05	0,09
vector of	hs2	0,23	0,13	**0,55**	0,13	0,32	0,20	0,14	0,11	0,04	0,05	**0,36**	0,20	**0,24**	0,17	0,10	0,10	0,22	0,20
probability	hs3	0,03	0,07	0,09	0,12	**0,46**	0,23	0,14	0,13	0,11	0,14	0,12	0,15	**0,29**	0,24	**0,26**	0,22	0,12	0,15
values	hs4	0,09	0,12	0,03	0,05	0,15	0,11	**0,48**	0,14	0,23	0,12	0,11	0,15	0,14	0,18	**0,35**	0,23	**0,29**	0,24
in 1995	hs5	0,04	0,05	0,02	0,04	0,03	0,06	0,22	0,16	**0,59**	0,21	0,10	0,14	0,15	0,16	0,28	0,13	**0,32**	0,18
Translation	hs1	**-0,21**		0,27		0,00		0,02		0,03		**-0,13**		0,08		0,01		0,05	
vector of	hs2	0,14		**-0,32**		0,24		0,12		-0,01		**-0,15**		**-0,15**		0,10		0,19	
probability	hs3	-0,01		0,04		**-0,41**		0,09		0,06		0,10		**-0,11**		**-0,15**		0,07	
values	hs4	0,05		-0,01		0,14		**-0,40**		0,14		0,10		0,13		**-0,06**		**-0,17**	
1990 to 1995	hs5	0,03		0,02		0,03		0,17		**-0,22**		0,08		0,06		0,11		**-0,13**	
Translation distance		0,259		0,42		0,50		0,46		0,27		0,26		0,24		0,22		0,30	

Spatial structure of the matrix

Finally the effect of vegetation dynamics on the spatial structure of the matrix is described. The spatial structure of the continuously varying matrix is recognised with variograms. Figure 4.5 depicts the variograms for the five distinguished herbaceous cover types. Because the variograms approach their maximum value asymptotically, the exponential function (eq. 4.4) fits to the experimental data. The exponential curve is governed by two parameters C and r, often denoted sill and range respectively. In case the variogram is derived from cell values in a field, the sill is equal to the variance of these field values and is therefore a proper parameter for the magnitude of variation in the area of interest. The range is the distance within which grid cells are spatially independent (Jongman et al., 1987). The presence of the sill and a constant variance at lags greater than the range means that cells separated by distances greater than the range can be treated as being statistically independent. This implies that the sample spacing is too large to resolve any structure anymore.

Three grassland types show a relatively high sill. Two cover types have a low sill value resulting from a lack of area with high probability values as was observed from the distribution of pseudo-probability values (fig. 4.5). From the reduction of high pseudo-probability values in this distribution it became apparent that the variation in the test site has levelled. This change in the matrix causes a decrease of the sills of four cover types. Between1990 and 1995 the sills of these four grassland types are reduced between 44 percent for class hs2 and 11 percent for hs5. Only hs1 shows an increase of the variability with 37 percent. Note that in 1990 the sill of hs2 was nearly triple the sill of hs1 and that the sill of both cover types have become nearly equal in 1995.

The ecological scale within the matrix is reduced testifying the decrease in range of all grassland types. This reduction ranges between 48 percent for class hs3 to 1 percent for hs5. The variogram calculated over all cover types simultaneously (fig. 4.5LR) shows that the spatial dependency in the matrix has reduced from 14.0 to 10.1 meter, which is a reduction with 27 percent. The overall variogram shows a reduction of the variability within the matrix with 20 percent.

Semi-variograms are frequently applied to determine the spatial structure in remotely sensed images (Woodcock et al., 1988; Simmons et al., 1992). In these cases the variogram is calculated from digital numbers or reflectance values in a spectral band. This approach can be helpful to recognise different spatial structures within a single image. However, the method is not suited to quantify temporal changes, because seasonal and yearly changes in vegetation cover are likely to disturb the variogram. By calculating the variogram from the interpretation result this and other irrelevant variation in the image has been removed allowing the comparison of the variograms in time. Moreover the variogram is directly related to a specific ecological variable, e.g. vegetation cover type, providing the spatial structure of the phenomenon of interest. Variograms calculated from spectral data are indirectly related to ecological features and are therefore more complicated to interpret.

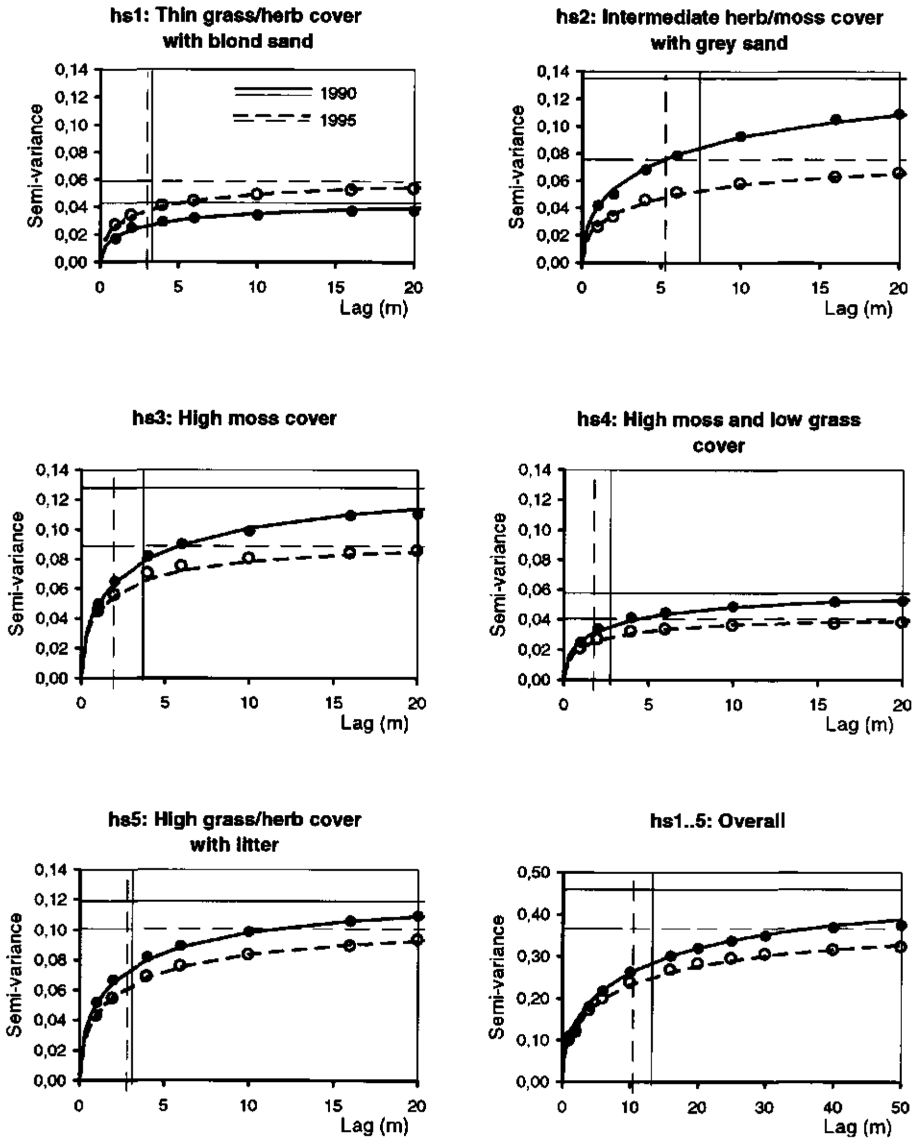


Figure 4.5 Variograms of the herbaceous cover types in the test site in 1990 and 1995 with sill and range indicated.

4.4 Conclusions

This chapter provided a selection of methods to quantify the spatial and temporal dynamics captured by the high resolution digital landscape model produced in chapter 3. The first analysis step of the utmost importance was the definition of an appropriate level of aggregation for the analysis of landscape dynamics. The construction of a specific landscape organisational level with its corresponding spatial objects needs to be motivated by ecological considerations under the constraint of minimising errors in the analysis results. These errors are caused by geometric and/or thematic inaccuracies present in any digital landscape model. The analysis of landscape dynamics should therefore not unthinkingly be performed on the level of aggregation provided by a measurement system. Amalgamation or non-nested aggregation is a robust and flexible operator to turn elementary objects provided by a measurement system to composite objects on a higher organisational landscape level.

The vegetation structural dynamics captured by the composite level of the digital landscape model is described in several ways. The methods were distinguished for discrete and continuous terrain features and aimed at disclosing the wealth of information captured by the landscape model. The level of detail in the landscape model allows a landscape manager to obtain detailed information that can not be obtained from current chloropleth maps. Important trends in aerial extent of classes and the turnover, as well as the spatial structure of the landscape, are more precisely quantified.

The methods presented in this chapter have a descriptive nature. It was not intended to explore the landscape model for the processes causing the landscape dynamics that have been observed. The progress in spatio-temporal landscape modelling has been slowed down by a lack op sufficiently detailed and reliable data. High resolution remote sensing images and dedicated image interpretation techniques can overcome this problem and allow for the generation of reliable spatio-temporal data models with sufficient detail. Operational monitoring systems can now provide the necessary data to boost explorative research by landscape ecologists and the development of spatial dynamic models on a longer term.

5. Mapping of fuzzy community types from environmental data

5.1 Introduction

This chapter deals with the mapping of the vegetation community types of the vegetation complex matrix. The notion of vegetation complexes was introduced in the previous chapter, where vegetation complexes were constructed from vegetation structural features obtained by the semi-automatic interpretation of digital CIR-orthophotos. The classification of structural aspects of natural vegetation in remote sensing images usually yields fairly accurate results (Belward et al., 1990; Foody, 1992), while the classification of vegetation composition, i.e. vegetation communities, is generally less accurate, even when high resolution imagery is used (Treitz et al., 1992). Attempts to improve the accuracy of mapping the vegetation communities can be categorised in two approaches.

Firstly, improvements can be achieved by increasing the explanatory power of the applied model. For example additionally to spectral data the process of image classification can be strengthened by the use of contextual information (Gurney and Townshend, 1983; Jeon and Landgrebe, 1992), environmental data (Satterwhite et al., 1984; Davis and Goetz, 1990) and/or knowledge (Plumb, 1993; Blonda et al., 1991; Mckeown et al., 1985).

A second approach to improve the accuracy of classifying vegetation communities is to alter the characteristics of these communities. This strategy aims at a better tuning of the community characteristics with the information content in an image. This can be achieved by stressing the abundant and relatively tall species during the construction of vegetation communities. While remotely sensed images contain mainly aggregated data of the vegetation canopy, rare and small species contribute less to the spectral data in an image. Consequently, vegetation communities can only match image data properly, if the discrimination of vegetation communities is primarily governed by abundant and relatively tall species, because these species primarily determine the spectral reflectance of the vegetation.

Emphasis on abundant species is one possibility to obtain better resemblance between vegetation communities and image characteristics. Secondly, more realistic vegetation communities are obtained by giving vegetation communities a more or less continuous character. Too often vegetation communities are defined as crisp clusters regardless of whether the vegetation exists as well defined mosaic or as a series of continua (Wood and Foody, 1989). Consequently, many classification errors can be attributed to artificial boundaries in the data where in reality gradients exist. Again it is asserted, that generally vegetation communities have more or less fuzzy characteristics. Therefore, crisp classification should be treated with some caution in patterns of natural landscapes (Roberts, 1987; 1989).

These introductory considerations are incorporated in the methods for the fuzzy classification and mapping of vegetation communities presented in the next section. After the presentation of the results the chapter will end with some conclusions.

5.2 Material and methods

The construction of a landscape model with five different composite object types was described in chapter 4, i.e. sandy-area, matrix, woodland, reed and water. Because sandy-area and water are considered to be bare and reed is occupied by a single vegetation community type, only the matrix and woodland accommodate several vegetation community types. It is presumed that the vegetation composition of the latter two object classes is significantly different and that vegetation communities occurring in the matrix and woodland are mutually exclusive. Consequently, two exclusive sets of community types are defined for the object classes woodland and matrix respectively. Note that the exclusivity of community types provides an ecological justification for the recognition of the two object classes, i.e. woodland and matrix. In this section, the mapping of the vegetation community types in the matrix is elaborated.

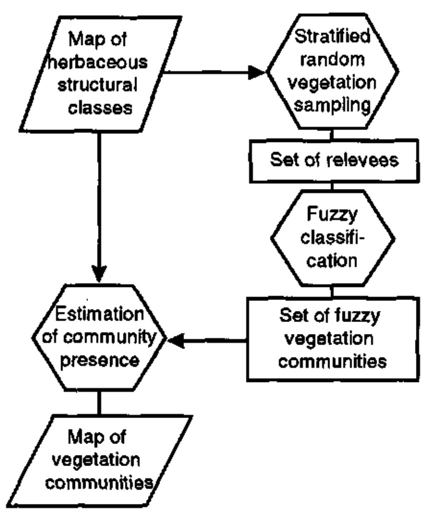


Figure 5.1 Procedure for the mapping of fuzzy vegetation communities.

Starting point for the mapping of vegetation community types is the landscape model or map with the composite objects in the test site (fig. 5.1). The production of the latter map was described in chapter 4. This map is used to perform a stratified random sampling of the vegetation composition in the matrix, where the strata are derived from differences in the internal vegetation structure of the matrix. The sampling of the vegetation composition yields a set of relevees. From this data set a set of fuzzy vegetation communities is constructed by means of fuzzy classification. Subsequently, the fuzzy vegetation communities and the map of the matrix objects is inputted to an estimation procedure for the mapping of vegetation communities. The latter modelling step results in a map of fuzzy vegetation communities. The major steps in the making of a map of vegetation communities can be summarised as follows:

- Stratified random sampling of the vegetation composition.
- Fuzzy classification of the herbaceous vegetation composition (sect. 5.2.1).
- Estimation of herbaceous community presence (sect. 5.2.2).
- Testing and sensitivity analysis (sect. 5.2.3).

Stratified random sampling of the vegetation composition

The spatial variability of the vegetation composition is not constant over the test site. Some herbaceous structural types are species rich while other types are constituted from a limited number of species. In order to minimise the sample size, i.e. the number of relevees, stratified random sampling is adopted, where structural characteristics of the herbaceous vegetation are used to stratify the area (Kenkel et al., 1989; Bunce et al., 1983).

Within a stratum the sample locations are randomly selected. The sample size for each stratum type depends on the variation in vegetation composition. The herbaceous structural classes showing much variation are sampled more intensively. Furthermore, the sample support is dependent on the stratum type. The square sample areas measure 4, 9 and 25m^2 for moss, herb/grass and scrub vegetation respectively (Den Held and Den Held, 1983; Curran and Williamson, 1986). The abundance of a species v_{sp} is scored in percentage cover.

When the set of relevees is used to estimate statistical parameters for the test site, the relevees need to be weighted in order to correct for the differences in sample density between the strata. The correction factor or weight ω_{hs} for a stratum type is calculated as:

$$\omega_{\mathbf{hs}} = p^A(\mathbf{hs})/p^R(\mathbf{hs}) \qquad 5.1$$

where $p^A(\mathbf{hs})$ and $p^R(\mathbf{hs})$ are the probability for herbaceous structural class **hs** in the test site A and in the set of relevees R and $\mathbf{hs} \in \{hs_1, hs_2, ...hs_5, \text{Buckthorn}, \text{Other\_shrubs}\}$

5.2.1 Fuzzy classification of herbaceous vegetation composition

Consider a conceptual vegetation space V constructed from the data in the set of relevees R. Let each species v_i in R define an axis of this space, with each axis scaled according to the measure of abundance. When R contains M species, $v = (v_1, v_2, ...v_m)$ represents a particular point in V, and $V = \{v : v=(v_1, v_2, ...v_m)\}$ represents the set of all possible points. Clustering techniques accomplish a partitioning of this space in a user defined number of clusters C by means of a membership function. Hence the relationship between a particular species composition v and a herbaceous community type **hc** $\in \{hc_1, hc_2, ...hc_c\}$ is made through the membership function M[**hc**,v]. If species composition v^j belongs to class **hc** this is represented by M[**hc**,v^j] = 1, and M[**hc**,v^j] = 0 if not. A two valued membership function brings on a crisp partitioning of V in non-overlapping subareas. Obviously, a crisp partitioning is only valid if no uncertainty is involved in this relationship.

Uncertainty in the relationship between species composition and community class is expressed by allowing the membership function to take any value $0 \leq$ M[**hc**,v^j] ≤ 1 enabling the quantification of partial membership. Partial membership results in overlapping or fuzzy clusters in V. The definition of fuzzy clusters usually provides a more realistic representation of real world vegetation patterns, because these patterns often bear a continuous character (Roberts, 1989).

The fuzzy clustering methods described in this section are compiled from the methods presented by Marsili-Libelli (1991) and Feoli and Zuccarello (1991). Fuzzy clustering techniques usually start from the notion of cluster centroids v^{hc} which are considered as prototypes of a cluster or class **hc**. A centroid provides the species composition that the typical constituent of that cluster should have. Between the cluster centroids gradients of membership occur. Hence the construction of class centroids is of primary concern.

In order to obtain cluster centroids the relevees R are grouped in C crisp classes **hc** $\in$ HC by two-way indicator species cluster analysis (TWINSPAN) (Hill, 1979; Jongman et al., 1987). The analysis is performed with more or less standard parameter setting and extra weight for abundant species (Treitz et al., 1992). Subsequently, the set of class centroids $\{v^{hc} \mid$ **hc** $= hc1, hc2, ...hcc\}$ is obtained by averaging the vegetation data of all relevees belonging to a specific class.

Now the resemblance of species composition v^j in relevee r_j with prototype v^{hc} is calculated as a function of the (dis)similarity between the two. A current dissimilarity measure is the Euclidean distance (Jongman et al., 1987):

$$D^2_{hc,j} = \sum_{i=1}^{m} [v^{hc}_i - v^j_i]^2 \qquad 5.2$$

where M is the number of species.

When the distances between v^j and all prototypes are calculated $\{D^2_{hc,j} \mid \mathbf{hc}=hc_1,hc_2,...hc_c\}$, the membership value for class **hc** is calculated as (Marsili-Libelli, 1991):

$$MV_{hc,j} = \frac{1}{\sum_{hc \in HC} [D_{hc,j}/D_{hc,j}]^{\alpha}} \qquad 5.3$$

where the exponent α determines the incidence of the membership function. When $\alpha \rightarrow \infty$ the classification becomes crisp. Smaller values of α result in smoother membership functions and thus in fuzzier membership values. For $\alpha=0$ the classification is maximally fuzzy and all membership values are equal. By applying eq. 5.3 to each prototype a vector of C membership values $(MV_{hc1}, MV_{hc2}, ...MV_{hcc})_j$ is obtained by which the fuzzy classification of relevee r_j is completed. The membership values in a single vector sum to unity.

5.2.2 Estimation of matrix community presence

In the previous section the presence of vegetation community types on a specific site was obtained by fuzzy classifying species abundance data to a vector of membership values. In case the species composition of a site is not described by a relevee, the presence of vegetation community types has to be estimated by means of an explanatory model. The latter model is based on the relationship between vegetation community types and their site characteristics described by environmental variables. These relationships are obtained from the generalisation of fuzzy vegetation community data and environmental data in the set of relevees R. The generalisation can be established within a probabilistic or possibilistic mathematical framework, where the strength of the relationship between certain site characteristics and a vegetation community type **hc** is expressed by a (pseudo-)probability p_{hc} or possibility p_{hc} value. In case of fuzzy vegetation mapping, the vegetation composition is quantified by a vector of C probability values $(p_{hc1}, p_{hc2}, ...p_{hcc})$ or possibility values $(\mathit{p}_{hc1}, \mathit{p}_{hc2}, ...\mathit{p}_{hcc})$. The choice for either of the two fuzzy measures determines the semantic interpretation of the membership values and the manner of calculating with membership values.

The estimation of vegetation communities is performed in three steps. Firstly, the presence of herbaceous community types is explained from the detailed fuzzy data on herbaceous structural features. The second step involves the estimation of the presence of vegetation communities by means of other environmental variables, like percentage shrub cover, depth of the water table, potential sunlight and organic matter content and acidity of the soil. The third and final step involves the combination of the estimations obtained in step 1 and 2 in an overall estimation of matrix community presence.

The estimation accuracy of vegetation communities is likely to improve when besides herbaceous structural information other environmental conditions are taken into account. For instance a single herbaceous vegetation structure present on different environmental conditions might accommodate different community types, e.g. a 'high grass/herb cover with litter' in a dune slack has another species composition than the same structural class on the north slope of a dune. Subsequently the three phases in the estimation of vegetation communities are elucidated.

Step 1: Estimation of vegetation community presence from herbaceous structural data

Consider the estimation of vegetation community presence from herbaceous structural data. Because the values of both the dependent and explanatory variable are nominal, the relationship between the vegetation community classes and the herbaceous structural classes can be quantified by a joint probability distribution. A joint probability p(**hc**,**hs**) quantifies the concurrence of vegetation community class **hc** $\in$ HC and herbaceous structural class **hs** $\in$ HS. The joint probability distribution is calculated from the membership values MV(**hc**) and probability values p(**hs**), which are available for each relevee. From the joint probability distribution conditional probabilities p(**hc**|**hs**) can be derived, providing the probability of a vegetation community **hc** given a herbaceous structural class **hs**.

The overall probability of vegetation community **hc** on a location xy is calculated from the conditional probabilities (p(**hc**|**hs**)|**hs** $\in$ HS) and the presence of the herbaceous structural classes p(**hs**)$_{xy}$:

$$p^s(\mathbf{hc})_{xy} = \sum_{hs \in HS} p(hs)_{xy} \,.\, p(\mathbf{hc}|hs) \,.\, C \qquad 5.4$$

where C is a normalisation factor making the probabilities of all vegetation community types on a single site sum to unity. Appendix II elucidates the calculation of the conditional probabilities p(**hc**|**hs**) from fuzzy vegetation data.

Alternatively, the relationship between vegetation community types and herbaceous structural types is established by a joint possibility distribution. The joint possibility distribution is also calculated from the membership values MV(**hc**) and possibilities p(**hs**), which are available for each relevee. From this distribution conditional possibilities p(**hc**|**hs**) can be derived (appendix II), providing the possibility of a vegetation community **hc** given a herbaceous structural class **hs**. The possibilistic counterpart for estimating the presence of a herbaceous community type on location xy is:

$$p^s(\mathbf{hc})_{xy} = \mathrm{MAX}_{hs \in HS} \,[\mathrm{MIN}(p(hs)_{xy}, p(\mathbf{hc}|hs)] \,.\, C \qquad 5.5$$

where the MAX and MIN functions are the standard combinational OR and AND operators in possibility theory (Klir and Folger, 1988) and C is a normalisation factor. Through normalisation the maximum possibility for one of the vegetation communities becomes one.

Step 2: Estimation of vegetation community presence from environmental data

Secondly, the presence of vegetation community types is estimated from their correlation with other environmental variables of which a spatial data set is available. The following variables were available from the test site: buckthorn shrub cover, cover by other shrubs, depth of the water table, potential sunlight. Note that shrub cover is regarded as an environmental variable, because scrub affects the micro climate of the herbaceous vegetation. The general relationship between these continuous variables and a vegetation community type is established by an environmental amplitude.

Consider an environmental space E, where each environmental attribute (e_i) in the data set defines an axis in this space. Each axis is scaled according to the measure for that environmental attribute. Each site occupies a particular point in this space determined by its environmental characteristics. When the data set contains m environmental variables, the vector $e = (e_1, e_2, ...e_m)$ represents a particular point in E and $E = \{e: e=(e_1, e_2, ...e_m)\}$ represents the set of all possible points.

Each community type occupies a subset of the environmental space, known as its environmental amplitude (a_{hc}), where the environmental characteristics are suitable for its appearance. For a given community type the amplitude is given by all points having a probability or possibility greater than 0:

$$a^{p}_{hc} = \{e: p > 0\} \text{ or } a^{p}_{hc} = \{e: p > 0\} \qquad 5.6$$

The environmental amplitudes of vegetation community classes have to be established from observations by regression analysis (Jongman et al., 1987) or interpolation techniques like kriging and trend surfaces. Here the method of weighted averaging is adopted because of its simplicity. The probability of a community class **hc** on a specific location in the environmental space is calculated as a weighted mean from all observations within a distance R:

$$p^{e}(\mathbf{hc}) = \sum_{r \in R} \omega_r . \omega_s . p(\mathbf{hc})_r . C \qquad 5.7$$

where ω_s is a weight for the stratum and the weight ω_r relates to the distance between the observation $p(\mathbf{hc})_r$ $r \in R$ and interpolation point e and C is a normalisation factor. In a sensitivity analysis the optimum value of R is determined. After the calculation of the environmental amplitude a^{p}_{hc}, the probability $p^{e}(\mathbf{hc})_{xy}$ of a vegetation community type **hc** for a site xy is easily looked up.

Alternatively, the possibility value is calculated as a weighted generalised means (Klir and Folger, 1988):

$$p^e(\mathbf{hc}) = \Big(\sum_{r \in R} \omega_r.\omega_s.p(\mathbf{hc})_r^{\beta} \Big)^{1/\beta} . C \qquad 5.8$$

where β=1 implies the calculation of the weighted mean, i.e. eq. 5.8 equals eq. 5.7 and $\beta \rightarrow \infty$ implies the application of the MAX-operator, which is the standard possibilistic OR operator. Through normalisation the maximum possibility value for one of the vegetation communities on a location in the environmental space becomes one. The possibility $p^e(\mathbf{hc})_{xy}$ for a specific grid cell xy is obtained by looking up the possibility in the environmental amplitude $a^p_{\mathbf{hc}}$.

Step 3: Overall estimation

The separately derived probabilities for a specific vegetation community type obtained from herbaceous structural data $p^s(hc)_{xy}$ and other environmental data $p^e(hc)_{xy}$, are combined to yield an overall probability:

$$p(\mathbf{hc})_{xy} = p^s(\mathbf{hc})_{xy} . p^e(\mathbf{hc})_{xy} . C \qquad 5.9$$

where C is a normalisation factor making the probabilities of all vegetation communities on a single site sum to unity. By applying these calculations to each grid cell in the matrix the probability fields $(p_{\mathbf{hc}}(x,y) \mid \mathbf{hc} \in HC)$ are obtained providing a probability map of vegetation communities in the matrix. Alternatively, the combined possibility for **hc** is obtained as:

$$p(\mathbf{hc})_{xy} = \mathrm{MAX}\,[p^s(\mathbf{hc})_{xy}, p^e(\mathbf{hc})_{xy}] . C \qquad 5.10$$

where C is a normalisation factor setting the maximum possibility value for one of the vegetation communities to one. By applying these calculations to each grid cell the possibility fields $(p_{\mathbf{hc}}(x,y) \mid \mathbf{hc} \in HC)$ are obtained providing a possibility map of vegetation communities.

5.2.3 Testing and sensitivity analysis

A set of 263 relevees was gathered in the summer of 1990. The position of each relevee was marked on a photograph enabling an accurate determination of its position on the digital orthophoto. The 100 most common species in the set of relevees were selected for further analysis.

First step in the mapping process is the selection of an optimal degree of fuzziness for the vegetation types. The degree of fuzziness of the classification can be adapted by changing parameter α in eq. 5.3. Appendix III describes a Monte Carlo analysis enabling the determination of an optimal degree of fuzziness. After the calibration of the estimation procedure with the optimal degree of fuzziness, the estimated presence of matrix communities is validated with the 'leaf-one-out'-method. The explanatory quality of the models is expressed by the coefficient of determination (Jongman et al., 1987),

$$R^2 = 1 - (\text{residual sum of squares} / \text{total sum of squares}) \qquad 5.11$$

This statistic quantifies the fraction of variance accounted for by the model.

5.3 Results and discussion

Fuzzy vegetation communities

The first step in the fuzzy classification of relevees is the construction of vegetation community prototypes. In a standard clustering procedure the maximum number of prototypes or vegetation communities was set to 17. These 17 community types provide a proper categorisation of the variety in vegetation composition throughout the test site. A short description of the vegetation types is presented in table 5.1. The types range from pioneer and moss vegetation to grassland and scrub. Most vegetation types indicate specific abiotic site conditions, like moisture content and acidity (Schaminee et al, 1996).

The second step in the fuzzy classification procedure involves the optimisation of the degree of vagueness for the fuzzy vegetation communities. Figure 5.2 shows the explanatory power of the fuzzy classification as a function of vagueness. In case of maximum fuzziness, i.e. $\alpha = 0$, the membership values for all vegetation communities are equal, i.e. MV_{hc} = 1/Ncommunities. In this case the explanatory power of the fuzzy classification is minimal. An increase of explanatory power is achieved by decreasing the degree of fuzziness. A maximum coefficient of determination ($R^2 = 0.73$) is reached at α=8. After this point a reduction in fuzziness results in a decrease of the coefficient of determination. When $\alpha \rightarrow \infty$ the classification becomes crisp, which results in a vector of membership values with a single one and zero for all other community types. For the subsequent analysis α was set to 8.

Table IV.1 shows the calculated vectors of membership values for the relevees. The maximum value in a vector of membership values provides a good indication for the vagueness of the classification of a relevee. Relevees with a high membership value, i.e. > 0.75, are primarily assigned to a single class. The higher the maximum membership value the crisper a relevee is assigned to this class, indicating that the relevee resembles primarily one vegetation community. A low maximum membership value, i.e. < 0.25, indicates a vague classification, because the relevee shows

Table 5.1 Description of the vegetation community types (hc) and herbaceous structural classes (hs). Between brackets the vegetation community according to Westhoff and Den Held (1969) and Schaminee et al. (1996) is indicated.

Vegetation community types

hc1	Dense scrub of *Ligustrum vulgare* (Hippophao-Ligustretum)
hc2	Open scrub of *Salix repens* and *Ligustrum vulgare*, mainly on slopes with a northern exposition (Taraxaco-Galietum fragarietosum)
hc3	Open scrub of *Ligustrum vulgare* (Taraxaco-Galietum cladonietosum)
hc4	Dense scrub of *Ligustrum vulgare* and *Hippophae rhamnoides* (Hippophao-Ligustretum)
hc5	Dense scrub of *Hippophae rhamnoides* (Hippophao-Sambucetum)
hc6	*Hippophae rhamnoides* and *Festuca rubra* covered with fresh sand
hc7	*Ammophila arenaria* covered with fresh sand (Elymo-Ammophiletum arenariae)
hc8	Very open moss vegetation with *Tortula ruralis var. ruraliformis* on calcareous soil (Phleo-Tortuletum typicum)
hc9	Open moss vegetation with *Tortula ruralis var. ruraliformis* on calcareous soil (Phleo-Tortuletum typicum)
hc10	Dense moss vegetation with *Tortula ruralis var. ruraliformis* on calcareous soil (Phleo-Tortuletum cladonietosum)
hc11	Dense moss vegetation dominated by *Dicranum scoparium* or *Campylopus intro-flexus* on decalcified soil (frame community Dicranum scoparium - [Koelerio - Corynephoretea] or derivate community Campylopus introflexus - [Koelerio - Corynephoretea])
hc12	Dense moss vegetation with *Hypnum cupressiforme* and *Cladonia spp.* on slightly decalcified soil (Phleo-Tortuletum cladonietosum and Taraxaco-Galietum cladonietosum)
hc13	Dune meadow with *Agrostis spp.* and *Galium verum* on decalcified soil (Festuco-Galietum cladonietosum)
hc14	Dune meadow with *Rubus ceasius* and *Dicranum scoparium* on slightly decalcified soil (Taraxaco-Galietum veri)
hc15	Dune meadow with *Cladonia spp* and *Calamagrostis epigejos* on calcareous soil (Taraxaco-Galietum veri)
hc16	High grass vegetation with *Holcus lanatus* and phreatophytes (frame community Holcus lanatus - [Molinio - Arrhenatheretea])
hc17	High grass vegetation dominated by *Calamagrostis epigejos* and *Carex arenaria* (frame community Calamagrostis epigejos - [Koelerio - Corynephoretea])

Herbaceous structural classes (see table 3.1)

hs1	Thin grass/herb cover with blond sand
hs2	Intermediate herb/moss cover with grey sand
hs3	High moss cover
hs4	High moss and low grass cover
hs5	High grass/herb cover with litter

resemblance with several vegetation communities. The distribution of the maximum membership values is presented in figure 5.3. Forty percent of the relevees has a maximum value higher than 0.75 in the vector of membership values. Hence all these relevees show a strong resemblance with only one community type. Relevees with a lower maximum membership value effectively represent gradient situations between one or more vegetation community.

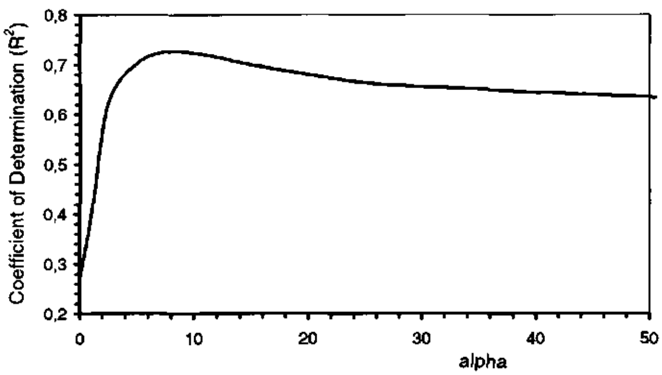


Figure 5.2 The explanatory power of fuzzy classification of vegetation communities in function of the degree of vagueness quantified by α in eq. 5.3.

The introduction of vagueness in the classification of vegetation communities enables the quantification of continuous turnover between communities, which results in a better correlation between the vector of membership values and the species composition compared to crisp classification. Although classification involves the reduction of the dimensionality of the feature space from the number of species to the number of classes, the loss of information is minimised by introducing a certain degree of vagueness (Roberts, 1989).

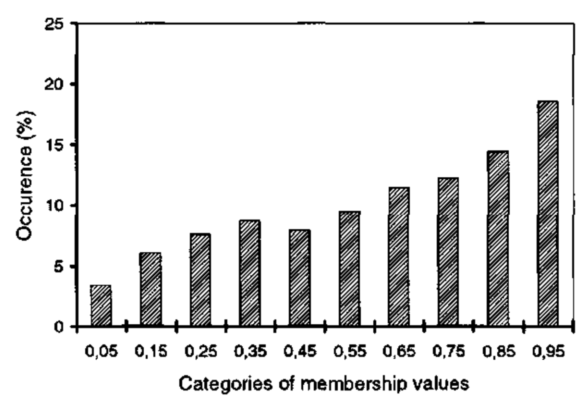


Figure 5.3 The degree of vagueness of fuzzy vegetation classification indicated by the distribution of the maximum values of 180 membership vectors (α = 8).

Relationship between fuzzy vegetation communities and herbaceous structural classes
Conditional probabilities provide the relationship between vegetation communities and herbaceous structural types (table 5.2a). Some of the vegetation communities show a preference for a single herbaceous structural type. For instance *high grass vegetation dominated by Calamagrostis epigejos* hc_{17}, only occurs when the herbaceous structure consists of *high grass/herb with litter* hs_5. Community type, *Ammophila arenaria covered with fresh sand* hc_7, is primarily related to *thin grass/herb cover with blond sand* hs_1. Other community types show preference for two herbaceous structural types, like hc_8 and hc_9. Although, the conditional probabilities properly describe the general relationships between 17 vegetation communities and 5 herbaceous structural types, the supernumeracy of the vegetation communities and the fact that many of the community types relate to 2 or more structural types, cause overall low probability values. Obviously, this will hamper the suitability of this statistic for the mapping of vegetation communities from vegetation structural data.

The conditional possibilities do not show the clear trends in the relationship between communities and structural types as could be detected in the probabilistic framework (table 5.2b). This effect can be attributed to the fact that the possibilistic generalisation operators, i.e. MIN and MAX, are rather sensitive to outliers in a data set (De Gruyter and McBratney, 1990). Vegetation data typically show much variation. When aiming at the detection of general relationships in vegetation data the applied generalisation method needs to be rather insensitive to outliers. Obviously, in such cases a probability measure is preferred over a possibility measure.

Environmental amplitudes
Out of the four spatial variables that were available of the test site only the buckthorn shrub cover and the coverage of other shurbs, primarily privet and willow, correlated well with the community types. The spatial variables depth of water table and potential sunlight did not produce proper amplitudes for any community type.

In particular the community types with more than 10 percent shrub cover show a clear amplitude in the two dimensional environmental space measure by the percentage cover of buckthorn and privet/willow (fig. 5.4). The amplitudes of community types hc_1 through hc_6 reflect the abundance of the two shrub types. The amplitudes of dense shrub of *Ligustrum vulgare* hc_1 and *Hippophae rhamnoides* hc_5 are located at high values of the corresponding environmental variables. Between these extreme clusters the community types with less dense shrub cover and scrub densely populated by both shrub species hc_4 are positioned in the environmental space. The environmental amplitudes expressed by probability values provide more specific information compared to the amplitudes quantified by possibility values. Again this is caused by the sensitivity of possibilistic generalisation operators to outliers in a data set.

Table 5.2 The relationship between herbaceous structural classes hs and herbaceous community classes hc (263 relevees).

A. Conditional probabilities

hc	p(hc|hs)					p(hc)
	hs1	hs2	hs3	hs4	hs5	
hc1	0.01	0.07	0.06	0.07	0.09	0.06
hc2	0.01	0.02	0.06	0.08	0.07	0.06
hc3	0.03	0.07	0.13	0.14	0.17	0.12
hc4	0.01	0.01	0.06	0.06	0.07	0.05
hc5	0.01	0.03	0.12	0.12	0.11	0.09
hc6	0.09	0.02	0.00	0.00	0.01	0.02
hc7	0.22	0.03	0.00	0.01	0.03	0.04
hc8	0.29	0.20	0.05	0.03	0.02	0.09
hc9	0.25	0.20	0.04	0.04	0.03	0.09
hc10	0.03	0.18	0.03	0.01	0.01	0.05
hc11	0.00	0.03	0.10	0.03	0.01	0.04
hc12	0.04	0.10	0.21	0.12	0.05	0.12
hc13	0.00	0.01	0.06	0.07	0.03	0.04
hc14	0.01	0.02	0.03	0.10	0.04	0.04
hc15	0.01	0.01	0.04	0.06	0.02	0.03
hc16	0.00	0.01	0.01	0.02	0.08	0.03
hc17	0.00	0.01	0.00	0.03	0.15	0.04

B. Conditional possibilities

hc	*p*(hc|hs)					*p*(hc)
	hs1	hs2	hs3	hs4	hs5	
hc1	0.07	0.31	0.36	0.38	0.40	0.40
hc2	0.04	0.16	0.38	0.42	0.36	0.42
hc3	0.13	0.38	0.78	0.73	0.80	0.80
hc4	0.04	0.09	0.33	0.31	0.33	0.33
hc5	0.04	0.20	0.60	0.58	0.56	0.60
hc6	0.22	0.13	0.04	0.02	0.07	0.22
hc7	0.31	0.20	0.04	0.07	0.18	0.31
hc8	0.71	0.73	0.40	0.24	0.18	0.73
hc9	0.62	0.69	0.36	0.29	0.20	0.69
hc10	0.16	0.56	0.16	0.07	0.04	0.56
hc11	0.00	0.22	0.40	0.24	0.11	0.40
hc12	0.20	0.58	1.00	0.69	0.49	1.00
hc13	0.02	0.09	0.36	0.38	0.20	0.38
hc14	0.02	0.07	0.16	0.36	0.29	0.36
hc15	0.02	0.11	0.24	0.29	0.20	0.29
hc16	0.01	0.02	0.13	0.20	0.38	0.38
hc17	0.01	0.02	0.09	0.29	0.49	0.49

Mapping of fuzzy vegetation communities

The calculated conditional probabilities are used to estimate the presence of vegetation communities throughout the test site, i.e. the mapping of vegetation communities. As expected, only the vegetation community types having a strong correlation with a specific explanatory variable are mapped with a satisfying accuracy (table 5.3). This is particularly the case for dense scrub of *Ligustrum vulgare* hc1 and dense scrub of *Hippophae* *rhamnoides* hc5. The probability fields of these two community types are presented in figure 5.5. None of the herbaceous community types are mapped with an adequate accuracy, which is not surprising because a single herbaceous structural type accommodates generally 2 or 3 vegetation community types. Although the introduced mapping procedure does not yield an accurate estimation of the presence of a vegetation community on a specific location, the method is unbiased and therefore yields more accurate aerial estimates of vegetation communities in a test site given a point data set and a spatial model of the herbaceous structure of the vegetation.

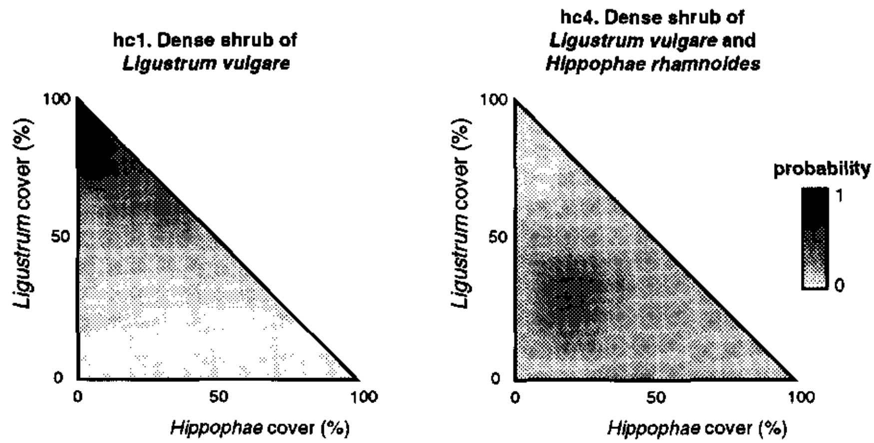


Figure 5.4 Examples of two dimensional environmental amplitudes of vegetation communities hc dominated by shrubs.

Table 5.3 Validation of the estimated presence of vegetation communities hc, where R^2 is the coefficient of determination and E^m is the average estimation error (N = 263 relevees).

Hc	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	all
R^2	0.63	0.31	0.35	0.34	0.57	0.36	0.26	0.21	0.23	0.18	0.24	0.22	0.18	0.21	0.19	0.16	0.28	0.27
E^m	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.02	0.00	0.00

Clearly the presence of vegetation communities can not be explained accurately from vegetation structural data only. Although several vegetation communities occur in single herbaceous structural types, they usually exist under different abiotic site conditions. The mapping of vegetation communities is likely to improve when besides biotic site characteristics also abiotic site conditions are incorporated in the model. The description of the vegetation communities (table 5.1) shows that for instance the acidity of the soil is a discriminating variable. However, soil characteristics like acidity have to be mapped in the field. Consequently, the construction of a detailed spatial data model of soil characteristics is a laborious and expensive task and it seems more efficient and practical to employ any available survey capacity in aid of vegetation mapping by means of manual photo-interpretation.

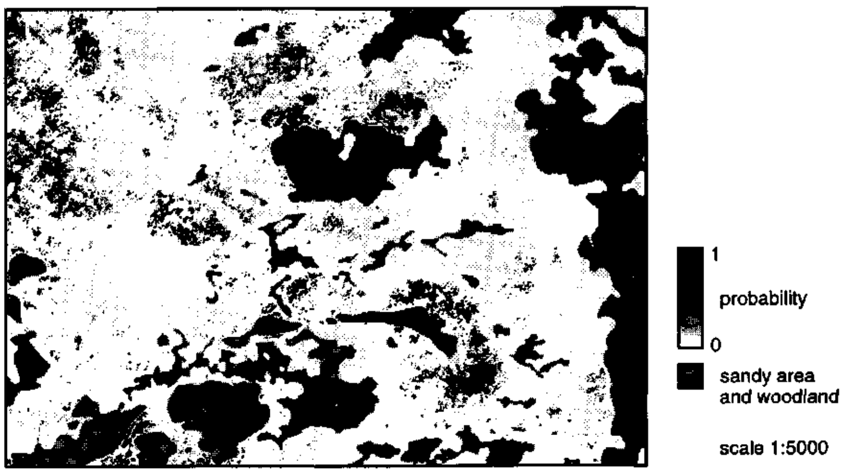


Figure 5.5 **Estimated presence of two herbaceous community types expressed by probability.**

5.4 Conclusions

Many landscape ecological processes can be monitored with a multi-temporal map of the vegetation structure. Also for the planning of many management measures a detailed map of the vegetation structure, conveniently obtained by the semi-automatic interpretation of high resolution imagery, is sufficient. However, the monitoring of developments in vegetation composition can not be performed with these maps. For this purpose a nature manager generally applies a temporal set of relevees obtained from permanent plots (Austin, 1981). Although the latter data set is suitable to analyse point processes, the nature of the data is not appropriate for the spatial analysis of vegetation dynamics. The objective of this chapter was to provide and test methods to link up spatial data on vegetation structure with a set of point data on vegetation composition, in order to obtain a digital spatial data model of the vegetation composition expressed by vegetation communities.

As was stated in the introductory section of this chapter an accurate procedure for the automatic mapping of vegetation communities from environmental variables requires a fine-tuned definition of the vegetation communities and a powerful explanatory model. The first condition was met by applying the concept of fuzzy vegetation communities. The vegetation community types were fine-tuned by assigning abundant species extra weight in the construction of the fuzzy community types and by optimising the degree of fuzziness. Fuzzy classification of the vegetation allows for the quantification of continuous turnover between community types. After the optimisation of the degree of vagueness the fuzzy community types show a closer resemblance with the vegetation abundance data in the relevees compared to the classical crisp classes. Therefore it can be concluded that vegetation communities in the dunes have a fuzzy nature.

The second objective, i.e. the construction of the explanatory model, was not successfully met. The generalised relationship between vegetation community types and herbaceous structural data was quantified by conditional probabilities and environmental amplitudes. Although these statistics provide a proper insight in the many to many relationship between the two data sets, an accurate map of the vegetation communities could not be produced. Clearly, vegetation structural data are not sufficient to map the vegetation composition in the dunes. Additional information regarding the abiotic site characteristics seem indispensible to improve the explanatory power of the model. However, maps with soils characteristics can only be obtained by a field survey and when doing fieldwork the direct mapping of vegetation communities is obviously more practical. Fieldwork seems indispensible for the accurate mapping of vegetation communities in the dunes, unless community types can be mapped with hyperspectral images. It is recommended to test the applicability of these images for the mapping of vegetation types in the dunes.

6. Fuzzy ecohydrological modelling of dune slacks

6.1 Introduction

Drinking-water production and nature conservation are the main functions of the Amsterdam Waterworks Dunes (sect. 1.5). Traditionally water production is the most important of the two. This often resulted in hydrological management operations which conflicted with nature's interest, especially in dune slacks. Since the start of the water production in 1850 many of the dune slacks are desiccated and lost their specific ecological values. Nowadays less than one percent of the area is moist were it used to be approximately 30 percent.

However, for some time now, the ecological functions have been revalued and have become more equivalent to the function of drinking-water production necessitating a redistribution of the resources in the area. In order to support deliberate decision making in hydrological and ecological management, the Amsterdam Water Supply conducted an ecohydrological study in the area. Central to this study was the construction of an ecohydrological model, by which the impact of the hydrological management on ecological values was studied. In scenario studies the possibilities to regenerate former dune slacks by reduction or reallocation of groundwater catchment should be tested, if necessary supported by nature management.

Existing ecohydrological models can be categorised in deterministic (Gremmen et al., 1990; Witte, 1998), statistical (Barendregt and Wassen, 1989), mathematical and expert models (Guerrin, 1991) quantifying species or ecotope behaviour on a local or regional scale. A review of ecohydrological models available in the Netherlands is given by Van der Veen (1994). At the start of the project, no ecohydrological model was calibrated for both young and old dune slacks, while data to do so were lacking. Despite a lack of data, experts gained some adequate knowledge about the ecohydrological system and it was decided to formalise this knowledge in a logical expert model.

This chapter describes a fuzzy ecohydrological expert model ECOMOD. The model estimates the major ecotope parameters, i.e. vegetation structure, moisture content, nutrient availability and acidity of the soil, from some easy to measure biotic and abiotic input variables. Although ECOMOD is an explanatory model, it can be used to predict future ecotopes by inputting predicted input variables.

ECOMOD is build with concepts from fuzzy mathematics. Fuzzy mathematics provides a mathematical framework which is more closely related to human reasoning compared to the classical Boolean set theory (Klir and Folger, 1988; Zimmermann, 1985). The application of fuzzy classification and fuzzy reasoning in ecology enables the modelling of ecological gradients in terms of continuously varying class combinations (sect. 2.2.3.) (e.g. Burrough, 1989; Bosserman and Ragade, 1982; Kollias and Voliotis, 1991; Salski, 1992). Wang et al. (1990) showed that fuzzy inference models can be easily implemented with standard functionality of GI systems.

The next section describes the construction of ECOMOD. ECOMOD is implemented with ARC/GRID and ARC Macro Language. By sensitivity analysis the significance of the model for ecohydrological scenario studies is tested.

6.2 Material and methods

After the goal definition, the creation of a fuzzy knowledge-based model generally involves the following development stages (after Salski, 1992):

- determination of the model structure (sect. 6.2.1)
- formulation of knowledge representation (sect. 6.2.2)
- definition of inference rules (sect. 6.2.3)
- defuzzification (sect. 6.2.4)
- calibration and sensitivity analysis (sect 6.2.5)

6.2.1 General model structure

The structure of ECOMOD is taken from Koerselman et al. (1992) and depicted in figure 6.1, showing the model in- and output as well as its submodels. The model input consists of some relatively easy to measure and/or to estimate variables (table 6.1) (Stevers et al., 1987). The water table is predicted by a quantitative hydrological model steered by a hydrological management scenario (Olsthoorn, 1998). The other input variables are prepared from elevation, soil and vegetation structural data and the nature management measures as specified by a management scenario. The implemented management measures are 'no action' (which is the default), mowing, sod cutting and topsoil removal. The effect of the latter three measures is quantified by a change in site conditions. For instance mowing causes the vegetation structure to be 'mowed herbaceous', while sod cutting and topsoil removal have effect on the organic matter content and acidity of the soil, the relief and vegetation structure. Neither the specification of the hydrological and management scenario, nor the preparation of the input variables is a part of the functionality of ECOMOD.

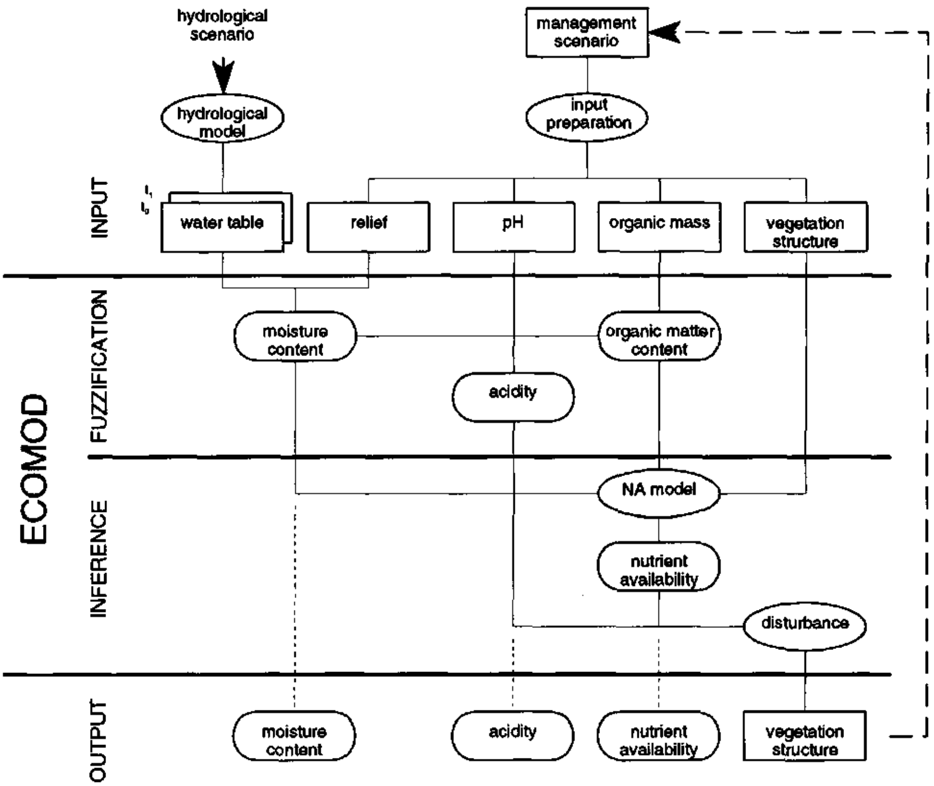


Figure 6.1 Diagram of ECOMOD.

The model output consists of four variables; vegetation structure VS, moisture content MC, nutrient availability NA and acidity AC (table 6.1). These four variables are chosen to enable a rough discrimination between different ecotope types. Moisture content and nutrient availability are highly discriminating attributes because together with light they form the primary production factors for vegetation. The irradiance is not used as a variable for it is on average spatially constant in more or less flat landscapes. The acidity is added to the feature space for it affects the species composition, as does the vegetation structure.

The variable 'vegetation structure' takes nominal values. The abiotic output variables take ordered values. For instance the variable moisture content takes the values dry, moist, wet and open water. For a specific site ECOMOD quantifies the strength of the relationship of the site characteristics with each class by a membership value. Because four ordinal moisture content classes are distinguished, the moisture content of a specific terrain element (i,j) is represented by a vector of four membership values

Table 6.1 The input and output of ECOMOD. The quantitative variables are specified by dimension. For a fuzzy variable a vector of membership values MV with class label is given.

variable	dimension or membership vector
INPUT	
springtime water table	m
terrain height	m
acidity	pH
organic mass	kg/m^2
vegetation structure	$(MV^{herbaceous}, MV^{rough}, MV^{mowed}, MV^{shrub})$
OUTPUT	
vegetation structure	$(MV^{herbaceous}, MV^{rough}, MV^{mowed}, MV^{shrub})$
moisture content	$(MV^{dry}, MV^{moist}, MV^{wet}, MV^{open\ water})$
nutrient availability	$(MV^{very\ oligotrophic}, MV^{oligotrophic}, MV^{mesotrophic}, MV^{eutrophic}, MV^{hypertrophic})$
acidity	$(MV^{acid}, MV^{neutral}, MV^{alkaline})$

$MC_{(i,j)} = (MV^{dry}, MV^{moist}, MV^{wet}, MV^{open\ water})^{MC}{}_{(i,j)}$. For instance, the vector $(0.0,0.4,0.6,0.0)^{MC}{}_{(i,j)}$ means that the site has nearly equal resemblance with the classes 'moist' and 'wet' and no resemblance with the classes 'dry' and 'open water'. For each output variable a vector of membership values is produced. Hence, ECOMOD expresses the ecohydrological conditions of a site in four vectors of membership values, i.e.

$$
\begin{aligned}
VS_{(i,j)} &= (MV^{herbaceous}, MV^{rough}, MV^{mowed}, MV^{shrub})^{VS}{}_{(i,j)} \\
MC_{(i,j)} &= (MV^{dry}, MV^{moist}, MV^{wet}, MV^{open\ water})^{MC}{}_{(i,j)} \\
NA_{(i,j)} &= (MV^{very\ oligotrophic}, MV^{oligotrophic}, MV^{mesotrophic}, MV^{eutrophic}, MV^{hypertrophic})^{NA}{}_{(i,j)} \\
AC_{(i,j)} &= (MV^{acid}, MV^{neutral}, MV^{alkaline})^{AC}{}_{(i,j)}
\end{aligned}
\qquad 6.1
$$

Note that the vegetation structure type 'mowed' is distinguished from the general type 'herbaceous'. This enables ECOMOD to infer a specific nutrient availability for this cover type.

The four output vectors of ECOMOD can be used to construct ecotope types, where an ecotope type is characterised by a unique combination of four classes, one from each output variable. For example an ecotope is characterised as 'herbaceous, moist, mesotrophic and alkaline'.

Two major submodels of ECOMOD process the input data to four output vectors of membership values (fig. 6.1):

- fuzzification of quantitative variables to the fuzzy variables moisture content MC, acidity AC and organic matter content OM
- inference of the nutrient availability NA and the vegetation structure VS

The first submodel transforms quantitative input variables to fuzzy data. This transformation is called fuzzification and yields a vector of membership values. The moisture content MC is calculated as a function of the depth of the water table and the organic matter content of the soil,

$$MC = f(\text{relief - water table, organic mass}) \tag{6.2}$$

The acidity AC is modelled as a function of the soil pH and the moisture content,

$$AC = f(pH, MC) \tag{6.3}$$

where the groundwater in the study area is presumed to be alkaline. The final fuzzification step is the calculation of the organic matter content OM as a function of organic mass in the topsoil,

$$OM = f(\text{organic mass}) \tag{6.4}$$

Subsequently, the three fuzzy variables together with the vegetation structure are fed in to a second submodel to infer the nutrient availability of the soil and the disturbance of the vegetation. The nutrient availability NA is derived as,

$$NA = f(VS, MC, AC, OM) \tag{6.5}$$

Sudden changes in the hydrological management might have an effect on the moisture content and acidity of the soil. In turn these changes in soil conditions disturb the vegetation. For instance a herbaceous vegetation might be covered with a growth of tangled species. The vegetation structure VS on time t_1, i.e. t_0 + 5-10 years, is inferred from the vegetation structure and organic matter content on t_0 as well as the change in moisture content and acidity of the soil between dates t_0 and t_1

$$VS_{t1} = f(VS_{t0}, MC_{t0}, MC_{t1}\ AC_{t0}, OM_{t0}) \tag{6.6}$$

The general structure of ECOMOD is captured by the equations in this section. In the next sections these functions are specified. The specification process falls apart in the formulation of expert knowledge (sect. 6.2.2) and the processing of this knowledge through the definition of inference rules (sect. 6.2.3).

6.2.2 Fuzzy knowledge representation

The input of expert knowledge concerns (1) the specification of the fuzzy variables, moisture content, acidity and organic matter content, enabling the fuzzification of quantitative variables and (2) the specification of decision rules enabling the inference of nutrient availability and vegetation disturbance. The set of decision rules is conveniently ordered in a fuzzy relation. Subsequently, the concepts of fuzzy variables and fuzzy relations are elucidated.

Definition of fuzzy variables

As explained in the previous section, the variables moisture content, acidity and organic matter content consist of some ordered classes. By defining a membership function for each class a variable is specified. For instance the variable organic matter content OM is represented by three ordinal classes, sandy, moderate humus, humus, defined along the quantitative variable 'organic matter' (fig. 6.2). The membership function of the class sandy is denoted as $MF^{sandy}(a)$. The variable OM is thus defined by three membership functions, one for each class:

$$OM = \{MF^{sandy}(a), MF^{moderate\ humus}(a), MF^{humus}(a)\} \quad 6.7$$

Because a membership function is allowed to take any value $0 \leq MF(a) \leq 1$, these membership functions specify fuzzy classes or fuzzy sets. Variables defined by several ordinal fuzzy sets are called fuzzy variables (Klir and Folger, 1988).

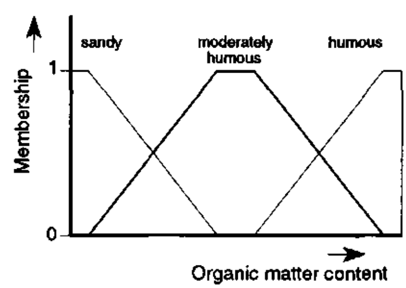


Figure 6.2 Fuzzy variable representing organic matter content.

The fuzzy sets of the fuzzy variables organic matter content and acidity are defined along a single variable. The fuzzy variable moisture content, however, is defined along two variables, i.e. depth of the water table A and the organic mass in the soil B. Consequently, the fuzzy sets of the fuzzy variable moisture content become two dimensional,

$$MC = \{MF^{dry}(a,b), MF^{moist}(a,b), MF^{wet}(a,b), MF^{open\ water}(a,b)\} \quad 6.8$$

In ECOMOD piece wise linear membership functions (eq. 2.3) are implemented. The parameters of a membership function are estimated by six experts independently under the condition that overlapping membership functions sum to one. A mean and standard deviation is calculated for each parameter. These statistics quantify the uncertainty in the fuzzy class definitions.

Definition of fuzzy relations (sets of decision rules)

The nutrient availability in sandy dunes is largely governed by processes depending on the following four variables: vegetation structure, moisture content, acidity and nutrient supply captured by the organic matter (Koerselman et al., 1992; Beckhoven, 1995). ECOMOD applies decision rules to infer the nutrient availability. Consider the following decision rule:

$$\text{IF } MV^{herbaceous}=1 \text{ and } MV^{dry}=1 \text{ and } MV^{acid}=1 \text{ and } MV^{humous}=1 \text{ THEN } MV^{very\ oligotrophic}=0.58 \text{ and } MV^{oligotrophic}=0.17 \text{ and } MV^{mesotrophic}=0.23 \text{ and } MV^{eutrophic}=0.02 \text{ and } MV^{hypertrophic}=0 \qquad 6.9$$

A combination of four classes, i.e. one from each fuzzy variable, provides the condition for which the conclusion holds. The conclusion consists of a vector of 5 membership values, where the membership grade indicates the strength of association between the conditional classes and the hypothetical nutrient availability class. By defining a decision rule for every possible combination of conditional classes, all hypothetical nutrient availability states are specified. The set of all decision rules is conveniently represented by a fuzzy relation.

The fuzzy relation describing the relationship between conditional classes and nutrient availability classes $R^{NA}(VS,MC,AC,OM,NA)$ is a subset of the Cartesian product of the five distinguished fuzzy variables,

$$R^{NA}(VS,MC,AC,OC,NA) \subset (VS \otimes MC \otimes AC \otimes OC) \otimes NA \qquad 6.10$$

The subset of the Cartesian product is defined by a membership function, such that a membership value is given for a nutrient availability class **na** under the presence of four conditional classes (**vs**,**mc**,**ac**,**oc**):

$$0 < MV^{R_{NA}}(\mathbf{na|vs,mc,ac,oc}) \leq 1 \qquad 6.11$$

In the fuzzy relation the variable vegetation structure VS is simplified to 3 classes, i.e. herbaceous, mowed and scrub. No decisions rules have been specified for 'open water'. Making all variables have three ordinal classes except for nutrient availability having 5 classes. Thus the fuzzy relation contains 405 (=3*3*3*3*5) ordered 5-tuples consisting of 5 classes and a membership value. Again the membership values are estimated by 6 experts. From these six independent values a mean membership value and a standard deviation is calculated. The latter statistic quantifies the intersubjective uncertainty.

Note that the intension of a nutrient availability class is not defined, i.e. the classes are not specified by a membership function along a quantitative variable. The nutrient availability classes therefore have a qualitative nature (Guerrin, 1991), contrarily to for instance the moisture content classes which are quantified by a membership function. If needed, the membership function of nutrient availability classes can be defined along a quantitative variable, like biomass production.

Next to the definition of a fuzzy relation enabling the inference of the nutrient availability, a second fuzzy relation is defined by which the vegetation structure is predicted after a change in soil moisture content. The fuzzy relation describing the relationship between conditional classes and the future vegetation structure $R^{VS}(VS_{t0},MC_{t0},MC_{t1},AC_{t0},OM_{t0},VS_{t1})$ is a subset of the Cartesian product of the six distinguished fuzzy variables,

$$R^{VS}(VS_{t0},MC_{t0},MC_{t1},AC_{t0},OM_{t0},VS_{t1}) \subset (VS_{t0}\otimes MC_{t0}\otimes MC_{t1}\otimes AC_{t0}\otimes OM_{t0})\otimes VS_{t1} \qquad 6.12$$

Again, the subset of the Cartesian product is defined by a membership function, such that a membership value is given for a vegetation structural class $\mathbf{vs_{t1}}$ under the presence of five conditional classes $(\mathbf{vs_{t0}},\mathbf{mc_{t0}},\mathbf{mc_{t1}},\mathbf{ac_{t0}},\mathbf{om_{t0}})$:

$$0 < MV^{R_{vs}}(\mathbf{vs_{t1}}|\mathbf{vs_{t0}},\mathbf{mc_{t0}},\mathbf{mc_{t1}},\mathbf{ac_{t0}},\mathbf{om_{t0}}) \leq 1 \qquad 6.13$$

The membership values are estimated by 6 experts independently, from which the mean and standard deviation are calculated.

6.2.3 Fuzzification and inference

Now that the expert knowledge is formalised in the membership functions of fuzzy sets and fuzzy relations respectively, the fuzzy operations can be defined for the processing of quantitative input variables to the output vectors of membership values.

Fuzzification of moisture content, acidity and organic matter content

First step is the fuzzification of the attribute values of the input variables ´depth of the water table´ (m), acidity (pH) and organic mass (kg/m^2) for a specific terrain element (i,j). By calculating the membership values for each fuzzy variable, three vectors of membership values are obtained, i.e. $(MV^{dry}, MV^{moist}, MV^{wet}, MV^{open\ water})^{MC}{}_{(i,j)}$, $(MV^{acid}, MV^{neutral}, MV^{alkaline})^{AC}{}_{(i,j)}$ and $(MV^{sandy}, MV^{moderate\ humus}, MV^{humus})^{OM}{}_{(i,j)}$. These vectors of membership values together with the decision rules, represented by the fuzzy relation $R^{NA}(VS,MC,AC,OM,NA)$, are used to infer the nutrient availability. The process of inference consists of the following 4 steps.

Inference of nutrient availability

Step 1:A membership value is calculated for the joint occurrence of the conditional classes in a terrain element (i,j). This so called joint membership value is equal to the minimum membership value associated with each conditional class. The minimum operator is the standard fuzzy equivalent for the Boolean intersection operator AND. The formula for one specific class combination is:

$$MV(\mathbf{vs,mc,ac,oc})_{(i,j)} = MIN[MV^{vs}{}_{(i,j)}, MV^{mc}{}_{(i,j)}, MV^{ac}{}_{(i,j)}, MV^{oc}{}_{(i,j)}] \qquad 6.14$$

where **vs**, **mc**, **ac** and **oc** stand for one of the classes of a fuzzy variable. By calculating eq. 6.14 for all class combinations the following fuzzy relation is obtained,

$$R(VS,MC,AC,OC)_{(i,j)} \subset VS \otimes MC \otimes AC \otimes OC \qquad 6.15$$

which defines a subset of the Cartesian product on the fuzzy variables VS, MC, AC and OC. The latter fuzzy relation provides a complete specification of the site characteristics of element (i,j). Note that fuzzy relations can be interpreted as fuzzy sets in product space, enabling the integration of the two concepts (Zimmermann, 1985).

Step 2: The relation produced in step 1 provides the input for the decision rules concerning the nutrient availability. A join of the latter relation with the fuzzy relation R^{NA} combines the fuzzy data of a specific terrain element with the nutrient availability:

$$R(VS,MC,AC,OC,NA)_{(i,j)} = R(VS,MC,AC,OC)_{(i,j)} * R^{NA}(VS,MC,AC,OC,NA) \qquad 6.16$$

The join is performed under the condition that the class combination is equal in both relations. Again the joint membership value is obtained by the minimum operator,

$$MV(\mathbf{vs,mc,ac,oc,na})_{(i,j)} = MIN[MV(\mathbf{vs,mc,ac,oc})_{(i,j)}, MV^{R^{NA}}(\mathbf{vs,mc,ac,oc,na})] \qquad 6.17$$

By calculating eq. 6.17 for all class combinations the fuzzy relation in eq. 6.16 is obtained.

Step 3: By projecting $R(VS,MC,AC,OC,NA)_{(i,j)}$ on the nutrient availability a fuzzy relation is obtained representing all possible nutrient availability classes and their membership values for a specific terrain element:

$$R(NA)_{(i,j)} = [R(VS,MC,AC,OC,NA)_{(i,j)} \downarrow (NA)] \qquad 6.18$$

The membership function is derived by a fuzzy union operator, which is equivalent to the Boolean OR. The marginal membership value is obtained by taking the maximum value:

$$MV(\mathbf{na})_{(i,j)} = \max_{\mathbf{vs}\in VS\ \mathbf{mc}\in MC\ \mathbf{ac}\in AC\ \mathbf{oc}\in OC} [MV_{(i,j)}(\mathbf{vs,mc,ac,oc,na})] \qquad 6.19$$

Step 4: Finally the membership values in $R(NA)_{(i,j)}$ are normalised and the relation is rewritten to a vector of 5 membership values $(MV^{very\ oligotrophic}, MV^{oligotrophic}, MV^{mesotrophic}, MV^{eutrophic}, MV^{hypertrophic})^{NA}{}_{(i,j)}$. Hence the membership values in the latter vector sum to one, as do the membership values of the other fuzzy variables. By performing step 4 the inference of the nutrient availability for a specific terrain element is completed.

Inference of vegetation structure

Additionally to the soil characteristics, vegetation structure and depth of the water table on a reference date t_0, the inference of the vegetation structure requires the ground water table at a date 5 years later t_1. Both water tables are estimated by a hydrological model and fuzzified, yielding MC_{t0} and MC_{t1}. When all fuzzy input variables are prepared the inference of the vegetation structure on time t_1 follows a procedure similar to the inference of the nutrient availability. In four steps the future vegetation structure expressed by $(MV^{herbaceous}, MV^{rough}, MV^{mowed}, MV^{shrub})^{VSt1}{}_{(i,j)}$ is derived from the fuzzy relation $R^{VS}(VS_{t0},MC_{t0},MC_{t1},AC_{t0},OM_{t0},VS_{t1})$ and the required input variables.

Construction of ecotopes

From the fuzzy data on vegetation structure, moisture content, nutrient availability and acidity, ecotope types can be constructed. The construction process holds the calculation of the cooccurence of the classes of the four mentioned variables. By aggregation a membership function is derived, which defines a subset of the Cartesian product on the fuzzy variables VS, MC, NA and AC. The result thus being a fuzzy relation,

$$R(VS,MC,NA,AC)_{(i,j)} \subset VS \otimes MC \otimes NA \otimes AC \qquad 6.20$$

The joint membership value is obtained by the standard fuzzy intersection operator. The formula for one specific class combination is:

$$MV(\mathbf{vs,mc,na,ac})_{(i,j)} = MIN[MV^{\mathbf{vs}}{}_{(i,j)},MV^{\mathbf{mc}}{}_{(i,j)},MV^{\mathbf{na}}{}_{(i,j)},MV^{\mathbf{ac}}{}_{(i,j)}] \qquad 6.21$$

By calculating eq. 6.21 for each class combination the fuzzy relation in eq 6.20 is obtained. Note that the model possibly outputs more than one ecotope type for a single site.

6.2.4 Defuzzification

ECOMOD yields a 15 dimensional fuzzy data model. Each axis of this space is defined by a single class of one of the four fuzzy variables, i.e. 4 vegetation structural classes, 3 moisture content classes, 5 nutrient availability classes and 3 acidity classes. The scale of the axes is measured by membership values. The construction of ecotope types in the previous section, is an example of creating a specific view on this data model by employing all its dimensions. However for some applications such a complex view on the data set is not needed and a synoptic view on the fuzzy data model might satisfy the information demand. For instance for visualisation (Hootsman and van der Wel, 1993). Synopsis can be obtained by reducing the dimensionality of the data model by defuzzification.

Consider for example a vector of membership values (0.14, 0.42, 0.29, 0.13, 0.02) indicating the nutrient availability of a specific site. This vector can be graphically presented along an ratio scale, where the ratio values, 0, 1, 2, 3, and 4 indicate the respective nutrient availability classes (fig. 6.3). Provided that it is justified to arrange the membership values along a ratio scale, the overall nutrient availability status can be expressed by the point of gravity (von Altrock, 1991). In this case the point of gravity measures 1.47, indicating that the nutrient availability is in between oligotrophic and mesotrophic. Although the nutrient availability is still expressed by continuous attribute values, the dimensionality of the nutrient availability vector is reduced to one and it is not possible to speak of fuzzy data any more.

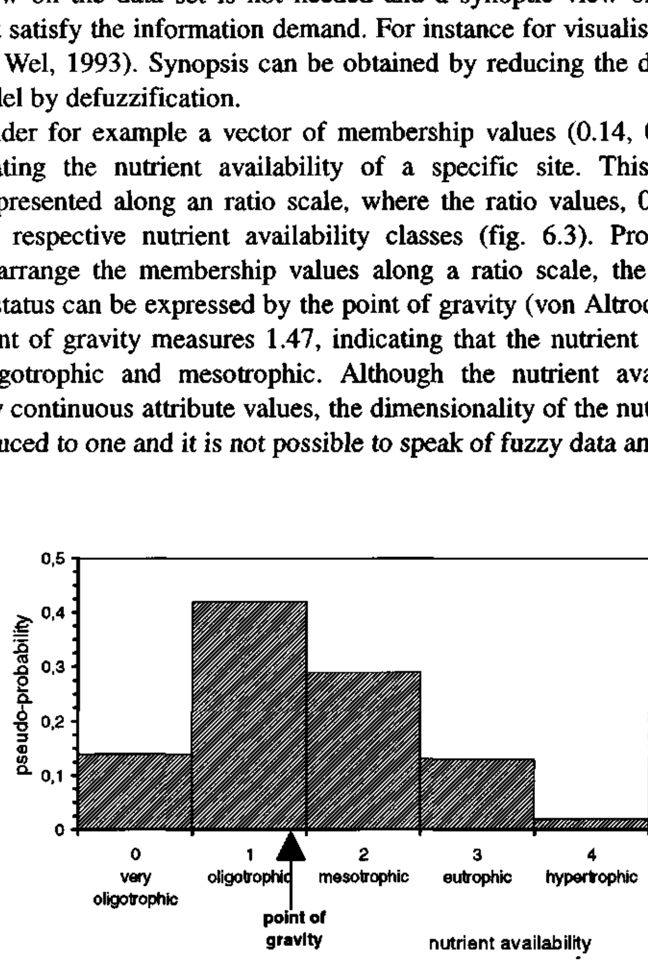


Figure 6.3 Defuzzification of a vector of membership values for nutrient availability by calculating a point of gravity along an ordinal scale.

6.2.5 Sensitivity analysis

A synthetic data set is used to run ECOMOD systematically for all realistic abiotic site conditions and test the behaviour of the model. This data set contains all realistic abiotic site conditions represented by the variables 'depth of water table', acidity and organic matter content for herbaceous sites. Monte Carlo analysis is employed to trace the propagation of errors through the model. The Monte Carlo method generates the distribution of the output membership values by repeatedly running the model with input attribute values and model parameters, that are randomly sampled from their probability distribution (Manly, 1991; Heuvelink, 1993). When the number of runs is sufficiently large the distribution of the output membership values approximates the true distribution of the membership values. Though computationally intensive, the Monte Carlo method is easily implemented and generally applicable to error propagation type of problems in GI systems (Heuvelink, 1993).

The Monte Carlo analysis can take both the uncertainty in model parameters and input variables into account. It is presumed that the input variables are uncorrelated and that the probability distributions are normally distributed. Also the model parameters are presumed to be normally distributed. Thousand runs were performed for each analysis, generating a massive amount of data. Thousand membership values are calculated for each output class and each grid cell. By calculating summary statistics the distribution of these values can be described (Heuvelink, 1993). Alternatively the membership values in a distribution are aggregated conform a method proposed by Klir and Folger (1988) (appendix II). By the aggregation process the thousand vectors of membership values are aggregated to a single vector of pseudo-probability values. When used in Monte Carlo mode, ECOMOD outputs for vectors of pseudo-probabilities to expresses the ecohydrological conditions of a site and eq. 6.1 becomes:

$$
\begin{aligned}
VS_{(i,j)} &= (p^{herbaceous}, p^{rough}, p^{mowed}, p^{shrub})^{VS}{}_{(i,j)} \\
MC_{(i,j)} &= (p^{dry}, p^{moist}, p^{wet}, p^{open\ water})^{MC}{}_{(i,j)} \\
NA_{(i,j)} &= (p^{very\ oligotrophic}, p^{oligotrophic}, p^{mesotrophic}, p^{eutrophic}, p^{hypertrophic})^{NA}{}_{(i,j)} \\
AC_{(i,j)} &= (p^{acid}, p^{neutral}, p^{alkaline})^{AC}{}_{(i,j)}
\end{aligned}
\qquad 6.22
$$

6.3 Results and discussion

The formalisation of expert knowledge not only requires an appropriate mathematical framework to enable the representation and processing of this knowledge, but also suitable methods for the extraction of knowledge from experts. Expert knowledge is needed to structure the model and to create a knowledge base. While the mathematical specification of the model is usually not the bottleneck, the process of knowledge extraction can bring about serious difficulties (Hoffman, 1987; Lundberg, 1989). This is particularly the case when the requirements for the knowledge base are not clearly specified. Due to its simple systematic model structure, the knowledge base of ECOMOD is fully specified by a set of membership functions. Therefore, a complete knowledge base is obtained by estimating the parameters of these functions.

Estimated membership functions

The calibration of ECOMOD for dune slacks is performed by a panel of 6 experts, who estimated the parameters of seperate linear membership functions. The membership functions of the fuzzy variables moisture content, acidity and organic matter content are presented in figure 6.4. The turn-over between two adjacent fuzzy classes is governed by the location of the cross-over point and the incidence of the membership functions. The incidence of the function, quantified by the range of overlap between the classes, determines the fuzziness of the transition. The wider the range, the more gradual the transition between classes becomes. The overlap can vary between classes of one fuzzy variable. For example, the separation between the moisture content classes dry and moist is more vague than the distinction between the classes moist and wet.

The Boolean equivalent of fuzzy classes is defined by exact class boundaries at a cross-over point. The turn-over between Boolean classes is abrupt and does not reflect the vagueness the experts seem to agree upon. Although there is agreement on the presence of vagueness between classes, the experts not always agree on the magnitude of the range of overlap as well as the location of the cross-over point. The uncertainty with respect to cross-over point and the incidence of a membership function is quantified by a standard deviation (fig. 6.4).

The team of experts was also consulted to estimate the membership function values related to the set of decision rules providing the relationship between site conditions, indicated by a combination of input classes, and their hypothetical nutrient availability status. Appendix V contains a listing of all decision rules. The decision rules are not equally fuzzy, i.e. for some soil conditions rather crisp judgements are obtained while other site characteristics yield rather vague decision rules. For example the nutrient availability of a dry, sandy and neutral soil is relatively sharp indicated by the following vector of membership values (0.17, 0.66, 0.17, 0, 0). This qualification does not apply to a soil with moist, very humus and acid characteristics, yielding a vague vector of membership values (0.00, 0.28, 0.22, 0.15, 0.18).

The membership values of a vague vector generally have a high standard deviation. Obviously, high standard deviations result from conflicting judgements produced by the experts. While each individual expert generally produced fairly crisp decision rules, much of the fuzziness proceeds from the aggregation of knowledge of several experts. The vagueness of decision rules as quantified by vectors of membership values provide an overall quantification of the inherent vagueness of the system and the intersubjectivity between experts.

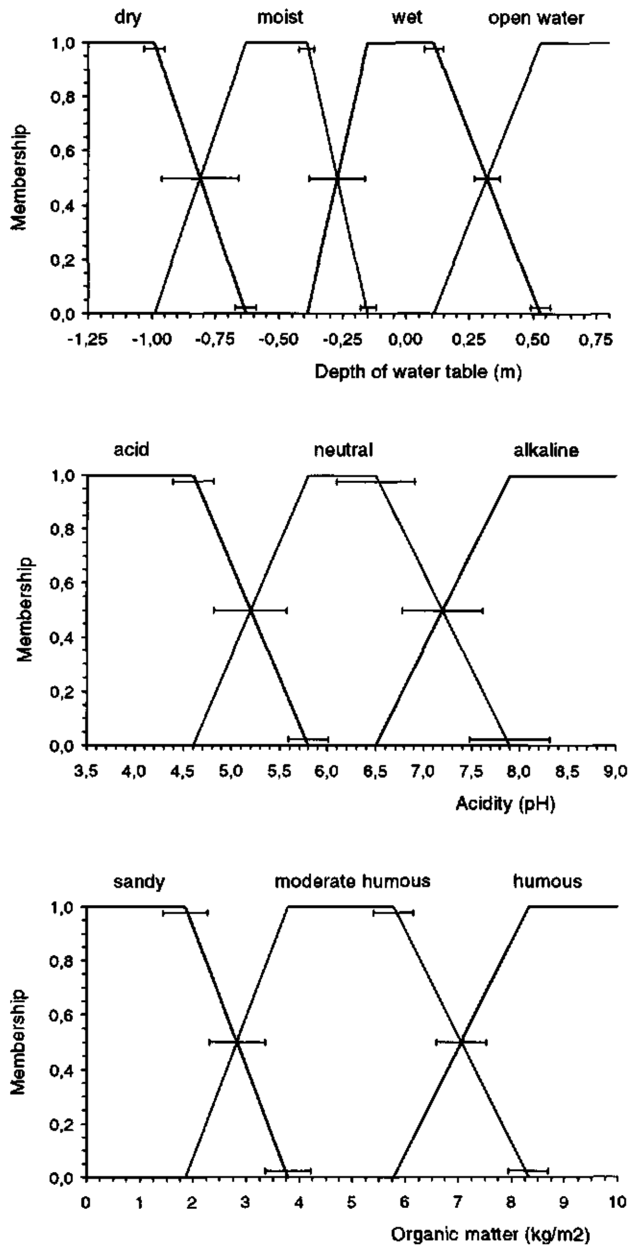


Figure 6.4 The estimated membership functions of the fuzzy sets used by ECOMOD. The function parameters are presented by mean and standard deviation.

The direct estimation of membership functions and/or membership function values given an a priori membership function is known as the semantic import model (Burrough, 1989). This approach is permitted when experts have a proper impression of the system they want to model. In particular they need to have a common notion of the distinguished classes in the model. By calculating the statistics of a set of parameters produced by a panel of experts an intersubjectively calibrated model is obtained. Because available knowledge is used, the semantic import of knowledge is a cheap and flexible method. The use of expert knowledge is flexible because there is no need for season dependent and time consuming field observations.

Sensitivity analysis

Central to ECOMOD is the explanation of the nutrient availability in the soil from soil moisture content, acidity, organic matter content and vegetation structure. ECOMOD outputs a vector of 5 pseudo-probabilities, i.e. one pseudo-probability for each nutrient availability class. Plate 3 shows the sensitivity of the estimated nutrient availability status for uncertainty in model parameters and input data. The model was run four times with a different input, these are:

- Mean parameters for membership functions and mean values for abiotic input.
- Normally distributed parameters for membership functions and mean values for abiotic input.
- Mean parameters for membership functions and normally distributed values for abiotic input.
- Normally distributed parameters for membership functions and normally distributed values for abiotic input.

Firstly, consider the uncertainty captured by the estimated membership functions in the model (run 1). Pseudo-probability values greater than 0.7 for a single class indicate a fairly certain estimation of the nutrient availability status. This is the case for dry/acid/sandy and moist/neutral/humus sites. For some abiotic conditions the model yields a vector with low pseudo-probability values indicating a high level of uncertainty. For instance very humus sites induce low probability values for the nutrient availability classes. Abiotic gradients between moisture content and/or acidity classes also result in uncertain estimations for the nutrient availability.

Secondly, the uncertainty in the parameters of the model is taken into account (run 2). The uncertainty related to the definition of fuzzy sets is restricted to the abiotic gradient situations. Variation in fuzzy sets cause wider and more gradual transition zones between the classes of the fuzzy variables moisture content, acidity and organic matter content. In case of abiotic gradients this results in smoothed pseudo-probability values for the nutrient availability classes. Uncertainty in the decision rules, i.e. the fuzzy relation, has no noticeable effect on the estimated nutrient availability status.

The third run shows the sensitivity of the nutrient availability model to uncertainty of the input parameters, i.e. the depth of water table, acidity and organic matter content of the soil (plate 3). For each variable a realistic mapping accuracy is adopted. In fact variation of an abiotic variable and variation in the turn-over point between fuzzy classes both have the same effect on the estimated pseudo-probabilities for the nutrient availability classes. For instance the depth of the water table is estimated with a standard deviation of 0.21 m, which is in the same order of magnitude of the standard deviation of the turn-over point between the classes dry/moist and moist/wet, however, more than twice the standard deviation of the turn-over point between the classes 'open water' and wet. For the latter classes uncertainty related to the abiotic input variables has more effect on the estimated nutrient availability than the uncertainty related to the model parameters. The uncertainty related to the mapped organic matter content is more than four times the uncertainty related to the definition of the organic matter content classes, i.e. standard deviation of 2.1 and 0.5 kg/m^2. The acidity (pH) of the soil can be estimated with an accuracy of 0.7 which is equal to the uncertainty related to the definition of the acidity classes. Compared to the model parameters, the input variables impose more uncertainty to the estimated pseudo-probability values for the nutrient availability classes as can be concluded from the results of run 2 and 3.

Finally, the overall uncertainty is calculated (run 4). Clearly the model output is not very specific any more and measures of fuzziness or ambiguity would give high values (Hootsman and van de Wel, 1993). In most situations the highest pseudo-probability value for a nutrient availability class does not exceed 0.50, indicating the high fuzziness of the output. Apparently, the estimated pseudo-probabilities are rather sensitive to the uncertainty in model parameters and input data.

Besides pseudo-probability values for each nutrient availability class, ECOMOD produces a defuzzified nutrient availability status. Defuzzification of the vector of 5 probability values yields the overall nutrient availability status of a site quantified by a point of gravity measured along a ratio scale. The overall nutrient availability status is plotted beyond the pseudo-probability values in plate 3. The defuzzified nutrient availability provides a convenient synoptic view on the general trends in the model output. Although the output is defuzzified, the nutrient availability status is expressed by a continuous measure. Moreover the output is obtained through fuzzy model calculations and inference, which is more appropriate than Boolean modelling.

Now consider the effect of increasing uncertainty on the overall nutrient availability status (fig. 6.5). Because the distribution of the differences in nutrient availability between the model runs is symmetric, adding uncertainty to the model does not result in a systematic shift in the estimated nutrient availability status. More than 97 percent of the sites show a deviation equal or smaller than 0.3 times the class width between the overall nutrient availability resulting from the first run of the model and the forth run with maximum uncertainty. The maximum deviation with a width of half a class, occurs on very few sites.

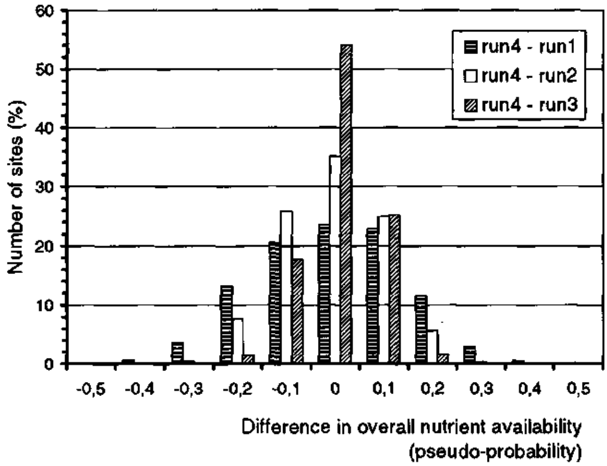


Figure 6.5 Distribution of the differences in overall nutrient availabilty between the four runs of ECOMOD.

Apparently, the defuzzified nutrient availability status is not very sensitive to uncertainty related to model parameters and input variables. Hence the synoptic view on the model results obtained by defuzzification allows you to discard these uncertainties. This is an economical option as it saves computing time. If one is primarily interested in the pseudo-probability for a specific class, then all sources of uncertainty have to be taken into account in a Monte Carlo analysis.

Application of ECOMOD in scenario studies

The Amsterdam Water Supply applies ECOMOD to study the impact of different hydrological management scenarios on the ecohydrological value of the Amsterdam Waterworks Dunes. Plate 4 shows the present ecohydrological status of a single dune slack in the test site. The soil variables are mapped by block kriging of point samples. The water table is estimated by a hydrological model. Only in a small part of the slack the topsoil is affected by ground water resulting in soil moisture conditions ranging from dry to moist. Large parts of the slack are dissicated.

Typically two successive runs of ECOMOD are needed to quantify future ecohydrological site characteristics. The first run predicts the future site characteristics resulting from a hydrological management scenario (fig. 6.1). The output of this run is used to analyse the effect of changes in the depth of the water table on the vegetation structure and soil characteristics. The latter analysis results in the planning of nature management measures to counteract undesired developments like the succession towards species poor rough vegetation types and high nutrient availability levels. The second run of ECOMOD takes both the hydrological and nature management scenario into account resulting in deliberated future ecohydrological site conditions.

Plate 4 presents the future characteristics of the dune slack after reallocation of the water production in the area. The latter measure results in a raise of the groundwater level which creates locally wet soil conditions and open water. These changes in the hydrological situation bring about some disturbance of the vegetation causing the herbaceous vegetation to develop into rough vegetation types. These impacts are counteracted by planning the nature management measures mowing and sod cutting. By sod cutting the organic matter content is reduced and the vegetation removed. Mowing of grasslands prevents the accumulation of biomass and litter.

The fuzzy data model generated by ECOMOD is the starting point for ecological analysis and scenario evaluation. By querying the data model many views can be created. In the previous section the data model was analysed to optimise the allocation of nature management measures. Scenarios can be evaluated by viewing on the impact of differences in management. This evaluation is performed by aggregating the ecohydrological variables to ecotope types. The development of two ecotope types is presented in figure 6.6. Both ecotope types represent high ecological values. The planned management measures will result in a significant increase in the presence of these types. If required the changes in aerial extent of the different ecotope types can be valued by rating each ecotope type according to its ecological significance.

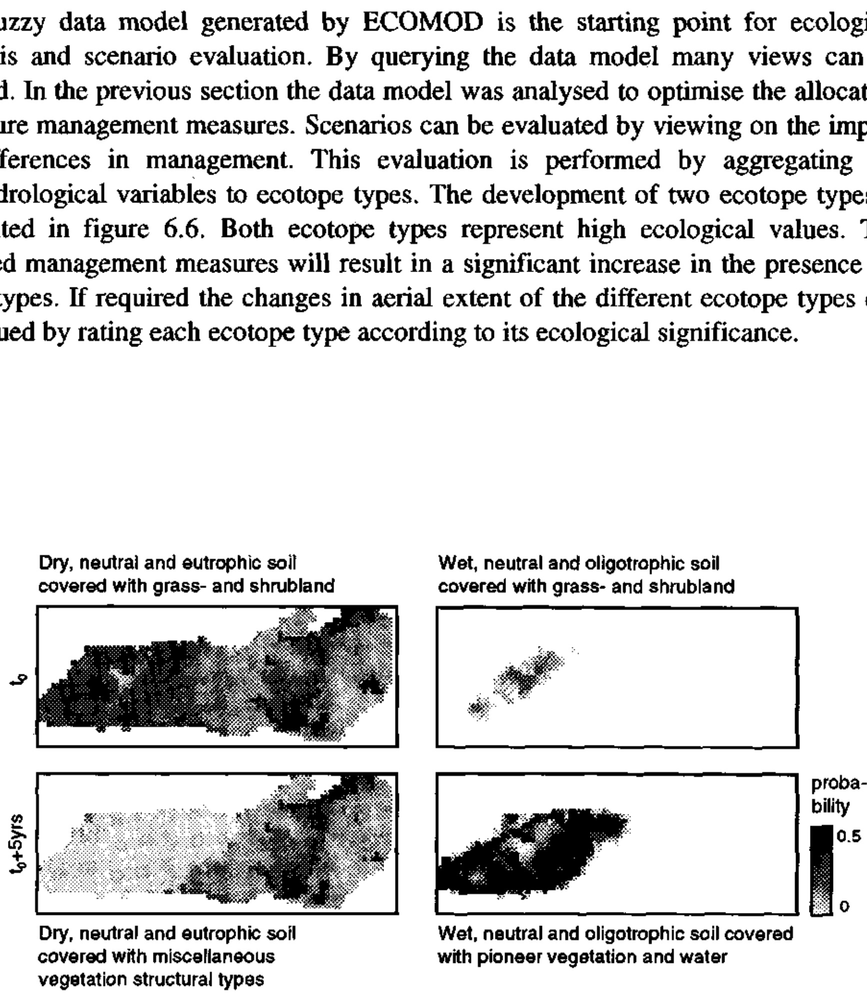


Figure 6.6 Change in the presence of two ecotope types in a dune slack after modifying the hydrological and nature management (see plate 4).

6.4 Conclusions

This chapter dealt with the specification of the fuzzy ecohydrological expert model ECOMOD. The model was calibrated for dune slacks by a team of experts. These experts estimated the parameters of the continuous membership functions that quantify the fuzzy classes and fuzzy relations constituting the model. Unlike the sharp turn-over between crisp classes, the turn-over between fuzzy classes can be made more or less vague. Experts apply vagueness or fuzziness in order to quantify continuous turnover between classes and to quantify the uncertainty related to their knowledge (Bosserman and Ragade, 1982; Salski, 1992).

The definition of fuzzy classes usually resembles much better the experts' perception of the character of data. As stated before, the fuzziness or vagueness seems to proceed from the graduality and complexity of ecological processes. By adapting the degree of fuzziness of the classes experts are able to express both aspects simultaneously. Crisp data do not reflect either of the two. Although seemingly less precise than crisp data, fuzzy data are in fact a more adequate representation of reality (Klir and Folger, 1988). Consequently, membership functions obtained by interviewing experts should not primarily be judged as subjective and weak components of the model, but more as a proper solution to express the inherent uncertainty related to expert knowledge.

Fuzzy expert models like ECOMOD enable the robust modelling of complex systems even in the case of relatively little data. These models are particularly suited for scenario studies and can be integrated with decision support systems. ECOMOD is a generic ecohydrological model that can be adapted and calibrated for other hydrological systems as well.

7. Conclusions and recommendations

The general objective of this thesis was to develop methods for the monitoring of landscape-ecological aspects of natural landscapes (sect. 1.3). Two aspects of landscape monitoring were studied in depth. First, the emphasis was put on the definition of customised spatial models. A spatial model specifies the structure of the digital landscape model and should be suited for a realistic digital representation of complex landscape patterns (chapt. 2). When a proper spatial model is defined for a landscape of interest, the definition of a measurement system is a second concern. A measurement system has to provide the data necessary for the construction of the digital landscape model. It was the objective of this thesis to obtain the spatial data through the automatic interpretation of digital aerial images (chapt. 3).

In order to test the proposed methods for landscape monitoring three cases were researched. These cases originated from the management practice in the Amsterdam Waterworks Dunes. The results are used to underpin the nature management and hydrological management of the area.

The first case concerned the definition of a measurement system based on the semi-automatic interpretation of high resolution digital CIR-photographs, by which a spatio-temporal model of the vegetation structure in the test site is constructed (chapt. 3 and 4). Secondly, methods for the specification of vegetation structural data to vegetation compositional data were proposed and tested (chapt. 5). The latter case aimed at the semi-automatic production of a digital vegetation map. Thirdly, an ecohydrological expert model was described enabling the prediction of ecotope changes in dune slacks (chapt. 6). This chapter describes the general conclusions proceeding from the case studies, as well as recommendations for future research.

7.1 General conclusions

1 The concept of spatial objects with nested fields enables realistic spatio-temporal modelling of natural landscapes

Generally, a pattern obtained from natural landscapes consists of both discrete and continuous phenomena. Discrete features are best represented by spatial objects, while continuous terrain characteristics should be modelled as a field. The concept of spatial objects with nested fields integrates the two concepts conveniently, providing full flexibility in spatio-temporal modelling. The concept was implemented by means of a cell raster.

Spatial objects with nested fields are defined in two phases. Firstly, the mosaic of spatial objects is specified representing the discrete landscape features. Secondly, the internal variability of the spatial objects is quantified as a field. Obviously, the latter phase is optional, i.e. not all spatial objects show an internal variation. Spatial models build from objects with an optionally defined nested field provide a much better representation of reality compared to the current digital chlorophleth maps as the latter maps allow the representation of discrete terrain features only.

2 Step-by-step interpretation of high resolution CIR-images by crisp and fuzzy classification techniques yields detailed measurements on land cover

Starting point for the interpretation of complex images is a land cover hierarchy. This hierarchy reflects the ordering of composite and elementary cover types in a top-down tree structure. Each specification of a cover type to subtypes requires a tailor made classifier. Crisp classification techniques are applied to segment a site in discrete objects representing vegetation structural and geomorphologic terrain characteristics. Subsequently, continuous internal variation of objects is quantified by fuzzy classification techniques. The fuzzy classifier is trained with fuzzy observations performed by an experienced interpreter. Although these observations have a subjective nature, the degree of subjectivity can be minimised by training experts with specimen.

The step-by-step, semi-automatic interpretation of high resolution imagery yielded more detailed information (both spatially and thematically) compared to manual interpretation. For the automated procedure the level of detail is related to the pixel size, while the level of detail in manually derived objects is restricted by labour costs and a minimum mapping unit.

3 Amalgamation is a proper operator to obtain aggregated objects populating higher organisational levels of a landscape

Landscapes can be modelled as hierarchical systems consisting of several linked organisational levels. Each level is populated with specific object types. The construction of a multi-level digital landscape model is not only relevant from an ecological perspective. Multi-level modelling is also a prerequisite for the linking of data from measurement systems operating on different spatial or temporal scales. Consider for example the coupling of vegetation structural data with a set of relevees (chapt. 5). The first data set consists of (elementary) objects obtained by image interpretation while the relevees are observed in the field. The elementary objects needed to be aggregated to composite objects whereupon a proper correlation the vegetation structural data with vegetation compositional data could be performed.

In topographical mapping aggregation is generally performed under the condition that the elementary objects are nested in the composite object. This condition is often too strict in landscape ecological modelling because objects representing natural features might have whimsical shapes. Dropping the condition of containment results in non-nested aggregation or amalgamation. An elementary object can be partially linked to two or more composite objects trough amalgamation, providing the flexibility needed to represent natural features realistically.

4 Vegetation types in the dunes have a fuzzy nature

Clustering and classification are accepted techniques to extract general information from the background of infinite complexity. The clustering of vegetation compositional data present in a set of relevees results in a set of vegetation types. The current crisp clustering or classification techniques start from the presumption of sharp thematic boundaries between these types. Alternatively, fuzzy classification starts from a gradual turnover between vegetation types. In cases where the transition between community types are predominantly vague, fuzzy vegetation communities represent the actual species composition better than the classical crisp vegetation types. This is the case for dune vegetation.

5 The mapping of dune vegetation types requires extensive fieldwork

Spectral data in high resolution images primarily reveal information on abundant species. Consequently, these images are more suited for the mapping of vegetation structural features than for the spatial modelling of vegetation composition. In chapter 5 a method was presented for the specification of vegetation structural data to vegetation classes. However, this approach did not yield an accurate vegetation map, because most vegetation structural and community types show a many to many relationship. Only the vegetation types having a strong correlation with a single structural type were properly mapped.

Apparently, the accurate mapping of vegetation classes requires additional explanatory variables besides vegetation structural data. These are for example abiotic site characteristics, like soil acidity and organic matter content, and succession history. The mapping of these variables requires, however, extensive fieldwork. Therefore, it may be better to map the vegetation directly in the field than indirectly through explanatory modelling or to employ fieldwork in aid of a manual photo-interpretation.

6 Expert knowledge about complex ecological systems, like dune slacks, is adequately formalised by means of fuzzy sets.

The application of GI systems in landscape ecological research forces ecologists to structure their methods and knowledge in formal models. On behalf of the ecohydrological modelling of dune slacks an expert model was compiled (chapt. 6). The knowledge of experts is formalised in a set of classes and decision rules. Experts apply vagueness or fuzziness in order to quantify continuous turnover between classes and to quantify the uncertainty related to their knowledge Due to the complexity of ecological systems, expert knowledge is to some extent incomplete and uncertain. Fuzzy sets allow an expert to express this uncertainty by adapting the degree of vagueness of the class boundaries. The fuzzy ecohydrological model reproduced the expert knowledge satisfactorily and was successfully applied for scenario studies.

7.2 Perspectives and recommendations

The evolution of landscape ecological monitoring systems towards operational tools for landscape management is steered by technical innovations as well as a deeper understanding of landscape ecological processes. In this section the development of monitoring systems in the near future is described primarily from a technical perspective. Three major perspectives will be illuminated:

- Growing availability of high resolution imagery especially from commercial satellite systems.
- Increasing efficiency of ecological fieldwork due to portable GI systems in combination with satellite positioning systems (GPS).
- Increasing functionality of GI systems with respect to handling of time series, dynamic modelling and visualisation.

Images are the major data source for landscape monitoring systems. For large scale mapping purposes airborne images are generally preferred over satellite data because of their higher spatial resolution. The resolution of airborne scans or digital orthophotos typically ranges from 0.1 to 1 m. The expenses for airborne remote sensing data are however substantial, which prevents landscape managers from the creation of time series with a high temporal resolution, e.g. images with a time interval less than 5 years. Further automation of the production of orthophoto mosaics by means of digital cameras, automatic aerotriangulation and improved radiometric correction techniques will however further improve the quality of airborne imagery and reduce production costs.

Satellite systems generally provide multiple images of a site per year for less costs. However, bad weather conditions might prevent the satellite to acquire an image within the required seasonal time window. Although considerably cheaper than aerial images, the maximum resolution of current multi-spectral satellite images is 15 m or less and therefore not sufficient for large scale vegetation mapping. The next generation earth observation satellites, scheduled to be launched by the end of 1998, will acquire images with extraordinary resolutions of 3 meter in the CIR up to 1 meter in panchromatic mode. With respect to spatial resolution these images can compete with airborne data for many mapping purposes. These developments in airborne and space-borne remote sensing will result in a growing availability of high resolution images. Landscape managers can benefit from this supply of images to collect time series with short intervals.

Next to the growing availability of images, portable GI systems running on pen-computers are presently having a major impact on landscape ecological practice. Both with respect to hard- and software powerful systems are presently available. These systems allow one to take spatial data sets in the field for analysis and manipulation on the spot. Raster data including images can be displayed and overlaid with vector data. The fitness of portable GI systems for fieldwork even increases through the coupling with GPS functionality, which enables real time positioning with an accuracy of 5 to 0.5m depending on the GPS solution. Real time positioning is used to display a cursor in the map or image and make the map automatically scroll over the display.

The combined use of portable GI systems with GPS equipment provides fascinating possibilities for the set up of ecological fieldwork. The system can be used to generate sample locations for the collection of field data or to select test-sites and guide you to the selected spot. Field data can be immediately tested and evaluated for completeness, size and number. Furthermore a portable GI system can be helpfull for the validation of the output of ecological models, for the inspection of a reserve or to mark off the extension of nature management measures. All these opportunities and many more will contribute to more efficient ecological fieldwork.

The final perspective concerns the functionality of GI systems. Being a central tool for monitoring systems, GI systems should provide proper tools for the storage, analysis and visualisation of time series. An aspect of data storage is the functionality to trace the life cycle of objects through the definition of multi-temporal spatial objects. Generic tools for dynamic modelling and modelling of error propagation are needed as well as 4D visualisation techniques for the virtual viewing of a digital landscape model. Many of these functions are available yet, however, still have to be integrated with commercially available GI systems. In order to serve the fast growing market for environmental monitoring extension of GI functionality is a prerequisite.

Considering the above mentioned perspectives and the general conclusions in section 7.1, research is recommended on the following topics:

1 Complementary use of digital orthophotos and high resolution satellite images for vegetation mapping

In the market segment of high resolution images the digital orthophoto has to compete with satellite images in the near future. CIR-orthophotos having a typical resolution of 25 cm are very suitable for the accurate delineation of discrete terrain features and the modelling of continuous phenomena. CIR satellite images will soon have a 2.5 meter resolution making these images particularly suited to map gradual changes in the terrain. The resolution is not sufficient to map small discrete terrain features accurately. Assuming that the cost of images is inversely related to the resolution, satellite images will be less costly. Therefore these images afford landscape managers to build up series with a higher temporal frequency as they were used to.

Ideally a landscape monitoring system is fuelled each year with an image acquired in the optimal time window. This high frequency is needed to obtain a better insight into the yearly variation in the vegetation due to different meteorological conditions or for instance differences in grazing pressure. It is known that this yearly variation primarily causes changes in the manifestation of the herbaceous vegetation in terrain and image. Woody species are less sensitive to seasonal changes. Moreover, these discrete patterns are less dynamic in time. Satellite images with a year interval enable to study the migration of the herbaceous classes through the feature space.

The higher frequency of satellite images will increase the accuracy of the modelling of herbaceous vegetation in the matrix. High resolution orthophotos remain necessary for the accurate mapping of discrete phenomena like shrubs and sand patches. By evaluating the costs and benefits of both image types the optimal mixture of airborne and space-borne images for landscape monitoring has to be determined.

2 Further objectification of fuzzy image classification

The increasing availability of high resolution images urges for reliable and efficient interpretation procedures. From the methods presented in this thesis, the fuzzy interpretation of the herbaceous vegetation structure is most vulnerable to subjectivity, because the fuzzy classifier was calibrated by fuzzy observations obtained by on screen image interpretation. Although the approach appeared valid after referencing with field observations, it is obvious that calibration of the classifier by means of fuzzy field observations will contribute to the objectification of the approach.

The sampling scheme for the fieldwork can either be based on the spectral variation in the image or the variation in vegetation structure in the field. If images are available shortly after the acquisition of the data, the selection of reference samples can be performed on image characteristics. The image with the indicated sample sites can be viewed in the field with portable GI system allowing the fuzzy observations to be performed in the field. This approach garantees that the spectral variability in the image is sampled adequately.

Alternatively, the sampling strategy starts from the variation in the test site. Several sampling strategies can be applied, like random or stratified random sampling and sampling along transects. The merits of these strategies should be analysed and evaluated.

Standardisation and specification of the definition of the fuzzy classes will also contribute to further objectification of fuzzy image interpretation. This can be achieved by building a library of specimens. Each specimen consists of a fuzzy field observation including a vector of membership values, the position of the sample, some meta data like the name of the interpreter and the date, and a digital photograph of the scene. When the database with digital specimen is stored in a multimedia portable GI system, the interpreter is able to consult and query the library on the spot.

3 Integration of in- and outdoor computer-aided vegetation mapping

One of the conclusions in this thesis is that the mapping of dune vegetation requires extensive fieldwork. Fieldwork is needed to acquire sufficient expert knowledge about the vegetation in the test site prior to manual photo-interpretation or fieldwork is needed to carry out the vegetation mapping in the field. Subsequently, an outline for computer-aided vegetation mapping is provided, which is dedicated to sites with a complex vegetation pattern, like the dunes. The proposed method of vegetation mapping consists of four major steps.

Firstly, the area is stratified in several major discrete object types by means of semi-automatic image interpretation. Each object type is populated with a specific set of vegetation communities. In a dune area the composite objects 'sandy area', matrix, woodland and water can act as strata. Secondly, the strata are systematically subdivided in quadrants measuring for instance 250*250m^2 or 100*100m^2. The third step involves the estimation of the presence of vegetation types in each quadrant, where the presence of each vegetation type is quantified by a membership value. By applying quadrants in stead of delineated spatial units, the emphasis in the process of vegetation mapping resides on thematic aspects of mapping rather than on the subjective task of delineating patches. The forth and final step involves the validation of the vegetation map with a set of reference data.

The estimation of the presence of each vegetation community in all quadrants, i.e. the estimation of a vector of pseudo-probabilities for each quadrant, is obviously the biggest task in the proposed method. These pseudo-probability values have be obtained by on screen image interpretation. When equipped with a portable GI system and GPS-positioning, a interpreter is free to alternate between indoor and outdoor mapping activities and pursue an optimal mapping strategy.

4 Implementation of the concept of spatial objects with nested field in GI systems

In this thesis the concept of spatial objects with nested fields was introduced to facilitate a realistic digital representation of natural landscapes. In the presented case study these spatial objects were constructed with standard functionality of raster GI systems. Although many GI systems provide data models for the representation of spatial objects in a vector format, these systems lack a dedicated data model for the efficient storage of spatial object types in raster format. This is particularly the case in the temporal domain, where raster data structures lack the functionality to represent spatial objects in time. Consequently, it is not possible to trace the life cycle of individual objects, like shrubs, woodlands and blow outs. Information that is needed landscape ecologists to obtain a detailed view on landscape dynamics and the underlying processes. It is recommended to investigate the feasibility of implementing the concept of spatial objects with nested field in a GI system.

5 Development of dynamic landscape ecological models

Only few dynamic landscape ecological models have been developed in the past. This is not because the mathematical tools to structure the model are lacking, but more because the massive amount of spatio-temporal data needed to calibrate and validate the model could not be obtained economically. Presently, this restraint is removed as reliable monitoring systems based on high resolution images and semi-automatic interpretation techniques can be configured for less costs. From a landscape ecological perspective the development of dynamic landscape models with predictive capabilities is very important, because reliable predictions on landscape development will help nature managers to turn from a reactive to a proactive management strategy.

Abstract

Droesen, W.J., 1999. Spatial modelling and monitoring of natural landscapes; with cases in the Amsterdam Waterworks Dunes. PhD thesis, Wageningen Agricultural University, Wageningen, the Netherlands.

The utilisation of geographic information systems and digital image processing techniques for the construction of digital landscape models necessitate for a reconsideration of the classical concepts for landscape ecological mapping. In this thesis, some methods are presented for the spatial modelling and monitoring of natural landscapes based upon digital workflow information.

In spatial information processing, two major approaches for the conceptual representation of spatial features are distinguished, the field and spatial object respectively. A field is a feature which is contiguously distributed over space and time. The object approach, on the contrary, assumes that the earth's surface is populated with spatially interacting discrete units. Because natural landscapes often show both continuous and discrete variation in space and time, a hybrid terrain description is proposed, denoted as 'spatial object with nested field'. In this hybrid approach the discrete landscape patterns are described by spatial objects, while the internal spatial variability within an spatial object is represented by a field.

Classification is applied during the construction of the spatial objects and nested fields, because it is acknowledged to be a powerful technique to extract essential information from the background of infinite complexity. Crisp classification yields discrete attribute values and is therefore suitable for the definition and construction of spatial objects. The representation of continuously varying terrain features requires a continuous type of classification, i.e. fuzzy classification. Throughout this thesis, fuzzy classification is applied to construct fields.

The concepts for spatial modelling, that were introduced above, were used in three cases resulting from the landscape management practice in the Amsterdam Waterworks Dunes:

Spatio-temporal mapping of the vegetation structure from high resolution CIR-images

Two radiometrically corrected, digital colour infrared orthophotos from the summer of 1990 and 1995 with a resolution of 0.25 metre were semi-automatically interpreted. Crisp and fuzzy classification techniques were applied to construct the spatial objects and their nested fields, representing the vegetation structure of the test site. Compared to manual photo-interpretation, the semi-automatic interpretation of vegetation

structure results in a more realistic, more detailed and less subjective digital representation of the landscape.
Subsequently, the vegetation structural dynamics were explored on the basis of this multi-temporal data set. Methods are presented to answer two primary questions relevant to nature managers, regarding the turnover between cover types and the changes in the spatial structure. It appeared necessary to aggregate the spatial objects provided by the image interpretation to composite objects prior to the spatio-temporal analysis, because thematic and geometric inaccuracies in the data can yield faulty analysis results.

Estimation of the spatial distribution of vegetation communities from environmental data
In addition to information about vegetation structural dynamics, there is a need for information on changes in the vegetation composition. This information can be provided by a multi-temporal map of vegetation communities. An experiment was conducted to estimate the presence of vegetation communities from environmental data, including vegetation structural data.
A reliable procedure for the automatic mapping of vegetation communities from environmental data requires a fine tuned definition of the vegetation communities and a powerful explanatory model. The first condition was met by applying the concept of fuzzy vegetation communities. After the optimisation of the degree of vagueness, the fuzzy vegetation community types show a closer resemblance with the vegetation abundance data in the relevees compared to the classical crisp vegetation classes. The second objective, i.e. the construction of a powerful explanatory model, was not successfully achieved. Clearly, vegetation structural data are not sufficient to map the vegetation composition in dunes. Additional information regarding some abiotic site characteristics seem indispensable to improve the explanatory power of the model.

Fuzzy ecohydrological expert modelling of dune slacks
The thesis also describes the fuzzy ecohydrological expert model ECOMOD. The model predicts the primary parameters for the specification of ecotopes, i.e. vegetation structure, moisture content, nutrient availability and acidity of the soil. ECOMOD is calibrated for dune slacks by a team of experts. These experts estimated the parameters of the membership functions that quantify the fuzzy classes and fuzzy relations constituting the model. Experts apply vagueness or fuzziness in order to quantify the continuous turnover between classes and to quantify the uncertainty related to their knowledge. Therefore, fuzzy expert models like ECOMOD enable the robust modelling of complex systems, even if relatively little data is available. Models like this are particularly suited for scenario studies. ECOMOD is a generic ecohydrological model that can be adapted and calibrated for other ecohydrological systems.

Keywords: geo-information, digital landscape models, monitoring, landscape ecology, ecohydrology, vegetation, remote sensing, image processing, fuzzy logic.

Samenvatting

Droesen, W.J., 1999, Ruimtelijke modellering en monitoring van natuurlijke landschappen; met voorbeelden uit de Amsterdamse Waterleidingduinen. Dissertatie, Landbouwuniversiteit Wageningen.
Een geografisch informatiesysteem in combinatie met automatische beeldverwerkingstechnieken biedt producenten van digitale landschapsmodellen naast het gemak van een digitale werkomgeving ook de uitdaging maximaal gebruik te maken van de mogelijkheden die deze technieken in zich hebben. In dit proefschrift worden enkele concepten beschreven voor het ruimtelijk modelleren en monitoren van natuurlijke landschappen met als doel een meer realistische en betrouwbare weergave van het landschap te creëren dan met behulp van traditionele werkwijzen.

In de informatietechnologie worden twee conceptuele benaderingen onderscheiden voor het representeren van ruimtelijke fenomenen: het ruimtelijk object en het veld. Beide benaderingen maken het mogelijk ruimtelijke patronen en processen in hun onderlinge samenhang te modelleren. Een veld is een ruimtelijke eenheid die onder invloed van een stelsel van krachten min of meer continu varieert in ruimte en tijd. De objectbenadering gaat uit van scherp begrensde eenheden met onderlinge interactie. Omdat natuurlijke landschappen veelal bestaan uit een combinatie van continue en discontinue patronen is één van de beschrijvingsvormen meestal niet afdoende voor het maken van een realistisch landschapsmodel. In dit proefschrift wordt de hybride terrein-beschrijving 'ruimtelijk object met intern veld' geïntroduceerd. Met deze aanpak worden discontinue patronen gerepresenteerd als ruimtelijke objecten, terwijl de ruimtelijke variatie binnen een object desgewenst kan worden weergegeven als een veld.

Voor het construeren van de ruimtelijke objecten en velden uit digitale beelden wordt in de landschapsecologie veelvuldig gebruikgemaakt van classificatie. Zo ook in dit proefschrift. De klassieke vormen van classificatie gaan uit van scherpe klassegrenzen en zijn daarom geschikt voor het construeren van ruimtelijke objecten. De representatie van gradueel variërende terreinkenmerken door middel van een veld vergt echter een continue vorm van classificatie. Daartoe wordt in dit proefschrift gebruik gemaakt van 'fuzzy' classificatie.

De geïntroduceerde concepten voor het modelleren van natuurlijke landschappen zijn in drie voorbeeldsituaties toegepast. Deze voorbeelden komen voort uit de praktijk van het landschapsbeheer in de Amsterdamse Waterleidingduinen.

Temporele kartering van de vegetatiestructuur met behulp van kleur-infrarood beelden

De vegetatiestructuur in de zomer van 1990 en 1995 is semi-automatisch geïnterpreteerd van twee digitale, radiometrisch gecorrigeerde, kleur-infrarood orthofotomozaïeken met een resolutie van 0.25 meter. Een hiërarchische ordening van vegetatiestructuurtypen vormt hierbij het uitgangspunt. De beelden zijn stapsgewijs geïnterpreteerd door de hiërarchie van bovenaf door te werken en bij iedere splitsing van een samengesteld structuurtype naar meerdere enkelvoudige structuurtypes een toegesneden classificatiemethode te gebruiken. Daarbij zijn de ruimtelijke objecten geconstrueerd door middel van klassieke classificatietechnieken en de velden door middel van fuzzy classificatie. In vergelijking met de handmatige interpretatie van de beelden resulteert de semi-automatische interpretatie in een realistischer, gedetailleerder en minder subjectieve weergave van de vegetatiestructuur.
De geproduceerde bestanden zijn vervolgens gebruikt voor het kwantificeren van veranderingen in de vegetatiestructuur tussen 1990 en 1995. Methoden worden gepresenteerd ten einde informatie te verkrijgen over de temporele overgangen tussen de vegetatiestructuurtypen en de veranderingen in de ruimtelijke structuur van de vegetatie. Voorafgaande aan deze analyses zijn de objecten door middel van amalgamatie geaggregeerd naar samengestelde objecten. Aggregatie is noodzakelijk, omdat thematische en geometrische onnauwkeurigheden in het landschapsmodel in sommige gevallen aanleiding geven tot foutieve analyseresultaten.

Kartering van fuzzy vegetatietypen met behulp van standplaatskenmerken

Veel vragen die voortkomen uit het landschapsbeheer kunnen worden beantwoord met informatie over de statische en dynamische eigenschappen van de vegetatiestructuur. Voor sommige toepassingen is echter informatie over de soortensamenstelling van de vegetatie noodzakelijk. Deze informatie wordt doorgaans verkregen uit een tijdreeks van vegetatiekaarten, waarop het voorkomen van vegetatietypen is aangegeven. Vegetatiekaarten kunnen echter niet betrouwbaar worden geproduceerd door een semi-automatische interpretatie van kleur-infrarood beelden. Daarom is een experiment uitgevoerd om het voorkomen van vegetatietypen automatisch te schatten met behulp van standplaatsfactoren.
Een betrouwbare procedure voor de automatische kartering van vegetatietypen met behulp van standplaatsfactoren moet zijn gebaseerd op een afgewogen definitie van de vegetatietypen en een verklarend model met een hoge nauwkeurigheid. Aan de eerste voorwaarde is in dit onderzoek voldaan door het concept van fuzzy oftewel vage vegetatietypen te hanteren. Na de optimalisering van de mate van vaagheid van de vegetatietypen, geven de fuzzy vegetatietypen een meer nauwkeurige weergave van de presentie van plantensoorten in vergelijking met de klassieke vegetatietypen. Klaarblijkelijk hebben duinvegetatietypen een fuzzy karakter. De tweede conditie,

zijnde de constructie van een betrouwbaar verklarend model, is niet succesvol bereikt. Naast vegetatiestructuurgegevens is additionele standplaatsinformatie nodig zoals bodem- en grondwaterkenmerken. Voor het karteren van deze variabelen is veldwerk noodzakelijk en het is dan ook praktischer dit veldwerk te benutten voor de kartering van de vegetatie.

Fuzzy ecohydrologisch expert model voor duinvalleien

In dit proefschrift wordt het fuzzy ecohydrologisch expertmodel ECOMOD beschreven. Het model voorspelt de belangrijkste parameters voor het specificeren van ecotopen, te weten de vegetatiestructuur, het bodemvochtgehalte, de beschikbaarheid van voedingsstoffen en de zuurgraad van de bodem. ECOMOD is door een team van deskundigen gekalibreerd voor duinvalleien. De experts hebben de parameters geschat van de fuzzy klassen en de eigenschappen van de beslisregels in het model. De experts gebruiken de mate van vaagheid in de definitie van klassen ten einde geleidelijke overgangen tussen de klassen te kunnen kwantificeren alsmede de onzekerheid van hun kennis uit te drukken. Daardoor zijn fuzzy expertmodellen zoals ECOMOD goed bruikbaar voor complexe ecologische systemen, zelfs als weinig gegevens voorhanden zijn. Het type model leent zich uitstekend voor scenario-studies. ECOMOD is een generiek ecohydrologisch model dat kan worden aangepast en gekalibreerd voor andere ecohydrologische systemen.

Geografische informatiesystemen in combinatie met beeldverwerkingstechnieken bieden legio mogelijkheden voor het monitoren van natuurlijke landschappen. De gepresenteerde methoden kunnen een bijdrage leveren aan de verdere operationalisering van landschapsmonitoringsystemen tot betrouwbare instrumenten voor landschapsbeheer. Aanvullend onderzoek dient gericht te zijn op de objectivering van fuzzy beeldinterpretatietechnieken, het bepalen van het effect van seizoensinvloeden op de kwaliteit van het landschapsmodel en het gebruik van veldcomputers en satellietplaatsbepaling ten behoeve van vegetatiekartering. Zodra operationele monitoringsystemen tijdreeksen met ruimtelijke informatie beginnen te leveren, dient de ontwikkeling van dynamische landschapsmodellen verder ter hand te worden genomen, zodat op termijn monitoringsystemen het landschap kunnen gaan voorspellen.

References

Ahmad, W., L.B. Jupp and M. Nunez, 1992. Land cover mapping in a rugged terrain area using Landsat MSS data. Int. J. of Remote Sensing 13(4): 673-683.

Albrecht, K-F., 1992. Problems of modelling and forecasting on the basis of phenomenological investigations. Ecological Modelling 63: 45-69.

Appelman, K., L.H.W.T. Geelen, P.Ketner en G. Baeyens, 1990. Een halve eeuw landschapsontwikkeling in de Amsterdamse waterleidingduinen 2; Westhoek en Paardenkerkhof. De levende natuur 4: 106-114.

Aspinall, R., 1992. An inductive modelling procedure based on Bayes' theorem for analysis of pattern in spatial data. Int. J. Geographical Information Systems 6(2): 105-121.

Assendorp, D. and F. van der Meulen, 1994. Habitat classification of dry coastal ecosytems, the integration of image and field sample. EARSeL Workshop on Remote Sensing and GIS for Coastal Zone Management, 24-26 Oct. 1994 Delft: 16-26.

Atkinson, P.M., R. Webster and P.J. Curran, 1992. Cokriging with Ground-Based Radiometry. Remote Sensing of Environment 41: 45-60.

Austin, M.P., 1981. Permanent quadrats: An interface for theory and practice. Vegetatio 46: 1-10.

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

Baker, W.L. and Y. Cai, 1992. The r.le programs for multiscale analysis of landscape structure using the GRASS geographical information system. Landscape Ecology 7(4): 291-302.

Bakker, T.W.M., J.A. Klijn en F.J. van Zadelhoff, 1979. Nederlandse kustduinen, landschapsecologie. Pudoc, Wageningen.

Barendrecht, A and M.J. Wassen, 1989. Het hydro-ecologisch model ICHORS; de relaties tussen water- en moerasplanten en milieufactoren in Noord-Holland. Rijksuniversiteit Utrecht, Utrecht.

Barnsley, M.J., 1984. Integration of multispectral data obtained at different view angles for vegetation analysis. Proc. Integrated Approaches in Remote Sensing, 8-11 April 1984 Guildford: 135-142.

Baumgardner, M.F., L.F. Silva, L.L. Biehl and E.R. Stoner, 1985. Reflectance Properties of Soils. Advances in Agronomy 38: 1-44.

Beckhoven, K., 1995. Rewetting of coastal dune slacks: effects on plant growth and soil processes. Vrije Universiteit, Amsterdam.

Belward, A.S., J.C. Taylor, M.J. Stuttard, E. Bignal, J. Mathews and D. Curtis, 1990. An unsupervised approach to the classification of semi-natural vegetation from Landsat Thematic Mapper data. Int. J. Remote Sensing 11(3): 429-445.

Bijlsma, R.J., 1993. The characterisation of natural vegetation using first-order and texture measurements in digitized, colour-infra-red photography. Int. J. Remote Sensing 14(8): 1547-1562.

Blonda, P.N., G. Pasquariello, S. Losito, A. Mori, F. Posa and D. Ragno, 1991. An experiment for the interpretation of multitemporal remotely sensed images based on a fuzzy logic approach. Int. J. Remote Sensing 12(3): 463-476.

Bosserman, R.W. and R.K. Ragade, 1982. Ecosystem analysis using fuzzy set theory. Ecological Modelling 16: 191-208.

Bunce, R.G.H., C.J. Barr and H. Whittaker, 1983. A stratification system for ecological sampling. Ecological mapping from ground, air and space. R.M. Fuller (ed), ITE (Inst. of Terrestrial Ecology) Cambridge.

Burrough, P.A., 1989. Fuzzy mathematical methods for soil survey and land evaluation. Journal of Soil Science 40: 477-492.

Carlile, D.W., J.R. Skalski, J.E. Batker, J.M. Thomas and V.I. Cullinan, 1989. Determination of ecological scale. Landscape Ecology 2(4): 203-213.

Chatfield, C., 1989. The analysis of time series. Chapman and Hall Ltd., London.

Clevers, J.G.P.W. and H.J. Buiten, 1991. Modelling and synergetic use of optical and microwave remote sensing. Netherlands remote sensing board, report 91-02.
Clevers, J.G.P.W., and H.T.C. van Stokkom, 1992. The quantitative evaluation of false colour photography with application of a red filter. Int. J. Remote Sensing 13(9): 1709-1733.
Cressie, N.A.C., 1991. Statistics for spatial data. John Wiley & Sons, New York.
Curran, P.J. 1988. The semivariogram in remote sensing: An introduction. Remote Sensing of Environment 24: 493-507.
Curran, P.J., and H.D. Williamson, 1986. Sample size for ground and remotely sensed data. Remote Sensing of Environment 20: 31-41.
Cushnie, J.L., 1987. The interactive effect of spatial resolution and degree of internal variability within land-cover types on classification accuracies. Int. J. Remote Sensing 8(1): 15-29.
Dancy, K.J., R. Webster and N.O.J. Abel, 1986. Estimating and mapping grass cover and biomass from low-level photographic sampling. Int. J. Remote Sensing 7(12): 1679-1704.
Davies, P., A.T. Williams and R.H.F. Curr, 1995. Decision making in dune management: theory and practice. Journal of Coastal Conservation 1: 87-96.
Davis, F.W. and S. Goetz, 1990. Modeling vegetation pattern using digital terrain data. Landscape Ecology 4(1): 69-80.
Davis, J.C., 1986. Statistics and data analysis in geology. John Wiley & Sons, New York.
De Gruyter, J.J. and A.B. McBratney, 1990. A Modified Fuzzy K-Means Method for Predictive Classification. Classification and Related Methods of Data Analysis. H.H. Bock (ed), Elsevier-Science Publishers, North-Holland.
Delhomme, J.P., 1978. Kriging in the Hydrosciences. Advances in Water Resources 1(5): 251-266.
Den Held, J.J. and A.J. den Held, 1983. Beknopte handleiding voor vegetatiekundig onderzoek. Wetenschappelijke medelingen K.N.N.V 97.
Dikau, R., 1990. Geomorphic Landform Modelling Based on Hierarchy Theory. Proc. of Int. Symp. on Spatial Data Handling, Zurich, Switzerland: 230-239.
Dunn, C.P., D.M. Sharpe, G.R. Guntenspergen, F. Stearns and Z. Yang, 1990. Methods for Analyzing Temporal Changes in Landscape Pattern. Quantitative Methods in Landscape Ecology. M.G. Turner and R.H. Gardner (eds.), Ecological Studies 82: 173-196.
Dymond, J.R., P.R. Stephens, P.F. Newsome and R.H. Wilde, 1992. Percentage vegetation cover of a degrading rangeland from SPOT. Int. J. Remote Sensing 13(11): 1999-2007.
Ebner, H. and K. Eder, 1992. State-of-the-art in digital terrain modelling. Proc. 3th European Conf. on Geographical Information Systems, Munich, March 23-26 1992: 681-690.
Ehrenburg, A. and G. Baeyens, 1992. Landscape-ecological mapping as basis for management of the Amsterdam Waterwork Dunes. In: Carter, Curtis & Sheeny-Skeffington (eds). Coastal Dunes. Balkema, Rotterdam.
Ehrenburg, A., L.H.W.T. Geelen, P. Ketner en G. Baeyens, 1988. Een halve eeuw landschapsontwikkeling in de Haasvelderduinen. De Levende Natuur 5: 150-157.
Feoli, E. and V. Zuccarello, 1991. Syntaxonomy: A Source of Useful Fuzzy Sets for Environmental Analysis? E. Feoli and L. Orloci (eds.), 1991, Computer Assisted Vegetation Analysis: 265-271. Kluwer Academic Publ.
Foody, G.M., 1992. A fuzzy sets approach to the representation of vegetation continua from remotely sensed data: An example from lowland heath. Photogrammetric Engineering & Remote Sensing 58(2): 221-225.
Forman, R.T.T. and M. Godron, 1986. Landscape Ecology. John Wiley & Sons, New York.
Fotheringham, A.S., and P.A. Rogerson, 1993. GIS and spatial analytical problems. Int, J. Geographical Information Systems 7(1): 3-19.
Geelen, L.H.W.T., 1990. Landscape Succession in a Dutch dune area. Proceedings of ISPRS symposium Victoria, Canada. Int Archives of Photogrammetry and Remote Sensing 28(7-1).
Girard, C.M., 1986. Spectral and botanical classification of grasslands: Auxois example. Symp. on Remote Sensing for Resources Development and Environmental Management, Enschede, Aug. 1986: 269-272.
Gold, C.M., 1989. Surface interpolation, spatial adjacency and GIS. Three dimensional applications in Geographic Information Systems, J.I. Raper (ed), Taylor & Francis: 21-35.
Goodchild, M.F., S. Guoqing and Y. Shiren, 1992. Development and test of an error model for categorical data. Int. J. Geographical Information Systems 6(2): 87-104.
Gremmen, N.J.M., M.J.S.M. Reijnen, J. Wiertz and G. van Wirdum, 1990. A Model to Predict and Asses the Effects of Groundwater Withdrawel on Vegetation in the Pleistocene Areas of the Netherlands. Journal of Environmental Management 31: 143-155.

Grensdoerffer, G. and Ralf Bill, 1994. Digital orthophotos for mapping and interpretation in hydrid GIS-environments. Fifth European Conference and Exhibition on Geographical Information Systems EGIS, march 29- april 1 1994 Paris: 1845-1856.

Guerrin, F., 1991. Qualitative reasoning about an ecological process: interpretation in hydroecology. Ecological Modelling 59: 165-201.

Gurnell, A.M., D. Simmons, P.J. Edwards, J. Ball, F. Feaver, A. Mclellan and C. Ogle, 1993. GIS and multivariate ecological analysis: an input to integrated river channel management. HydroGIS 93: Application of Geographic Information Systems in Hydrology and Water Resources (Proceedings of the Vienna Conference, April 1993). IAHS Publ. 211: 363-374.

Gurney, C.M. and J.R.G. Townshend, 1983. The Use of Contextual Information in the Classification of Remotely Sensed Data. Photogrammetric Engineering and Remote Sensing 49(1): 55-64.

Haefner, H., 1987. Assesment and monitoring of renewable natural resources: concepts and applications. Applied Geography 7: 7-15.

Haines-Young, R., D.R. Green and S.H. Cousins (eds), 1993. Landscape ecology and geographic information systems. Taylor & Francis, London.

Haralick, R.M., 1979. Statistical and Structural Approaches to Texture. Proceedings of the IEEE 67(5).

Heil, G.W., F. van der Meulen and M.J. ten Harkel, 1990. Invloed van atmosferische depositie op de ontwikkeling van droge duingrasland vegetaties. K.N.A.G. Geografisch Tijdschrift XXIV(5): 427-436.

Heuvelink, G.B.M., 1993. Error propagation in quantitative spatial modelling; applications in geographical information systems. PhD thesis, University Utrecht, Utrecht.

Hill, M.O., 1979. TWINSPAN - A fortran program for arranging multivariate data in an ordered two-way table by classification of the individuals and attributes. Cornell University, Ithaca.

Hoffman, R.R., 1987. The Problem of Extracting the Knowledge of Experts from the Perspective of Experimental Psychology. AI Magazine 8(2): 53-67.

Holben, B and C. Justice, 1981. An examination of spectral band ratioing to reduce the topographic effect on remotely sensed data. Int. J. Remote Sensing 2(2): 115-133.

Holbrook, J.A., T.W. Rideout and R.G. Healey, 1992. GIS for conservation management: scientific and organisational issues. Proc. 3th European Conf. on Geographical Information Systems, Munich, Germany. March 23-26 1992: 1111-1120.

Holly, B.P., 1978. The Problem of Scale in Time-Space Research. Timing Space and Spacing Time, Vol 3. Time and Regional Dynamics. T. Carlstein, D. Parks and N. Thrift (ed). Edward Arnold Ltd, London.

Hootsman, R. and F. v.d. Wel, 1993. Detection and visualisation of ambiguity and fuzzyness in composite spatial datasets. EGIS'93, 4th European Conference on Geographical Information Systems, Genoa, Italy, march 29 - april 1 1993: 1035-1046.

Hope, A.S., J.S. Kimball and D.A. Stow, 1993. The relationship between tussock tundra spectral reflectance properties and biomass and vegetation composition. Int. J. Remote Sensing 14(10): 1861-1874.

Huising, J., 1993. Land use zones and land use patterns in the Atlantic zone of Costa Rica; a pattern recognition approach to land use inventory at the sub-regional scale, using remote sensing and GIS, applying an object-oriented and data-driven strategy. PhD thesis, Wageningen Agricultural University, Wageningen.

Jacobs, H. and M. Sties, 1995. Multitemporale Landnutzungsklassifizierung und Analyse der Nutzungsanderung im Oberrheingraben. ZPF, Zeitschrift fur Photogrammetrie und Fernerkundung 4:160-173.

Jakubauskas, M.E., 1989. Utilizing a Geographic Information System for Vegetation Change Detection. Technical Papers 1989 ASPRS/ACSM, Annual Convention 4: 56-64.

Janssen, J.A.M., 1996. Inventarisatie van onzekerheden in vegetatiekarteringen met behulp van luchtfoto's en voorstellen voor kwantificatietesten. Deelrapport 1, Project Kwantitatieve Validatie Vegetatiekaarten. Meetkundige Dienst van Rijkswaterstaat, Delft.

Janssen, L., 1994. Methodology for updating terrain object data from remote sensing data; the application of Landsat TM data with respect to agricultural fields. PhD thesis, Wageningen Agricultural University, Wageningen.

Jeon, B. and D.A. Landgrebe, 1992. Classification with Spatio-Temporal Interpixel Class Dependency Contexts. IEEE Transactions on Geoscience and Remote Sensing 30(4): 663-672.

Johnson, L.B., 1990. Analyzing spatial and temporal phenomena using geographical information systems (A Review of Ecological Applications). Landscape Ecology 4(1): 31-43.

Jongman, R.H.G., C.J.F. ter Braak and O.F.R. van Tongeren (eds), 1987. Data analysis in community and landscape ecology. Pudoc, Wageningen.
Jungerius, P.D. and F. van der Meulen, 1988. Erosion processes in a dune landscape along the dutch coast. Catena 15: 217-228.
Justice, C.O., S.W. Wharton and B.N. Holben, 1981. Application of digital terrain data to quantify and reduce the topographic effect on Landsat data. Int. J. Remote Sensing 2(3): 213-230.
Kemp, K.K., 1993. Environmental modelling and GIS: dealing with spatial continuity. HydroGIS 93: Application of Geographic Information Systems in Hydrology and Water Resources (Proceedings of the Vienna Conference, April 1993). IAHS Publ. 211: 107-115.
Kenkel, N.C., P. Juhasz-Nagy and J. Podani, 1989. On sampling procedures in population and community ecology. Vegetatio 83: 209-222.
Klir, G.J. and T.A. Folger, 1988. Fuzzy sets, uncertainty, and information. Prentice-Hall International, London.
Knipling, E.B., 1970. Physical and Physiological Basis for the Reflectance of Visible and Near-Infrared Radiation from Vegetation. Remote Sensing of Environment 1: 155-159.
Koerselman, W., H. Doing, L.H.W.T. Geelen, G.M. Leltz and E.M. Nijssen, 1992. De voedselrijkdom van duinvalleien in relatie tot standplaatscondities en externe inputs. KIWA rapport SWE 91.037, Nieuwegein.
Kolasa, J. and C.D. Rollo, 1991. Introduction: The Heterogeneity of Heterogeneity: A Glossary. Ecological Studies 86. J. Kolasa ans S.T.A. Pickett (eds.), Springer-Verlag, New York: 1-23.
Kolbl, O. and H. Trachsler, 1980. Regional land use survey based on point sampling on aerial photographs. Int. Archives of Photogrammetry XXIII(10): 536-549.
Kollias, V.J. and A. Voliotis, 1991. Fuzzy reasoning in the development of geographical information systems. FRSIS: a prototype soil information system with fuzzy retrieval capabilities. Int. J. Geographical Information Systems 5(2): 209-223.
Kotliar, N.B. and J.A. Wiens, 1990. Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. OIKOS 59: 253-260.
Lacaze, B., S. Rambal and T. Winkel, 1994. Identifying spatial patterns of Mediterranean landscapes from geostatistical analysis of remotely-sensed data. Int. J. Remote Sensing 15(12): 2437-2450.
LaGro, J., 1991. Assessing Patch Shape in Landscape Mosaics. Photogrammetric Engineering & Remote Sensing 57(3): 285-293.
Langran, G., 1989. A review of temporal database research and its use in GIS applications. Int. J. Geographical Information Systems 3(3): 215-232.
Legendre, P. and M-J Fortin, 1989. Spatial pattern and ecological analysis. Vegetatio 80: 107-138.
Leprieur, C.E., J.M. Durand and J.L. Peyron, 1988. Influence of Topography on Forest Reflectance Using Landsat Thematic Mapper and Digital Terrain Data. Photogrammetric Engineering and Remote Sensing 54(4): 491-496.
Leser, H., 1991. Landschafts ökologie. Uni Taschenbücher 521, Ulmer, Stuttgart.
Lillesand, T.M. and R.W. Kiefer, 1994. Remote sensing and image interpretation. John Wiley & Sons, New York.
Lippe, E., J.T. de Smidt and D.C. Glenn-Lewin, 1985. Markov models and succession: a test from a heathland in the Netherlands. J. of Ecology 73: 775-751.
Lodwick, W.A., W. Monson and Larry Svoboda, 1990. Attribute error and sensitivity analysis of map operations in geographical information systems: suitability analysis. Int. J. Geographical Information Systems, 1990 4(4): 413-428.
Lundberg, C.G., 1989. Knowledge Acquisition and Expertise Evaluation. Professional Geographer 41(3): 272-283.
Manly, B.F.J., 1991. Randomization and Monte Carlo methods in biology. Chapman and Hall, London.
Marsili-Libelli, S., 1991. Fuzzy Clustering of Ecological Data. E. Feoli and L. Orloci (eds.), Computer Assisted Vegetation Analysis: 173-184. Kluwer Academic Publ.
McKeown, D.M., W.A. Harvey and J. McDermott, 1985. Rule-Based Interpretation of Aerial Imagery. IEEE Transactions on Pattern Analysis and Machine Intelligence. PAMI-7(5).
Meentemeyer, V., 1989. Geographical perspectives of space, time, and scale. Landscape Ecology 3(3,4):163-173.
Middelkoop, H., 1990. Uncertainty in a GIS: a test for quantifying interpretation output. ITC journal 3.

Miller, D. and J. Morrice, 1993. Coupling of process-based vegetation models to GIS and knowledge based systems for analysis of vegetation change. EGIS'93, 4th European Conference on Geographical Information Systems, Genoa, Italy, march 29 - april 1 1993: 334-343.

Milne, A.K. and A.L. O'Neill, 1990. Mapping and monitoring land cover in the Willandra Lakes World Heritage Region. Int. J. Remote Sensing 11(11): 2035-2049.

Molenaar, M., 1994. A syntactic approach for handling the semantics of fuzzy spatial objects. GISDATA, Baden (Austria), june 1994.

Molenaar, M., 1998. Introduction to theory of spatial object modelling for GIS. Taylor & Francis, New York.

Mouat, D.A., G.G. Mahin and J. Lancaster, 1993. Remote Sensing Techniques in the Analysis of Change Detection. Geocarto International 8(2): 39-50.

Mueller, F., 1992. Hierarchical approaches to ecosystem theory. Ecological Modelling 63: 215-242.

Musick, H.B. and H.D. Grover, 1991. Image textural measures as indices of landscape pattern. Quantitative methods in landscape ecology. M.G. Turner and R.H. Gardner (eds.), Ecological Studies 82: 77-103.

Nellis, M.D. and J.M. Briggs, 1989. The effect of spatial scale on Konza landscape classification using textural analysis. Landscape Ecology 2(2): 93-100.

Nguyen, H.T., 1978. On conditional possibility distributions. Fuzzy Sets and Systems 1: 299-309.

Oliver, M.A. and R. Webster, 1990. Kriging: a method of interpolation for geographical information systems. Int. J. Geographical Information Systems 4(3): 313-332.

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

Olsthoorn, T.N., 1998. Groundwater modelling: Calibration and the use of spreadsheets. PhD-thesis, Delft University Press, Delft.

O'Neill, R.V., J.R. Krummel, R.H. Gardner, G. Sugihara, B. Jackson, D.L. Deangelis, B.T. Milne and M.G. Turner, 1989. Indices of landscape pattern. Landscape Ecology 1(3): 153-162.

O'Neill, R.V., A.R. Johnson and A.W. King, 1989. A hierarchical framework for the analysis of scale. Landscape Ecology 3(3,4): 193-205.

Openshaw, S., 1989. Learning to live with errors in spatial databases. Accuracy of Spatial Databases, Goodchild, M., and S. Gopal (eds), Taylor & Francis, London: 263-276.

Oxborrow, E. and Z. Kemp, 1989. An Object-Oriented Approach to the Management of Geographical Data. Univ. of Canterbury

Pastor, J. and M. Broschart, 1990. The spatial pattern of a nothern conifer-hardwood landscape. Landscape Ecology 4(1): 55-68.

Perez-Trejo, F., 1993. Landscape response units: process-based self-organising systems. In Landscape ecology and GIS, R. Haines-Young (ed), Taylor & Francis.

Philipson, W.R. (ed), 1997. Manual of photographic interpretation. American Society for Photogrammetry and Remote Sensing, Maryland.

Pickett, S.T.A., J. Kolasa, J.J. Armesto and S.L. Collins, 1989. The ecological concept of disturbance and its expression at various hierarchical levels. OIKOS 54: 129-136.

Piotrowska, H., 1988. The dynamics of the dune vegetation on the Polish Baltic coast. Vegetatio 77: 169-175.

Piwowar, J.M., E.F. LeDrew and D.J. Dudycha, 1990. Integration of Spatial data in vector and raster formats in a geographic information system environment. Int. J. Geographical Information Systems 4(4): 429-444.

Plumb, G.A., 1993. Knowledge-Based Digital Mapping of Vegetation Types in Big Bend National Park, Texas. Geocarto International 8(2): 29-38.

Puech, C., 1994. Thresholds of homogeneity in targets in the landscape. Relationship with remote sensing. Int. J. Remote Sensing 15(12): 2421-2435.

Quattrochi, D.A. and R.E. Pelletier, 1990. Remote Sensing for Analysis of Landscapes: An Introduction. Quantitative Methods in Landscape Ecology. M.G. Turner and R.H. Gardner (eds.), Ecological Studies 82: 51-76. Springer-Verlag.

Rastetter, E.B., 1990. A Spatially Explicit Model of Vegetation-Habitat Interactions on Barrier Islands. Quantitative Methods in Landscape Ecology. M.G. Turner and R.H. Gardner (eds.), Ecological Studies 82:. 353-378. Springer-Verlag.

Richardson, D.E., 1993. Automated spatial and thematic generalization using a context transformation model. PhD thesis Wageningen Agricultural University, Wageningen.

Roberts, D.W., 1987. A dynamical systems perspective on vegetation theory. Vegetatio 69: 27-33.

Roberts, D.W., 1989. Fuzzy systems vegetation theory. Vegetatio, 83: 71-80.

Rosenfeld, A. and A.C. Kak, 1982. Digital picture processing. Vol 1 and 2, Academic Press Inc. Orlando.
Salski, A., 1992. Fuzzy knowledge-based models in ecological research. Ecological Modelling 63: 103-112.
Satterwhite, M., W. Rice and J. Shipman, 1984. Using Landform and Vegetative Factors to Improve the Interpretation of Landsat Imagery. Photogrammetric Engineering and Remote Sensing 50(1): 83-91.
Schaminee, J.H.J. , A.H.F. Stortelder and V. Westhoff, 1995. De vegetatie van Nederland; deel 1, Inleiding tot de plantensociologie - grondslagen, methoden en toepassingen. Opulus Press, Leiden.
Schwabe, A., 1991. A method for the analysis of temporal changes in vegetation pattern at the landscape level. Vegetatio 95: 1-19.
Simmons, M.A., V.I. Cullinan and J.M. Thomas, 1992. Satellite imagery as a tool to evaluate ecological scale. Landscape Ecology 7(2), 77-85.
Stevers, R.A.M., J. Runhaar, H.A. Udo de Haes en C.L.G. Groen, 1987. Het cml-ecotopensysteem, een landelijke ecosysteemtypologie toegespitst op de vegetatie. Landschap 2: 135-150.
Strahler, A.H., C.E. Woodcock and J.A. Smith, 1986. On the nature of models in remote sensing. Remote Sensing of Environment 20: 121-139.
Suryana, N., 1997. A geo-information theoretical approach to inductive erosion modelling based on terrain mapping units. PhD thesis, Wageningen Agricultural University, Wageningen.
Ten Harkel, M.J. and F. van der Meulen, 1996. Impact of grazing and atmospheric nitrogen deposition on the vegetation of dry coastal dune grasslands. Journel of Vegetation Science 7: 445-452.
Tobler, W.R., 1989. Frame independent spatial analysis. Accuracy of Spatial Databases, Goodchild, M., and S. Gopal (eds), Taylor & Francis, London: 115-122.
Ton, J., J. Sticklen and A.K. Jain, 1991. Knowledge-Based Segmentation of Landsat Images. IEEE Transactions on Geoscience and Remote Sensing 29(2): 222-231.
Treitz, P.M., P.J. Howarth, R.C. Suffling and P. Smith, 1992. Application of Detailed Ground Information to Vegetation Mapping with High Spatial Resolution Digital Imagery. Remote Sensing of Environment 42: 65-82.
Turner, M.G., 1987. Spatial simulation of landscape changes in Georgia: A comparison of 3 transition models. Landscape Ecology 1(1): 29-36.
Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns. Landscape Ecology 4(1):21-30.
Turner, M.G. and R.H. Gardner (eds), 1990. Quantitative methods in landscape ecology; the analysis and interpretation of landscape heterogeneity. Springer-Verlag, New York.
Turner, M.G., R.V. O'Neill, R.H. Gardner and B.T. Milne, 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology 3(3,4): 153-162.
Turner, S.J., R.V. O'Neill, W. Conley, M.R. Conley and C. Humphries, 1990. Pattern and Scale: Statistics for Landscape Ecology. Quantitative Methods in Landscape Ecology. M.G. Turner and R.H. Gardner (eds.), Ecological Studies 82: 17,49. Springer-Verlag.
Upton, G.J.G. and B. Fingleton, 1985. Spatial data analysis by example; Vol. 1, Point pattern and quantitative data. John Wiley & Sons, New York.
Urban, D.L., R.V. O'Neill and H.H. Shugart, 1987. Landscape Ecology, A hierarchical perspective can help scientist understand spatial patterns. BioScience 37(2): 119-127.
Usher, M.B., 1981. Modelling ecological succession, with particular reference to Markovian models. Vegetatio 46: 11-18.
Van der Maarel, E., 1981. Fluctuations in coastal dune grassland due to fluctuations in rainfall: experimental evidence. Vegetatio 47: 259-265.
Van der Veen, G.J., 1994. Kennisoverzicht ecohydrology: een inventarisatie van kennis en expertise op het gebied van ecohydrologie en verdroging. Hageman Verpakkers, Zoetermeer.
Van Deursen, W.P.A., 1995. Geographical Information Systems and Dynamic Models; Development and application of a prototype spatial modelling language. PhD thesis, University Utrecht, Utrecht.
Van Dorp, D., R. Boot and E. van der Maarel, 1985. Vegetation succession on the dunes near Oostvoorne, The Netherlands, since 1934, interpreted from air photographs and vegetation maps. Vegetatio 58: 123-136.
Van Leeuwen, C.G. and E. van der Maarel, 1971. Pattern and process in coastal dune vegetations. Acta Botanica Neerlandica 20(1): 191-198.

Van Leeuwen, G., 1966. A relation theoretical approach to pattern and process in vegetation. Wentia 15: 25-46.

Van Leeuwen, H.J.C., 1996. Methodology for combining optical and microwave remote sensing in agricultural crop monitoring; the sugar beet crop as special case. PhD thesis, Wageningen Agricultural University, Wageningen.

Ver Hoef, J.M., D.C. Glenn-Lewin and M.J.A. Werger, 1989. Relationship between horizontal pattern and vertical structure in a chalk grassland. Vegetatio 83: 147-155.

Veregin, H., 1989. Error modeling for the map overlay operation. Accuracy of Spatial Databases, Goodchild, M., and S. Gopal (eds), Taylor & Francis, London: 3-18.

Von Altrock, C., 1991. Über den daumen gepeilt. Fuzzy logic: scharfe theorie der unscharfen mengen. Compute it 3: 188-206.

Wang, F., G.B. Hall and Subaryono, 1990. Fuzzy information and processing in conventional GIS software: database design and application. Int. J. Geographical Information Systems 4(3): 261-283.

Wardley, N.W., E.J. Milton and C.T. Hill, 1987. Remote sensing of structurally complex semi-natural vegetation - an example from heathland. Int. J. Remote Sensing 8(1): 31-42.

Webster, R. and M.A. Oliver, 1990. Statistical methods in soil and land resource survey. Oxford University Press, Oxford.

Welch, R., M. Remillard and J. Alberts, 1992. Integration of GPS, Remote Sensing, and GIS Techniques for Coastal Resource Management. Photogrammetric Engineering & Remote Sensing 58(11): 1571-1578.

Werth, L.F. and E.A. Work, 1992. Applications of Large-Scale Aerial Photography for Rangeland Monitoring. Geocarto International 7(1):11-18.

Westhoff, V. and A.J. den Held, 1969. Plantengemeenschappen in Nederland. Thieme, Zutphen.

Whittaker, R.H., 1967. Gradient analysis of vegetation. Biol. Rev. 42: 207-264.

Wiegleb, G., 1989. Explanation and prediction in vegetation science. Vegetatio 83: 17-34.

Wildi, O., 1988. Linear trend in multi-species time series. Vegetatio 77: 51-56.

Wissel, Ch., 1991. A Model for the Mosaic-Cycle Concept. Ecological Studies 85: 22-45. Springer-Verlag Berlin.

Witte, J.P.M., 1998. National water management and the value of nature. PhD thesis Wageningen Agricultural University.

Wood, T.F. and G.M. Foody, 1989. Analysis and representation of vegetation continua from Landsat Thematic Mapper data for lowland heath. Int. J. Remote Sensing 10(1): 181-191.

Woodcock, C.E., A.H. Strahler and D.L.B. Jupp, 1988. The Use of Variograms in Remote Sensing: I. Real Digital Images. Remote Sensing of Environment 25: 349-379.

Woodcock, C.E. and A.H. Strahler, 1987. The Factor of Scale in Remote Sensing. Remote Sensing of Environment 21: 311-332.

Zimmerman, H.J., 1985. Fuzzy set theory and its applications. Kluwer Academic Publishers Group, Dordrecht.

Zonneveld, I.S., 1989. The land unit - A fundamental concept in landscape ecology, and its applications. Landscape Ecology 3(2): 67-86.

Appendix I. Production of digital orthophoto mosaics

Systematic aerial photo surveys of the test site (sect. 1.5) are performed almost every decade since 1938. In 1979 panchromatic photography was replaced by false-colour photography and the survey interval was reduced to five years. Comparably to true colour film the sensitivity of the dyes in false colour film is shifted from red, green and blue radiation to infra-red, red and green radiation respectively. The photographs taken in the summer of 1990 and 1995 (scale 1:5000) are used for orthophoto production. Photographs are taken from two runs with an in strip forward overlap of 60 percent and 20 percent overlap between the strips. However, the latter overlap varies considerably due to poor navigation.

A typical list of processing steps in the transformation of analogue photographs to digital orthophotos is scanning, radiometric correction, geometric correction and mosaicing (fig. 4.1). Before the photographs are scanned the spatial resolution of the final orthophoto is to be determined. Although the pixel size is primarily suggested by the intentional application of the orthophoto, practical constraints, especially storage capacity and processing facilities, set a practical limit to the minimum pixel size. When choosing an initial pixel size one has to consider that it is easy to resample an image to coarser resolutions, while the reverse operation is usually not possible (Cushnie, 1987; Woodcock and Strahler, 1987). Here an orthophoto is produced with a 0.5 metre resolution, supposing to provide sufficient detail and a manageable data volume.

Scanning

Diapositive film is digitised by measuring the density D in spectral band $\lambda \in$ {infra-red, red, green} on sample location i,j in the photograph:

$$D_{\lambda ij} = -\log(T_{\lambda ij}) \qquad \text{I.1}$$

where T is the fraction of incident light transmitted by the film. The scanner (AGFA-horizon) linearly rescales the density values between 0 and 3 to 8 bit digital numbers (DN). The density is measured on 600 dots per inch (DPI) in photographs with a scale 1:5000 resulting in digital photos with a 0.21 metre resolution (during the geometric correction the image is resampled to a 0.25 metre resolution). Both the geometric and radiometric precision of the scanner amply exceed the precision of the digital photograph.

Radiometric correction

Density variations in a photograph are not solely related to variations in terrain conditions. Factors influencing the density variation having nothing to do with the actual terrain characteristics are termed extraneous effects (Lillesand and Kiefer, 1987). Extraneous effects are of two general types: geometric and atmospheric. The magnitude of geometric factors varies structurally over the image while atmospheric effects are constant throughout the image. Obviously, these effects prevent false colour photographs from an accurate quantitative interpretation (Barnsley, 1984; Wardley et al., 1987).

Clevers and Van Stokkom (1992) present a method to undo false colour photographs from all extraneous effects in order to derive reflectance factors. However, the method requires some information on camera and film characteristics and reference measurements in the field, which are usually not available. For classification purposes relative differences in density, which can be attributed to differences in the terrain, suffice. The latter is achieved by removing geometric deviations in density. Lillesand and Kiefer (1987) enumerate some important geometric effects influencing film density:

- light fall-off caused by a geometrically based decrease in illumination at the film plane with increasing distance from the centre of the photograph.
- differential scattering by the atmosphere.
- non-lambertian reflection by natural objects.
- differential shading caused by relief in the vegetation cover, especially shrubs and trees.

Contrarily to the first two effects which are indifferent to terrain cover, the latter two factors are dependent on the terrain surface characteristics. Consequently, corrected density values D^c are obtained by applying the following model:

$$D^c_{k\lambda ij} = D_{k\lambda ij} . C_{k\lambda ij} \qquad \text{I.2}$$

where C is a correction factor, $k \in \{1,2,...,n\}$ is a land-cover type. The application of the model provides a paradox, because a land cover classification has to be available, while the radiometric correction is performed to be able to classify the land-cover properly. To overcome this dilemma the correction factor is estimated for a single land-cover type (l) with an intermediate response to geometric effects and subsequently applied to all land cover types:

$$D^c_{\lambda ij} = D_{\lambda ij} . C_{l\lambda ij} \qquad \text{I.3}$$

The single correction factor for all geometric effects is calculated as the ratio of the mean density D^m for this class in the image and the density on a specific location in the image:

$$C_{l\lambda ij} = D^m_{l\lambda} / D_{l\lambda ij} \qquad \text{I.4}$$

Due to an intermediate surface roughness compared to mosses and shrubs, herbaceous vegetation is the land cover type with intermediate radiometric deviations and selected to estimate the correction factor (Barnsley, 1984). The herbaceous vegetation was extensively sampled throughout several photographs except for the angular points where vignetting effects occur. The data from different photographs were merged in a single set. The latter set was used to fit a two dimensional second order polynomial function by least square regression:

$$D_{l\lambda}(i,j) = a_{0\lambda} + a_{1\lambda}i + a_{2\lambda}j + a_{3\lambda}i^2 + a_{4\lambda}ij + a_{5\lambda}j^2 \qquad \text{I.5}$$

The result of eq. I.5 is subsequently used to calculate the correction factor in eq. I.4. Due to a lack of reference data no quantitative evaluation of the radiometric accuracy has been performed. However, a visual check of the orthophoto after mosaicing revealed only some minor local deviations at stitches.

Now structural deviations in density values are removed, only local deviation in density values occur caused by variations in illumination due to relief, i.e. slope and orientation (Leprieur et al., 1988). Band ratioing is a simple and frequently used method to reduce shading effects (Holben and Justice, 1981). However, band ratioing reduces the effective number of bands, which can be disadvantageous for its interpretation. Alternatively, radiance modelling can be applied (Ahmad et al., 1992; Justice et al., 1981). The application of this technique is not possible without an accurate digital model of the terrain height. The available height model was not sufficiently accurate. Hence the produced orthophotos show density variations resulting from relief. Because the aerial photographs are always recorded in the mid summer just before noon, these deviations and therefore eventual misinterpretations occur on the same spots.

Geometric correction

The geometric transformation of images with a central projection to orthogonal images is a standard technique nowadays (Grensdoerffer and Bill, 1994). In order to perform this correction the position and orientation of the camera need to be known to re-establish the central projection. Furthermore a digital terrain model is needed to correct the image distortions caused by relief displacement. When both the projection parameters and digital terrain model are available, terrain positions can be calculated from image coordinates.

In practice, the position and orientation of the camera are usually not known and have to be estimated through the analysis of a number of ground control points of which both the image and terrain coordinates are available. At least three ground control points are needed per image, but preferably many more. When it is not possible to gather enough ground control points per image the projection parameters have to be re-established by an aerotriangulation (Philipson, 1997). The latter was the case for the test data.

During the geometric correction the pixels in photo coordinates are resampled to pixels in terrain coordinates with a resolution of 0.25 metre. Cubic convolution was applied as resampling method. Finally, the geometrically rectified images are mosaiced by using the central part of each image resulting in a field S(x,y), where S is a vector of three spectral bands, s_{ir}, s_r and s_g respectively. The geometric accuracy is calculated using 15 ground control points. The RMS-error ranges between 0.31 and 0.39 metre for both years, which is approximately 1.5 times the pixel size.

Appendix II. Aggregation of fuzzy data

The aggregation of fuzzy data is dealt with by Klir and Folger (1988). Consider for example the aggregation of a set of five vectors of membership values I describing the presence of herbaceous structural classes **hs** $\in$ {hs1, hs2,... hs5}(table II.1). First step is the calculation of a *pseudo-frequency* N(**hs**) for each state of the aggregate. Since values of N(**hs**) need not be whole numbers, it is better not to use the term frequency. In order to accomplish that each vector contributes equally to the pseudo-frequencies the membership values of a single vector have to sum to one. If not so, the membership values have to be normalised in this sense. The pseudo-frequency for each state or class is calculated by the formula:

$$N(\mathbf{hs}) = \sum_{i \in I} MV_{\mathbf{hs}}(i) \qquad \text{II.1}$$

where the sum is taken over five membership values. Subsequently, the pseudo-frequencies are used to estimate the value of a fuzzy measure indicating the strength of the relationship between the aggregate and a class. Two fuzzy measures are considered, the possibility ρ and pseudo-probability p respectively. When the pseudo-frequency distribution (N(**hs**) | **hs** $\in$ HS) is normalised a possibility distribution is obtained:

$$\rho(\mathbf{hs}) = \frac{N(\mathbf{hs})}{\max_{\mathbf{z} \in HS} N(\mathbf{z})} \qquad \text{II.2}$$

Alternatively, the pseudo-probability distribution is calculated by dividing a pseudo-frequency by the sum of all pseudo-frequencies:

$$p(\mathbf{hs}) = \frac{N(\mathbf{hs})}{\sum_{\mathbf{z} \in HS} N(\mathbf{z})} \qquad \text{II.3}$$

The relationship between a possibility distribution and probability distribution is that the possibility equals 1 where the probability is at a maximum and the possibility equals 0 where the probability is 0. The sum of the possibility values does not equal 1, unlike the sum of the probability values.

Note that the link between the concept of fuzzy sets and fuzzy measures is effectuated by the pseudo-frequency distribution. Consequently, the choice for one of the fuzzy measures determines how the membership values are interpreted, i.e. a possibilistic or probabilistic context. The choice for one of the two fuzzy measures should be based on the perception of the data.

Table II.1 Aggregation of five vectors of membership values to a pseudo-frequency distribution N(hs), possibility distribution ρ(hs) and pseudo-probability distribution p(hs), where hs indicates a herbaceous structural class.

hs	MV(1)	MV(2)	MV(3)	MV(4)	MV(5)	N(hs)	ρ(hs)	p(hs)
hs_1	0.2	0.0	0.5	0.0	0.0	0.7	0.32	0.14
hs_2	0.8	0.3	0.1	1.0	0.0	2.2	1.00	0.44
hs_3	0.0	0.6	0.4	0.0	0.7	1.7	0.77	0.34
hs_4	0.0	0.1	0.0	0.0	0.3	0.4	0.18	0.08
hs_5	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00

Appendix III. Statistics from fuzzy vegetation data

Section 5.2.2 dealt with the specification of herbaceous structural data to vegetation community data. The relationship between herbaceous structural classes and community types was established by conditional statistics. The relationship between a herbaceous community type **hc** $\in$ HC and a herbaceous structural class **hs** $\in$ HS was established by a conditional probability p(**hc**|**hs**) and a conditional possibility *p*(**hc**|**hs**). This appendix elucidates the calculation of the latter statistics from fuzzy vegetation data.

Conditional probability p(hc|hs)

The conditional (pseudo-)probability p(**hc**|**hs**) is obtained from a *joint pseudo-probability distribution* (p(**hc**,**hs**)|**hc** $\in$ HC, **hs** $\in$ HS) which in turn results from the joint pseudo-frequency distribution (N(**hc**,**hs**)|**hc** $\in$ HC, **hs** $\in$ HS). A pseudo-frequency is obtained by aggregating data on vegetation community classes and herbaceous structural types available on the N locations of the relevees:

$$N(\mathbf{hc},\mathbf{hs}) = \sum_{i=1}^{n} \omega_i \, . \, MV(\mathbf{hc})_i \, . \, p(\mathbf{hs})_i \qquad \text{III.1}$$

where p(**hs**) is the pseudo-probability for a herbaceous structural class (chapt. 3), MV(**hc**) is the membership value for a vegetation class (sect 5.2.1) and ω is a weight for the stratum of relevee i. Next, the pseudo-probability distribution is calculated by dividing a pseudo-frequency by the sum of all pseudo-frequencies:

$$p(\mathbf{hc},\mathbf{hs}) = \frac{N(\mathbf{hc},\mathbf{hs})}{\sum_{hc \in HC} \sum_{hs \in HS} N(hc,hs)} \qquad \text{III.2}$$

Subsequently, conditional pseudo-probabilities are obtained by:

$$p(\mathbf{hc}|\mathbf{hs}) = p(\mathbf{hc},\mathbf{hs}) \, / \, p(\mathbf{hs}) \qquad \text{III.3}$$

where p(**hs**) is the marginal pseudo-probability.

Conditional possibility p(hc|hs)

Alternatively, the relationship between herbaceous structural types and vegetation community classes is estimated within the framework of possibility theory. In the latter approach a conditional possibility $p(\mathbf{hc}|\mathbf{hs})$ is obtained from the *joint possibility distribution* ($p(\mathbf{hc},\mathbf{hs})$ | $\mathbf{hc} \in$ HC, $\mathbf{hs} \in$ HS), which in turn is calculated from the joint pseudo-frequency distribution (N($\mathbf{hc},\mathbf{hs}$) | $\mathbf{hc} \in$ HC, $\mathbf{hs} \in$ HS). A pseudo-frequency is acquired by aggregating data on vegetation communities and herbaceous structural data available on the N locations of the relevees:

$$N(\mathbf{hc},\mathbf{hs}) = \sum_{i=1}^{n} \omega_i \,.\, \mathrm{MIN}\,[\, MV^n(\mathbf{hc})_i, p(\mathbf{hs})_i] \qquad \text{III.4}$$

where the minimum operator is the standard function in possibility theory to perform the combinational AND. $p(\mathbf{hs})$ is the possibility of a herbaceous structural class (chapt. 3), $MV^n(\mathbf{hc})$ is the membership value for a vegetation community class (sect 5.2.1) and ω is the weight for the stratum of relevee i. Because the possibility values for the herbaceous structural classes are normalised it is reasonable to demand that the membership values are normalised too:

$$MV^n(\mathbf{hc}) = \frac{MV(\mathbf{hc})}{\underset{hc \in HC}{\mathrm{MAX}}\ MV(hc)} \qquad \text{III.5}$$

When the joint pseudo-frequency distribution is normalised a possibility distribution is obtained:

$$p(hc,hs) = \frac{N(hc,hs)}{\underset{hc \in HC}{\mathrm{MAX}}\ [\ \underset{hs \in HS}{\mathrm{MAX}}\ N(hc,hs)]} \qquad \text{III.6}$$

Subsequently, conditional possibilities are calculated by (Nguyen, 1978):

$$p(\mathbf{hc}|\mathbf{hs}) = \begin{cases} p(\mathbf{hc},\mathbf{hs}) & \text{if } p(\mathbf{hc}) \leq p(\mathbf{hs}) \\ p(\mathbf{hc},\mathbf{hs})\,.\,p(\mathbf{hc})/p(\mathbf{hs}) & \text{otherwise} \end{cases} \qquad \text{III.7}$$

where $p(\mathbf{hc})$ and $p(\mathbf{hs})$ are marginal possibilities and $p(\mathbf{hc})/p(\mathbf{hs})$ is a normalisation factor.

Appendix IV. Optimising the fuzziness of vegetation types

By fuzzy vegetation classification a relevee j, i.e. a vector of species abundance data $(v_1,v_2,...v_m)_j$ is turned into a vector of membership values $(MV_{hc1},MV_{hc2},...MV_{hcc})_j$, where each membership value indicates the resemblance of the relevee with a vegetation class **hc**. Ideally, this vector of membership values allows for an accurate estimation of the species abundance data from which the membership values were derived. This means that the inverse calculation of species abundance data from membership values should result in a species composition similar to the original abundance data.

This inverse process of fuzzification is called defuzzification and the accuracy of defuzzification is dependant on the degree of fuzziness applied to the community classes. The optimum degree of vagueness, governed by α in eq. 5.3, is somewhere between total fuzziness (α=0) for which the explanatory quality is very low and the crisp case ($\alpha=\infty$) (see fig. 5.2).

Equation 5.3 for fuzzy classification can not be inverted to perform the defuzzification. Therefore Monte Carlo analysis is applied to estimate the explanatory quality of fuzzy classification. The procedure is presented in pseudo code in figure IV.1. Central to the procedure is the simulation of a species composition $(v_1,v_2,...v_m)^{sim}$ and subsequent fuzzy classification of the simulated abundance data $(MV_{hc1},MV_{hc2},...MV_{hcc})^{sim}$.

The simulated vector of membership values is compared with the membership vectors $(MV_{hc1},MV_{hc2},...MV_{hcc})^{r}$ derived from real abundance data in the set of relevees R. If the two vectors of membership values resemble, the difference between the simulated species composition v^{sim} and the relevee data v^{r} indicates the accuracy of the process of defuzzification. After performing a sufficiently large number of simulations the coefficient of determination is calculated from the observed differences quantifying the explanatory power of the fuzzy classification. Tests revealed that a number of 20,000 runs is sufficiently large.

Problem in this approach is the effect of outliers on the estimation accuracy. The simulation of species abundance data might yield outliers, i.e. vegetation compositions that hardly occur in reality. The effect of outliers or extragrades in fuzzy classification has been extensively dealt with by De Gruyter and McBratney (1990). They suggest to reduce the effect of outliers by accommodating them in a special class. The membership value for the outlier class for a particular vegetation composition *v* in vegetation space *V* is calculated as:

$$MV_{outlier} = Nocc / 10 \qquad \text{IV.1}$$
$$= 1 \qquad \text{when } Nocc >= 10$$

where Nocc is the number of relevees in *V* occurring within a specific distance from *v*.

```
/* set the degree of fuzziness
set α

/* fuzzy classification of relevees
DOfor Nrelevees
        take species composition (v1, v2, ...vNsp)^r of relevee r ∈ R
        calculate membership of outlier class Mv^r_outlier
        IF MV^r_outlier < 1
                calculate membership vegetation communities (MVhc1, MVhc2,... MVhcc)^r
                correct for outlier membership (MVhc1, MVhc2,... MVhcc, MVoutlier)^r
                endIF
        endDO

/* Monte Carlo analysis
DOfor Nruns
        /* fuzzy classification of simulated species composition
        simulate species composition (v1, v2, ...vNsp)^sim
        calculate membership of outlier class Mv^sim_outlier
        IF MV^sim_outlier < 1
                calculate membership vegetation communities (MVhc1, MVhc2,... MVhcc)^sim
                correct for outlier membership (MVhc1, MVhc2,... MVhcc, MVoutlier)^sim
                endIF
        /* compare simulated membership values with relevee membership values
        DOfor Nrelevees
                IF all MV^sim_hc > MV^r_hc  hc ∈ HC
                        fuzzy characteristics of simulated species composition and
                                relevee data resemble
                        add simulated abundance (v1, v2, ...vNsp)^sim to statistics
                                for relevee r; (v1, v2, ...vNsp)^r_mean_sim
                        endIF
                endDO
        endDO

/* calculate summary statistic
calculate coefficient of determination from (v1, v2, ...vNsp)^r and (v1, v2, ...vNsp)^r_mean_sim where r ∈ R
```

Figure IV.1 Procedure in pseudo code for the estimation of the explanatory power of fuzzy vegetation classification.

Table IV.1 Membership values obtained by the fuzzy classification of 263 relevees, where the *bold* membership values *indicate* the vegetation community hc assigned to a relevee in a crisp clustering.

Relevee	hc1	hc2	hc3	hc4	hc5	hc6	hc7	hc8	hc9	hc10	hc11	hc12	hc13	hc14	hc15	hc16	hc17
19	**0.14**	0.18	0.02	0.31	0.05	0.05	0.09	0.04	0.02	0.03	0.01	0.02	0.01	0.01	0.02	0.01	0.01
199	**0.83**	0.01	0.00	0.01	0.02	0.02	0.03	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	**0.30**	0.20	0.02	0.06	0.13	0.05	0.03	0.02	0.03	0.03	0.01	0.03	0.01	0.02	0.02	0.02	0.02
103	**0.76**	0.02	0.00	0.02	0.13	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	**0.41**	0.21	0.01	0.11	0.11	0.03	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01
59	**0.95**	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
61	**0.75**	0.04	0.00	0.01	0.04	0.05	0.03	0.04	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
101	**0.98**	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
148	**0.92**	0.02	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
149	**0.98**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
157	**0.97**	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
158	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
163	**0.86**	0.07	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
178	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
181	**0.99**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
183	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
210	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
211	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
218	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
239	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
253	**0.99**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
167	**0.86**	0.07	0.00	0.00	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
200	**0.77**	0.05	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.03	0.01	0.01	0.00	0.01	0.01	0.01	0.01
226	**0.79**	0.04	0.01	0.01	0.03	0.02	0.01	0.01	0.02	0.03	0.00	0.02	0.00	0.01	0.01	0.01	0.00
252	**0.82**	0.06	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.00
245	0.04	**0.02**	0.05	0.01	0.04	0.02	0.02	0.08	0.16	0.25	0.02	0.05	0.01	0.03	0.16	0.04	0.02
51	0.07	**0.43**	0.03	0.20	0.06	0.04	0.02	0.02	0.02	0.02	0.01	0.03	0.01	0.01	0.01	0.01	0.01
12	0.11	**0.54**	0.01	0.05	0.05	0.08	0.02	0.01	0.01	0.01	0.01	0.05	0.01	0.01	0.01	0.01	0.01
32	0.38	**0.27**	0.01	0.02	0.04	0.06	0.02	0.02	0.03	0.03	0.01	0.06	0.01	0.01	0.02	0.01	0.01
36	0.04	**0.71**	0.01	0.07	0.03	0.04	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.01	0.01
54	0.08	**0.67**	0.01	0.04	0.04	0.05	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.01	0.01
28	0.05	**0.85**	0.00	0.03	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
43	0.09	**0.44**	0.02	0.12	0.07	0.08	0.03	0.01	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.01	0.01
44	0.06	**0.52**	0.01	0.04	0.03	0.15	0.02	0.01	0.01	0.01	0.01	0.08	0.01	0.03	0.01	0.01	0.01
53	0.14	**0.49**	0.01	0.06	0.03	0.06	0.02	0.02	0.02	0.03	0.01	0.04	0.01	0.03	0.02	0.01	0.01
52	0.04	**0.38**	0.01	0.37	0.02	0.04	0.04	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
92	0.00	0.00	**0.91**	0.01	0.01	0.00	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.01	0.01	0.01
112	0.01	0.01	**0.85**	0.01	0.02	0.00	0.01	0.01	0.02	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.01
115	0.01	0.01	**0.69**	0.01	0.02	0.00	0.01	0.02	0.06	0.11	0.01	0.01	0.00	0.01	0.02	0.02	0.01
117	0.01	0.01	**0.78**	0.01	0.02	0.01	0.01	0.02	0.03	0.04	0.01	0.01	0.01	0.01	0.02	0.01	0.01
4	0.02	0.03	**0.67**	0.04	0.07	0.02	0.02	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.01	0.01	0.01
5	0.03	0.03	**0.17**	0.04	0.09	0.02	0.04	0.09	0.09	0.11	0.03	0.04	0.02	0.04	0.04	0.10	0.05
8	0.02	0.02	0.02	**0.11**	0.19	0.07	0.27	0.08	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.03	0.04
14	0.01	0.04	0.01	**0.32**	0.10	0.04	0.35	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
25	0.01	0.06	0.01	**0.82**	0.03	0.01	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.11	0.20	0.04	**0.25**	0.12	0.06	0.05	0.02	0.02	0.02	0.01	0.04	0.01	0.01	0.02	0.02	0.02
39	0.01	0.10	0.01	**0.76**	0.03	0.02	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
50	0.03	0.24	0.02	**0.50**	0.04	0.04	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
73	0.01	0.02	0.01	**0.81**	0.03	0.02	0.07	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
79	0.04	0.09	0.02	**0.68**	0.03	0.04	0.05	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
83	0.04	0.17	0.03	**0.52**	0.03	0.04	0.06	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01
87	0.05	0.07	0.02	**0.57**	0.08	0.03	0.10	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
95	0.02	0.04	0.03	**0.34**	0.09	0.05	0.24	0.05	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.03
98	0.03	0.09	0.01	**0.70**	0.04	0.02	0.05	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00
99	0.02	0.03	0.02	**0.12**	0.16	0.05	0.36	0.10	0.02	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.02
114	0.03	0.03	0.08	0.06	**0.21**	0.03	0.05	0.05	0.06	0.08	0.02	0.03	0.02	0.03	0.03	0.11	0.09
3	0.01	0.02	0.12	0.04	**0.60**	0.02	0.03	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.01	0.02	0.02
6	0.01	0.01	0.01	0.03	**0.35**	0.03	0.42	0.09	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
11	0.02	0.02	0.04	0.02	**0.54**	0.02	0.02	0.06	0.06	0.08	0.01	0.02	0.01	0.02	0.02	0.03	0.02
18	0.05	0.12	0.02	0.16	**0.48**	0.03	0.03	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01
58	0.08	0.06	0.01	0.09	**0.33**	0.12	0.09	0.05	0.02	0.02	0.01	0.04	0.02	0.02	0.01	0.01	0.02

65	0.01	0.01	0.04	0.01	**0.68**	0.01	0.02	0.03	0.04	0.06	0.01	0.01	0.00	0.01	0.02	0.03	0.02
75	0.06	0.05	0.02	0.07	**0.12**	0.15	0.10	0.05	0.03	0.03	0.02	0.06	0.04	0.02	0.02	0.03	0.14
88	0.02	0.02	0.03	0.02	**0.47**	0.02	0.02	0.08	0.07	0.09	0.02	0.03	0.01	0.02	0.02	0.04	0.02
89	0.05	0.06	0.01	0.15	**0.57**	0.04	0.06	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
91	0.02	0.02	0.03	0.02	**0.49**	0.02	0.03	0.03	0.05	0.06	0.02	0.03	0.02	0.03	0.02	0.04	0.10
96	0.01	0.01	0.01	0.01	**0.80**	0.01	0.01	0.02	0.02	0.04	0.01	0.01	0.00	0.01	0.01	0.02	0.02
97	0.02	0.02	0.02	0.06	**0.09**	0.16	0.16	0.04	0.02	0.02	0.03	0.06	0.13	0.06	0.01	0.04	0.06
100	0.05	0.07	0.02	0.04	**0.47**	0.08	0.02	0.02	0.02	0.02	0.01	0.07	0.02	0.03	0.01	0.02	0.03
102	0.05	0.02	0.01	0.01	**0.83**	0.01	0.01	0.01	0.01	0.02	0.00	0.01	0.00	0.00	0.01	0.01	0.01
104	0.04	0.02	0.01	0.02	**0.65**	0.09	0.05	0.06	0.01	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.01
105	0.03	0.01	0.01	0.01	**0.85**	0.01	0.01	0.01	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.01
106	0.03	0.02	0.01	0.01	**0.87**	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
109	0.02	0.04	0.03	0.03	**0.41**	0.03	0.03	0.06	0.07	0.08	0.02	0.04	0.02	0.04	0.02	0.04	0.03
147	0.13	0.03	0.01	0.01	**0.72**	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.01	0.00	0.00
161	0.04	0.02	0.01	0.03	**0.50**	0.05	0.16	0.13	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.01
222	0.06	0.04	0.01	0.02	**0.51**	0.03	0.02	0.03	0.05	0.05	0.03	0.09	0.01	0.02	0.02	0.01	0.01
230	0.01	0.02	0.00	0.02	**0.16**	0.20	0.43	0.05	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.00	0.00
231	0.09	0.08	0.01	0.08	**0.36**	0.07	0.17	0.04	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01
232	0.02	0.02	0.01	0.02	**0.13**	0.22	0.14	0.05	0.01	0.02	0.03	0.08	0.07	0.16	0.01	0.01	0.01
23	0.01	0.01	0.01	0.02	0.05	**0.20**	0.14	0.04	0.01	0.02	0.02	0.29	0.06	0.07	0.01	0.02	0.03
37	0.05	0.36	0.01	0.09	0.07	**0.13**	0.06	0.04	0.01	0.02	0.01	0.08	0.02	0.02	0.02	0.01	0.01
38	0.04	0.24	0.01	0.05	0.04	**0.29**	0.03	0.02	0.01	0.02	0.01	0.15	0.02	0.03	0.02	0.01	0.02
40	0.04	0.06	0.01	0.11	0.05	**0.35**	0.18	0.04	0.01	0.02	0.02	0.04	0.03	0.03	0.01	0.01	0.01
56	0.05	0.03	0.01	0.02	0.03	**0.42**	0.08	0.06	0.02	0.02	0.02	0.09	0.04	0.06	0.01	0.02	0.03
57	0.01	0.02	0.00	0.01	0.02	**0.77**	0.05	0.01	0.00	0.00	0.00	0.06	0.02	0.01	0.00	0.00	0.01
69	0.02	0.04	0.00	0.01	0.01	**0.79**	0.02	0.01	0.00	0.00	0.00	0.05	0.01	0.01	0.00	0.00	0.00
77	0.03	0.14	0.01	0.02	0.02	**0.55**	0.02	0.01	0.01	0.01	0.01	0.12	0.02	0.02	0.01	0.01	0.01
78	0.01	0.01	0.00	0.00	0.01	**0.86**	0.01	0.00	0.00	0.00	0.00	0.08	0.01	0.01	0.00	0.00	0.00
84	0.02	0.15	0.01	0.05	0.03	**0.58**	0.03	0.01	0.01	0.01	0.01	0.06	0.02	0.02	0.01	0.01	0.01
86	0.02	0.02	0.00	0.01	0.02	**0.85**	0.02	0.01	0.00	0.00	0.00	0.04	0.01	0.01	0.00	0.00	0.00
160	0.03	0.04	0.01	0.04	0.15	**0.37**	0.20	0.06	0.01	0.02	0.01	0.04	0.01	0.01	0.01	0.01	0.01
215	0.02	0.04	0.02	0.04	0.06	**0.31**	0.16	0.07	0.03	0.03	0.03	0.06	0.04	0.05	0.02	0.02	0.02
216	0.03	0.03	0.02	0.02	0.04	**0.31**	0.08	0.10	0.04	0.06	0.03	0.08	0.03	0.04	0.03	0.03	0.05
229	0.02	0.03	0.01	0.03	0.10	**0.36**	0.16	0.03	0.02	0.02	0.02	0.06	0.04	0.07	0.01	0.01	0.01
135	0.04	0.11	0.04	0.07	0.10	**0.09**	0.05	0.04	0.05	0.06	0.03	0.10	0.03	0.05	0.04	0.05	0.04
1	0.02	0.04	0.02	0.32	0.04	0.03	**0.35**	0.06	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01
9	0.02	0.02	0.02	0.18	0.05	0.04	**0.49**	0.06	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01
10	0.00	0.01	0.00	0.03	0.02	0.01	**0.86**	0.04	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21	0.01	0.02	0.01	0.10	0.10	0.03	**0.60**	0.07	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
22	0.03	0.07	0.10	0.16	0.06	0.06	**0.32**	0.05	0.02	0.02	0.01	0.03	0.01	0.01	0.02	0.02	0.01
35	0.01	0.01	0.01	0.02	0.02	0.17	**0.26**	0.08	0.02	0.03	0.04	0.07	0.08	0.08	0.02	0.03	0.05
46	0.01	0.02	0.00	0.02	0.03	0.21	**0.49**	0.05	0.01	0.01	0.01	0.07	0.04	0.03	0.01	0.00	0.01
47	0.02	0.05	0.02	0.27	0.06	0.06	**0.31**	0.07	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.02
60	0.01	0.01	0.01	0.07	0.04	0.04	**0.66**	0.09	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
66	0.01	0.03	0.04	0.26	0.03	0.02	**0.41**	0.10	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01
71	0.01	0.01	0.01	0.01	0.02	0.11	**0.39**	0.14	0.02	0.03	0.04	0.04	0.06	0.06	0.01	0.02	0.03
85	0.02	0.02	0.01	0.14	0.07	0.05	**0.51**	0.08	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01
94	0.01	0.01	0.01	0.02	0.02	0.02	**0.55**	0.26	0.02	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01
150	0.01	0.01	0.00	0.01	0.04	0.07	**0.59**	0.14	0.01	0.02	0.02	0.04	0.02	0.02	0.01	0.00	0.00
151	0.01	0.01	0.01	0.01	0.03	0.04	**0.42**	0.17	0.04	0.04	0.15	0.03	0.02	0.01	0.01	0.01	0.01
166	0.03	0.04	0.02	0.14	0.04	0.05	**0.43**	0.10	0.02	0.03	0.01	0.02	0.01	0.01	0.02	0.02	0.02
170	0.01	0.01	0.00	0.02	0.03	0.05	**0.80**	0.05	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
177	0.01	0.01	0.00	0.03	0.05	0.06	**0.76**	0.04	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00
179	0.01	0.01	0.01	0.06	0.03	0.02	**0.80**	0.05	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
198	0.01	0.00	0.00	0.01	0.03	0.04	**0.78**	0.08	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
236	0.01	0.00	0.00	0.00	0.00	0.00	0.02	**0.95**	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
243	0.01	0.00	0.00	0.01	0.02	0.02	0.35	**0.51**	0.01	0.01	0.01	0.01	0.01	0.00	0.02	0.00	0.00
254	0.01	0.01	0.01	0.01	0.03	0.20	0.32	**0.06**	0.01	0.02	0.03	0.06	0.07	0.14	0.01	0.01	0.01
257	0.00	0.00	0.00	0.00	0.00	0.00	0.02	**0.97**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
110	0.01	0.01	0.02	0.01	0.04	0.01	0.06	**0.73**	0.03	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01
111	0.02	0.01	0.03	0.04	0.09	0.03	0.13	**0.49**	0.03	0.04	0.01	0.02	0.01	0.01	0.01	0.01	0.01
173	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.99**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
203	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.97**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
206	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
221	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.94**	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
223	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.96**	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
234	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.99**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
235	0.00	0.00	0.00	0.00	0.00	0.00	0.02	**0.95**	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
260	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

55	0.03	0.02	0.07	0.02	0.06	0.02	0.03	**0.05**	0.10	0.17	0.03	0.02	0.01	0.03	0.05	0.24	0.06
136	0.03	0.02	0.05	0.01	0.05	0.02	0.02	**0.15**	0.19	0.24	0.03	0.04	0.01	0.03	0.05	0.05	0.03
138	0.03	0.03	0.04	0.04	0.15	0.05	0.12	**0.26**	0.06	0.07	0.02	0.03	0.02	0.02	0.03	0.02	0.02
107	0.02	0.02	0.03	0.02	0.06	0.02	0.05	**0.42**	0.09	0.11	0.02	0.03	0.01	0.02	0.03	0.03	0.02
171	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.07	**0.24**	0.64	0.00	0.00	0.00	0.00	0.01	0.01	0.00
172	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	**0.17**	0.78	0.00	0.00	0.00	0.00	0.01	0.00	0.00
233	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.77	**0.06**	0.11	0.00	0.00	0.00	0.00	0.02	0.00	0.00
224	0.04	0.02	0.04	0.02	0.05	0.03	0.07	0.16	**0.13**	0.20	0.04	0.03	0.02	0.03	0.06	0.05	0.03
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.57**	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00
45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.73**	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00
68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.40**	0.56	0.00	0.00	0.00	0.00	0.01	0.00	0.00
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.83**	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
139	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.74**	0.21	0.04	0.00	0.00	0.00	0.00	0.00	0.00
140	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.98**	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
145	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.50**	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00
152	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.61**	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00
159	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.70**	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00
164	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.92**	0.07	0.01	0.00	0.00	0.00	0.00	0.00	0.00
174	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.99**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
176	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.95**	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
213	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.98**	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
228	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.88**	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00
242	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.90**	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00
186	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	**0.85**	0.00	0.00	0.00	0.00	0.01	0.00	0.00
193	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	**0.89**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
195	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	**0.97**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
201	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	**0.96**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
202	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	**0.89**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
248	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	**0.95**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
249	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	**0.98**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
255	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	**0.92**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
256	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	**0.94**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
128	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.07	0.06	**0.72**	0.01	0.04	0.01	0.01	0.02	0.01
146	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.02	0.27	0.12	**0.38**	0.02	0.03	0.04	0.02	0.02	0.02
175	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	0.09	**0.06**	0.00	0.00	0.00	0.00	0.00	0.00
187	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.71	0.24	**0.02**	0.01	0.00	0.00	0.01	0.00	0.00
121	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.03	0.02	**0.86**	0.01	0.01	0.01	0.00	0.00	0.00
122	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	**0.94**	0.00	0.01	0.01	0.00	0.00	0.00
124	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	**0.85**	0.01	0.04	0.02	0.01	0.01	0.00
125	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	**0.94**	0.01	0.01	0.01	0.00	0.00	0.00
130	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03	**0.58**	0.02	0.16	0.14	0.01	0.01	0.00
132	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.17	0.06	**0.71**	0.01	0.01	0.01	0.01	0.01	0.00
191	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	**0.93**	0.00	0.01	0.01	0.00	0.00	0.00
192	0.01	0.01	0.01	0.01	0.01	0.03	0.05	0.04	0.03	0.04	**0.62**	0.03	0.03	0.08	0.01	0.01	0.01
214	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.04	0.02	0.03	**0.80**	0.01	0.01	0.02	0.01	0.00	0.00
188	0.01	0.00	0.01	0.00	0.02	0.01	0.05	0.32	0.07	0.14	0.01	**0.01**	0.00	0.01	0.33	0.01	0.01
15	0.02	0.02	0.01	0.01	0.02	0.06	0.01	0.01	0.03	0.02	0.03	**0.48**	0.07	0.09	0.02	0.04	0.06
17	0.02	0.03	0.01	0.01	0.02	0.07	0.01	0.01	0.01	0.01	0.01	**0.65**	0.05	0.06	0.01	0.01	0.02
26	0.08	0.04	0.01	0.01	0.04	0.08	0.01	0.02	0.04	0.03	0.02	**0.46**	0.04	0.08	0.02	0.01	0.02
42	0.02	0.03	0.01	0.01	0.03	0.08	0.01	0.02	0.02	0.02	0.02	**0.58**	0.04	0.11	0.01	0.01	0.01
49	0.03	0.06	0.02	0.02	0.04	0.11	0.03	0.03	0.03	0.03	0.02	**0.38**	0.04	0.08	0.03	0.02	0.03
76	0.00	0.01	0.00	0.00	0.02	0.05	0.01	0.01	0.01	0.01	0.01	**0.65**	0.10	0.06	0.01	0.01	0.05
82	0.05	0.07	0.02	0.02	0.05	0.17	0.02	0.02	0.02	0.03	0.02	**0.22**	0.08	0.11	0.02	0.04	0.05
134	0.01	0.01	0.01	0.01	0.04	0.03	0.01	0.01	0.04	0.03	0.15	**0.21**	0.24	0.13	0.01	0.03	0.05
24	0.01	0.02	0.01	0.01	0.05	0.16	0.02	0.01	0.01	0.02	0.01	**0.51**	0.04	0.08	0.01	0.02	0.02
30	0.03	0.04	0.01	0.01	0.02	0.07	0.01	0.01	0.02	0.02	0.01	**0.63**	0.03	0.06	0.01	0.01	0.01
48	0.01	0.02	0.02	0.01	0.03	0.03	0.02	0.03	0.04	0.05	0.03	**0.31**	0.12	0.13	0.12	0.03	0.02
62	0.01	0.01	0.01	0.01	0.02	0.08	0.07	0.07	0.02	0.03	0.02	**0.51**	0.03	0.11	0.02	0.01	0.01
72	0.01	0.01	0.00	0.00	0.01	0.39	0.02	0.01	0.01	0.01	0.01	**0.43**	0.04	0.04	0.01	0.01	0.01
182	0.01	0.01	0.01	0.00	0.02	0.03	0.01	0.02	0.03	0.04	0.03	**0.26**	0.05	0.24	0.19	0.03	0.03
189	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.02	0.08	0.08	0.34	**0.18**	0.03	0.16	0.03	0.01	0.01
212	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**0.66**	0.02	0.22	0.01	0.01	0.00
217	0.01	0.01	0.01	0.01	0.04	0.06	0.10	0.12	0.05	0.04	0.30	**0.06**	0.07	0.10	0.01	0.01	0.01
143	0.03	0.02	0.03	0.01	0.04	0.02	0.03	0.04	0.16	0.28	0.04	0.09	**0.04**	0.05	0.05	0.04	0.03
13	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.02	0.02	0.03	0.14	**0.53**	0.07	0.02	0.03	0.05
41	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	**0.88**	0.02	0.00	0.00	0.01
74	0.00	0.00	0.00	0.00	0.01	0.03	0.03	0.02	0.01	0.01	0.03	0.03	**0.74**	0.06	0.01	0.01	0.01
81	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.04	0.02	**0.84**	0.03	0.00	0.00	0.01
126	0.00	0.01	0.00	0.00	0.01	0.03	0.02	0.01	0.01	0.01	0.05	0.06	**0.68**	0.09	0.01	0.01	0.01

127	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.03	0.13	**0.67**	0.09	0.01	0.01	0.01
129	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.03	0.03	**0.79**	0.08	0.00	0.01	0.02
34	0.01	0.02	0.01	0.01	0.03	0.19	0.05	0.02	0.02	0.02	0.04	0.14	0.12	**0.24**	0.05	0.02	0.02
67	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.04	0.05	0.05	0.08	0.11	**0.45**	0.03	0.08	0.02
142	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.02	0.04	0.06	0.03	0.19	0.03	**0.50**	0.03	0.03	0.01
154	0.01	0.01	0.01	0.01	0.01	0.04	0.01	0.01	0.02	0.03	0.02	0.29	0.03	**0.43**	0.02	0.03	0.02
155	0.00	0.01	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.09	0.03	**0.76**	0.01	0.01	0.01
162	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.26	0.04	**0.63**	0.01	0.01	0.00
165	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.09	0.02	**0.85**	0.00	0.00	0.00
168	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.02	0.02	0.02	0.06	0.03	**0.77**	0.01	0.02	0.02
169	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.23	0.01	**0.69**	0.01	0.01	0.00
180	0.01	0.02	0.01	0.01	0.03	0.16	0.01	0.02	0.02	0.03	0.02	0.26	0.06	**0.29**	0.02	0.02	0.02
185	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.05	0.02	0.02	**0.88**	0.00	0.00	0.00
194	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	**0.95**	0.00	0.00	0.00
204	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.03	0.01	**0.88**	0.01	0.03	0.01
205	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	**0.94**	0.00	0.00	0.00
207	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.02	0.01	**0.90**	0.00	0.01	0.00
208	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.04	0.04	**0.78**	0.01	0.01	0.01
227	0.01	0.02	0.01	0.01	0.03	0.06	0.01	0.01	0.01	0.02	0.02	0.33	0.04	**0.41**	0.01	0.01	0.01
237	0.01	0.01	0.01	0.00	0.01	0.04	0.01	0.01	0.02	0.02	0.02	0.39	0.04	**0.38**	0.04	0.01	0.01
238	0.01	0.01	0.01	0.00	0.02	0.03	0.01	0.01	0.01	0.02	0.04	0.28	0.06	**0.46**	0.04	0.01	0.01
241	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.99**	0.00	0.00	0.00
244	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.02	0.17	0.02	**0.73**	0.01	0.01	0.00
246	0.01	0.01	0.01	0.01	0.03	0.17	0.13	0.04	0.01	0.01	0.03	0.16	0.12	**0.24**	0.01	0.01	0.01
247	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	**0.96**	0.00	0.00	0.00
250	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	**0.97**	0.00	0.00	0.00
251	0.01	0.01	0.00	0.01	0.02	0.13	0.10	0.03	0.01	0.02	0.03	0.08	0.10	**0.45**	0.01	0.01	0.01
262	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.03	**0.87**	0.01	0.01	0.00
258	0.02	0.02	0.02	0.01	0.04	0.02	0.02	0.04	0.08	0.11	0.03	0.11	0.04	**0.35**	0.04	0.06	0.02
259	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.02	0.03	0.02	0.11	0.03	**0.66**	0.02	0.02	0.01
131	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.03	0.02	0.11	0.08	0.26	**0.41**	0.01	0.01	0.01
153	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.03	0.03	0.04	0.04	0.05	**0.74**	0.01	0.02	0.01
196	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.05	0.45	0.03	0.03	**0.36**	0.01	0.01	0.00
197	0.01	0.01	0.01	0.01	0.02	0.06	0.06	0.05	0.03	0.04	0.08	0.07	0.08	**0.40**	0.02	0.04	0.02
263	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.05	0.07	0.04	0.07	0.07	**0.45**	0.02	0.09	0.08
141	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.01	0.05	0.05	0.07	0.05	0.13	**0.50**	0.02	0.05	0.02
144	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.03	0.08	0.08	0.10	0.09	0.06	**0.44**	0.03	0.03	0.01
209	0.01	0.01	0.01	0.01	0.04	0.02	0.01	0.02	0.05	0.08	0.15	0.07	0.11	**0.34**	0.02	0.03	0.02
184	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00
225	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.15	0.02	0.17	**0.56**	0.01	0.01
240	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.98**	0.00	0.00
190	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	**0.99**	0.00	0.00
219	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.04	0.05	0.09	0.00	0.00	0.00	0.00	**0.78**	0.00	0.00
220	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	**0.96**	0.00	0.00
113	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.05	0.08	0.01	0.02	0.01	0.02	0.02	**0.57**	0.10
118	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	**0.83**	0.05
120	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.02	0.03	0.04	0.01	0.01	0.01	0.02	0.01	**0.68**	0.11
137	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.03	0.04	0.02	0.02	0.02	0.02	0.02	**0.67**	0.09
108	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.03	0.04	0.01	0.02	0.01	0.02	0.02	**0.66**	0.09
116	0.01	0.01	0.02	0.01	0.03	0.01	0.02	0.03	0.05	0.09	0.02	0.04	0.02	0.09	0.03	**0.49**	0.04
93	0.01	0.00	0.01	0.00	0.02	0.01	0.01	0.01	0.02	0.03	0.01	0.02	0.01	0.03	0.01	**0.70**	0.10
123	0.01	0.01	0.01	0.01	0.03	0.07	0.04	0.03	0.02	0.02	0.04	0.07	0.40	0.11	0.01	**0.07**	0.06
261	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.02	0.05	0.08	0.04	0.05	0.05	0.29	0.03	**0.28**	0.05
80	0.02	0.01	0.03	0.01	0.04	0.02	0.02	0.02	0.04	0.05	0.02	0.03	0.02	0.03	0.02	**0.36**	0.29
20	0.01	0.01	0.02	0.01	0.03	0.03	0.01	0.02	0.04	0.05	0.03	0.10	0.05	0.07	0.02	**0.13**	0.38
64	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.02	0.00	0.01	0.00	0.01	0.01	0.03	**0.90**
90	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.21	**0.66**
119	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.03	0.05	0.01	0.02	0.01	0.01	0.02	0.14	**0.61**
2	0.01	0.01	0.01	0.01	0.04	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.19	**0.63**
7	0.01	0.01	0.01	0.01	0.04	0.04	0.03	0.02	0.01	0.01	0.01	0.05	0.02	0.01	0.01	0.03	**0.69**
70	0.01	0.01	0.01	0.01	0.03	0.05	0.05	0.03	0.01	0.02	0.01	0.03	0.04	0.03	0.01	0.04	**0.62**
63	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.07	**0.80**
133	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.04	0.05	0.03	0.03	0.08	0.03	0.02	0.15	**0.50**
156	0.02	0.01	0.03	0.01	0.04	0.01	0.02	0.04	0.15	0.15	0.03	0.03	0.02	0.04	0.03	0.09	**0.28**

Appendix V. Fuzzy decision rules for nutrient availability

Table V.1 Listing of the fuzzy relation R^{NA} (Chapter 6). The fuzzy relation contains the set of decision rules for the inference of the nutrient availability *given specific abiotic site conditions and specific* vegetation structure. The mean membership value MV^m and the standard deviation MV^s are calculated from the estimations made by 6 experts.

soil characteristics				vegetation structure					
moisture	*acidity*	*organic matter*	*nutrient availability*	*grassland*		*mowed grassland*		*shrubland*	
				MVm	MVs	MVm	MVs	MVm	MVs
dry	acid	sandy	very oligotrophic	73	31	73	31	98	31
dry	acid	sandy	oligotrophic	25	28	25	28	2	4
dry	acid	sandy	mesotrophic	2	4	2	4	0	0
dry	acid	sandy	eutrophic	0	0	0	0	0	0
dry	acid	sandy	hypertrophic	0	0	0	0	0	0
dry	acid	humus	very oligotrophic	0	0	8	9	52	39
dry	acid	humus	oligotrophic	32	44	44	23	48	29
dry	acid	humus	mesotrophic	44	37	48	29	0	0
dry	acid	humus	eutrophic	24	25	0	0	0	0
dry	acid	humus	hypertrophic	0	0	0	0	0	0
dry	acid	very humus	very oligotrophic	2	4	22	31	58	31
dry	acid	very humus	oligotrophic	40	44	37	34	17	10
dry	acid	very humus	mesotrophic	8	10	17	10	23	37
dry	acid	very humus	eutrophic	22	40	23	37	2	4
dry	acid	very humus	hypertrophic	12	29	2	4	0	0
dry	neutral	sandy	very oligotrophic	17	5	17	5	83	9
dry	neutral	sandy	oligotrophic	67	12	67	12	17	10
dry	neutral	sandy	mesotrophic	17	10	17	10	0	0
dry	neutral	sandy	eutrophic	0	0	0	0	0	0
dry	neutral	sandy	hypertrophic	0	0	0	0	0	0
dry	neutral	humus	very oligotrophic	0	0	12	29	27	20
dry	neutral	humus	oligotrophic	5	8	15	12	60	33
dry	neutral	humus	mesotrophic	52	35	60	33	13	12
dry	neutral	humus	eutrophic	22	19	13	12	0	0
dry	neutral	humus	hypertrophic	5	12	0	0	0	0
dry	neutral	very humus	very oligotrophic	0	0	10	25	23	17
dry	neutral	very humus	oligotrophic	12	20	13	10	38	29
dry	neutral	very humus	mesotrophic	35	40	38	29	32	33
dry	neutral	very humus	eutrophic	18	27	32	33	7	12
dry	neutral	very humus	hypertrophic	18	33	7	12	0	0
dry	alkaline	sandy	very oligotrophic	5	8	5	8	60	16
dry	alkaline	sandy	oligotrophic	55	24	55	24	37	21
dry	alkaline	sandy	mesotrophic	37	21	37	21	3	8
dry	alkaline	sandy	eutrophic	3	8	3	8	0	0
dry	alkaline	sandy	hypertrophic	0	0	0	0	0	0
dry	alkaline	humus	very oligotrophic	0	0	0	0	7	16
dry	alkaline	humus	oligotrophic	3	8	7	16	62	10
dry	alkaline	humus	mesotrophic	30	30	62	10	32	18
dry	alkaline	humus	eutrophic	43	29	32	18	0	0
dry	alkaline	humus	hypertrophic	7	16	0	0	0	0
dry	alkaline	very humus	very oligotrophic	0	0	0	0	0	0
dry	alkaline	very humus	oligotrophic	0	0	0	0	37	32

dry	alkaline	very humus	mesotrophic	33	38	37	32	47	16
dry	alkaline	very humus	eutrophic	20	19	47	16	17	27
dry	alkaline	very humus	hypertrophic	30	47	17	27	0	0
moist	acid	sandy	very oligotrophic	43	33	43	33	92	30
moist	acid	sandy	oligotrophic	48	27	48	27	8	13
moist	acid	sandy	mesotrophic	8	13	8	13	0	0
moist	acid	sandy	eutrophic	0	0	0	0	0	0
moist	acid	sandy	hypertrophic	0	0	0	0	0	0
moist	acid	humus	very oligotrophic	0	0	8	13	47	20
moist	acid	humus	oligotrophic	37	41	38	26	45	32
moist	acid	humus	mesotrophic	28	20	45	32	8	13
moist	acid	humus	eutrophic	13	21	8	13	0	0
moist	acid	humus	hypertrophic	5	12	0	0	0	0
moist	acid	very humus	very oligotrophic	0	0	5	8	38	23
moist	acid	very humus	oligotrophic	28	31	33	37	32	32
moist	acid	very humus	mesotrophic	22	24	32	32	22	33
moist	acid	very humus	eutrophic	15	25	22	33	8	13
moist	acid	very humus	hypertrophic	18	30	8	13	0	0
moist	neutral	sandy	very oligotrophic	0	0	3	8	52	18
moist	neutral	sandy	oligotrophic	48	27	48	27	45	24
moist	neutral	sandy	mesotrophic	45	24	45	24	3	8
moist	neutral	sandy	eutrophic	3	8	3	8	0	0
moist	neutral	sandy	hypertrophic	0	0	0	0	0	0
moist	neutral	humus	very oligotrophic	0	0	0	0	3	8
moist	neutral	humus	oligotrophic	0	0	3	8	63	8
moist	neutral	humus	mesotrophic	37	30	63	8	33	10
moist	neutral	humus	eutrophic	40	23	33	10	0	0
moist	neutral	humus	hypertrophic	7	16	0	0	0	0
moist	neutral	very humus	very oligotrophic	0	0	0	0	12	20
moist	neutral	very humus	oligotrophic	3	8	12	20	33	27
moist	neutral	very humus	mesotrophic	28	34	33	27	37	24
moist	neutral	very humus	eutrophic	20	27	37	24	18	30
moist	neutral	very humus	hypertrophic	32	49	18	30	0	0
moist	alkaline	sandy	very oligotrophic	2	4	2	4	45	17
moist	alkaline	sandy	oligotrophic	43	29	43	29	47	22
moist	alkaline	sandy	mesotrophic	47	22	47	22	8	13
moist	alkaline	sandy	eutrophic	8	13	8	13	0	0
moist	alkaline	sandy	hypertrophic	0	0	0	0	0	0
moist	alkaline	humus	very oligotrophic	0	0	0	0	0	0
moist	alkaline	humus	oligotrophic	0	0	0	0	50	27
moist	alkaline	humus	mesotrophic	25	25	50	27	50	27
moist	alkaline	humus	eutrophic	48	30	50	27	0	0
moist	alkaline	humus	hypertrophic	10	25	0	0	0	0
moist	alkaline	very humus	very oligotrophic	0	0	0	0	0	0
moist	alkaline	very humus	oligotrophic	0	0	0	0	23	30
moist	alkaline	very humus	mesotrophic	27	35	23	30	50	25
moist	alkaline	very humus	eutrophic	23	32	50	25	27	35
moist	alkaline	very humus	hypertrophic	33	52	27	35	0	0
wet	acid	sandy	very oligotrophic	60	29	60	29	100	29
wet	acid	sandy	oligotrophic	40	29	40	29	0	0
wet	acid	sandy	mesotrophic	0	0	0	0	0	0
wet	acid	sandy	eutrophic	0	0	0	0	0	0
wet	acid	sandy	hypertrophic	0	0	0	0	0	0
wet	acid	humus	very oligotrophic	0	0	12	20	68	17
wet	acid	humus	oligotrophic	7	16	57	14	32	22
wet	acid	humus	mesotrophic	57	32	32	22	0	0
wet	acid	humus	eutrophic	20	22	0	0	0	0
wet	acid	humus	hypertrophic	0	0	0	0	0	0
wet	acid	very humus	very oligotrophic	0	0	8	13	55	22
wet	acid	very humus	oligotrophic	27	41	47	31	35	28
wet	acid	very humus	mesotrophic	32	38	35	28	10	25
wet	acid	very humus	eutrophic	15	24	10	25	0	0
wet	acid	very humus	hypertrophic	10	25	0	0	0	0
wet	neutral	sandy	very oligotrophic	13	15	13	15	70	20
wet	neutral	sandy	oligotrophic	57	24	57	24	28	28
wet	neutral	sandy	mesotrophic	28	28	28	28	2	4
wet	neutral	sandy	eutrophic	2	4	2	4	0	0
wet	neutral	sandy	hypertrophic	0	0	0	0	0	0
wet	neutral	humus	very oligotrophic	0	0	0	0	12	8

wet	neutral	humus	oligotrophic	2	4	12	8	72	13
wet	neutral	humus	mesotrophic	55	40	72	13	17	14
wet	neutral	humus	eutrophic	22	22	17	14	0	0
wet	neutral	humus	hypertrophic	5	12	0	0	0	0
wet	neutral	very humus	very oligotrophic	0	0	0	0	10	11
wet	neutral	very humus	oligotrophic	7	10	10	11	62	27
wet	neutral	very humus	mesotrophic	40	34	62	27	23	20
wet	neutral	very humus	eutrophic	22	24	23	20	5	12
wet	neutral	very humus	hypertrophic	15	37	5	12	0	0
wet	alkaline	sandy	very oligotrophic	5	8	5	8	57	18
wet	alkaline	sandy	oligotrophic	52	27	52	27	40	30
wet	alkaline	sandy	mesotrophic	40	30	40	30	3	8
wet	alkaline	sandy	eutrophic	3	8	3	8	0	0
wet	alkaline	sandy	hypertrophic	0	0	0	0	0	0
wet	alkaline	humus	very oligotrophic	0	0	0	0	2	4
wet	alkaline	humus	oligotrophic	0	0	2	4	57	25
wet	alkaline	humus	mesotrophic	33	28	57	25	42	28
wet	alkaline	humus	eutrophic	43	24	42	28	0	0
wet	alkaline	humus	hypertrophic	7	16	0	0	0	0
wet	alkaline	very humus	very oligotrophic	0	0	0	0	0	0
wet	alkaline	very humus	oligotrophic	0	0	0	0	45	30
wet	alkaline	very humus	mesotrophic	8	10	45	30	48	21
wet	alkaline	very humus	eutrophic	57	45	48	21	7	16
wet	alkaline	very humus	hypertrophic	18	40	7	16	0	0

Curriculum vitae

Willem Jozef Droesen was born on 6^{th} May 1962 in Tilburg, the Netherlands. After finishing his Gymnasium at the St. Ursula College in Horn in 1980, he started his studies land and water management at the Wageningen Agricultural University (WAU) in the same year. In 1987 he graduated from this university, majoring in the application of remote sensing and GI systems in agrohydrology. During his studies, he spent six months in Nepal investigating soil erosion processes. From the end of 1987 till mid 1989, he fulfilled his social service which involved being seconded to the Remote Sensing Department of the Winand Staring Centre in Wageningen. Following this he worked for six months as researcher at the Department of Land Surveying and Remote Sensing of the WAU. In the spring of 1990, he started a PhD research at the Department of Physical Geography of the University of Amsterdam and the Department of Land Surveying and Remote Sensing of the WAU, researching a monitoring system for dry and wet systems in the Amsterdam Waterworks Dunes, of which this thesis is the result. In the summer of 1995, he joined Grontmij Geogroep bv in Roosendaal. On behalf of Grontmij Geogroep he advises organisations in the private and public sector regarding geo-information issues.

1990

1995

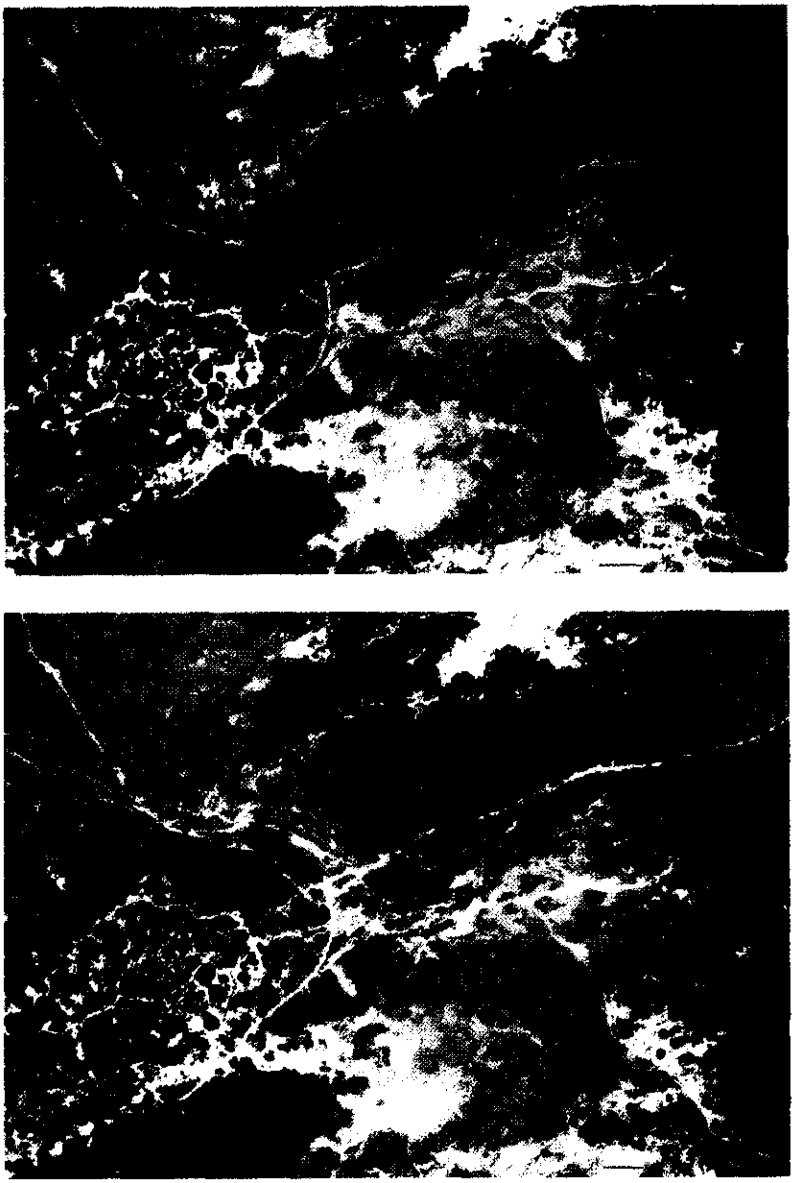
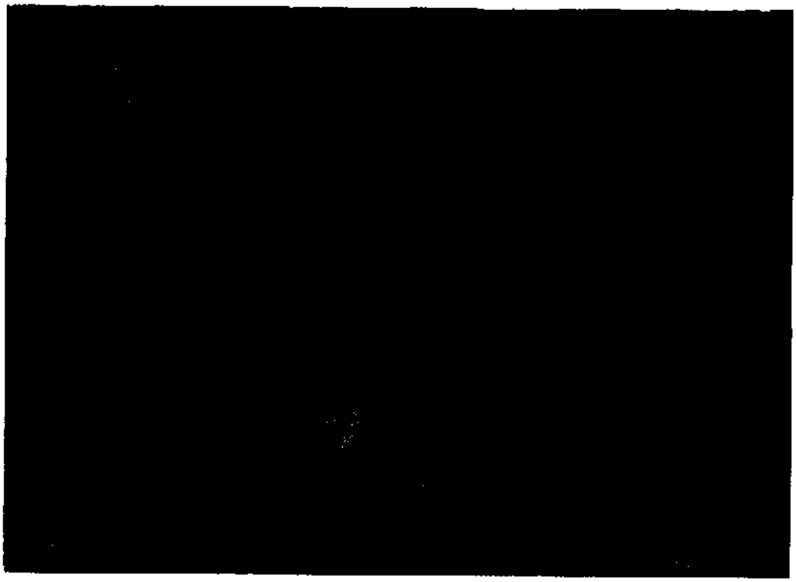


Plate 1 Colour infrared orthophotos of a subarea of the test site in 1990 and 1995 (scale 1:4000).

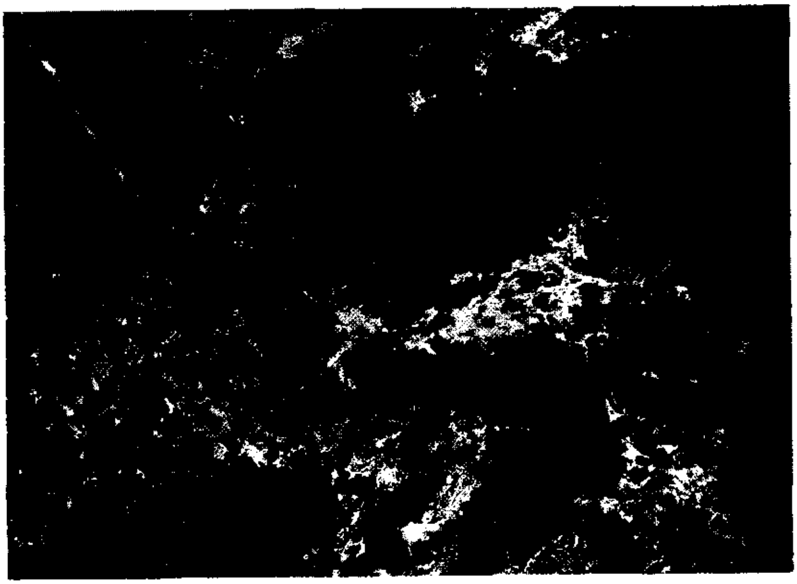
1990



1995

Plate 1 Elementery vegetation structural objects with the nested field of grassland subtype hs1 ´Thin herb/grass cover with blond sand´ in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

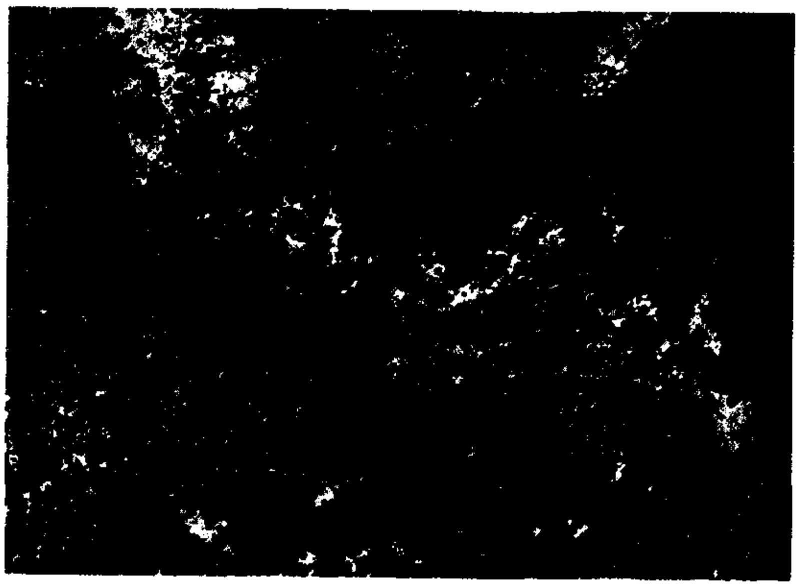
1990



1995

Plate 1 **Elementery vegetation structural objects with the nested field of grassland subtype hs2 'Intermediate herb/moss cover with grey sand' in the test site in 1990 and 1995 (legend on page 155).**

1990



1995

Plate 1 Elementery vegetation structural objects with the nested field of grassland subtype hs3 'High moss cover' in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

1990

1995

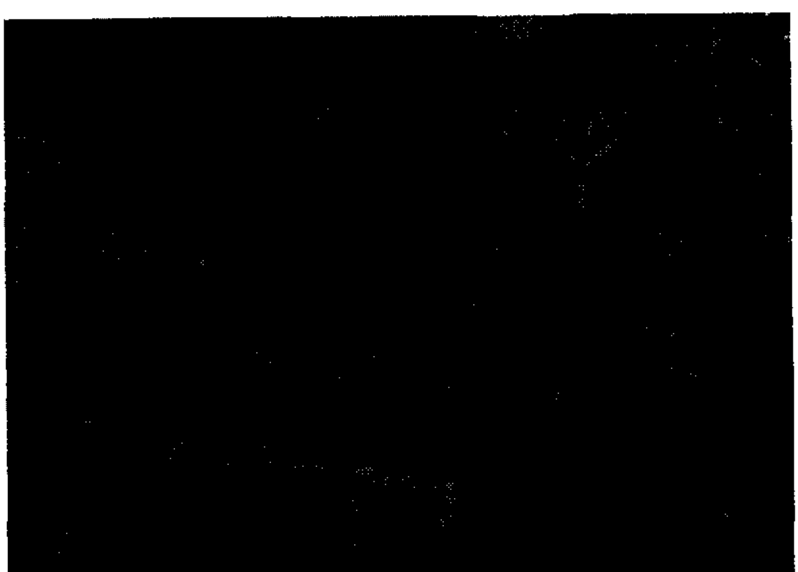


Plate 1 Elementery vegetation structural objects with the nested field of grassland subtype hs4 'High moss cover and low grass cover' in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

1990

1995

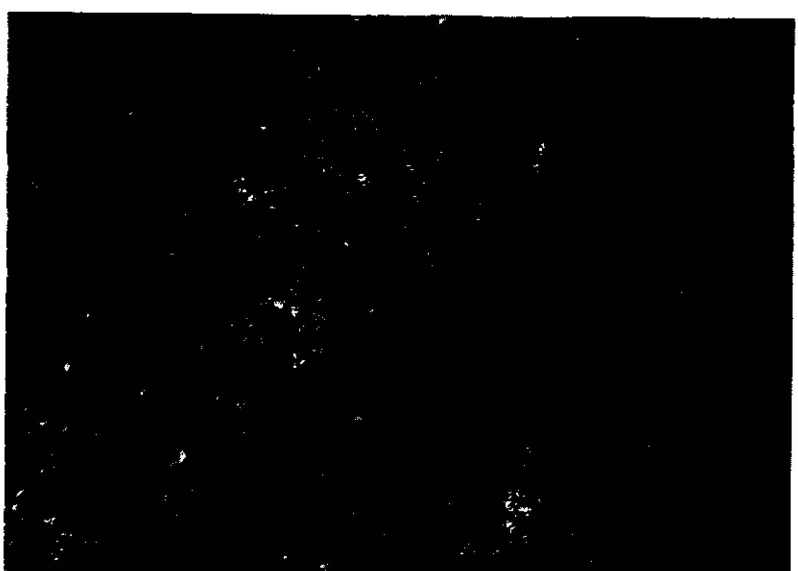


Plate 1 Elementery vegetation structural objects with the nested field of grassland subtype hs5 'High grass/herb cover with litter' in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

Legend of plate 1.

Blond sand

1

Grassland types hs_1, hs_2... hs_5 (in probability)

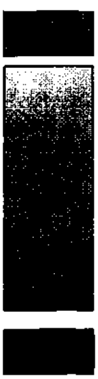
0

Sea buckthorn

Low scrubs

High scrubs and trees

Legend of plate 2.



Sandy area

1

Matrix types (in probability)

0

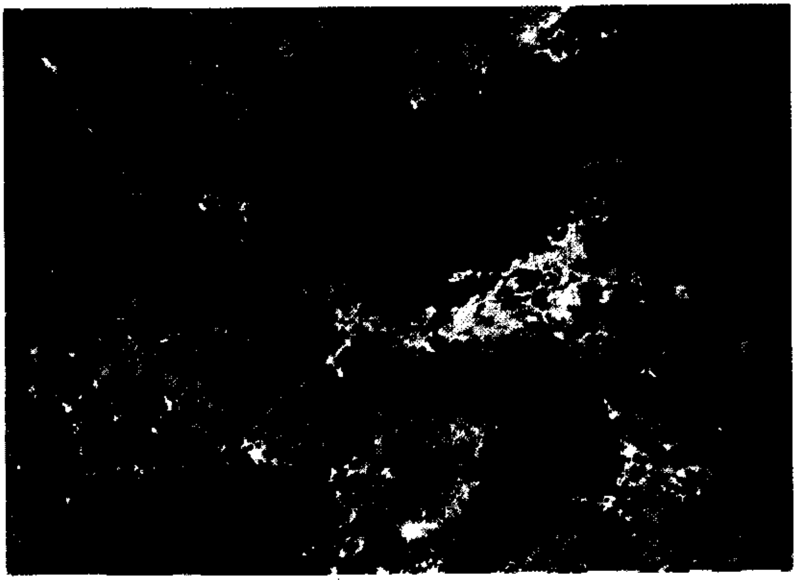
Woodland

1990

1995

Plate 2 Composite vegetation structural objects with the nested field of matrix subtype 'Blond sand' in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

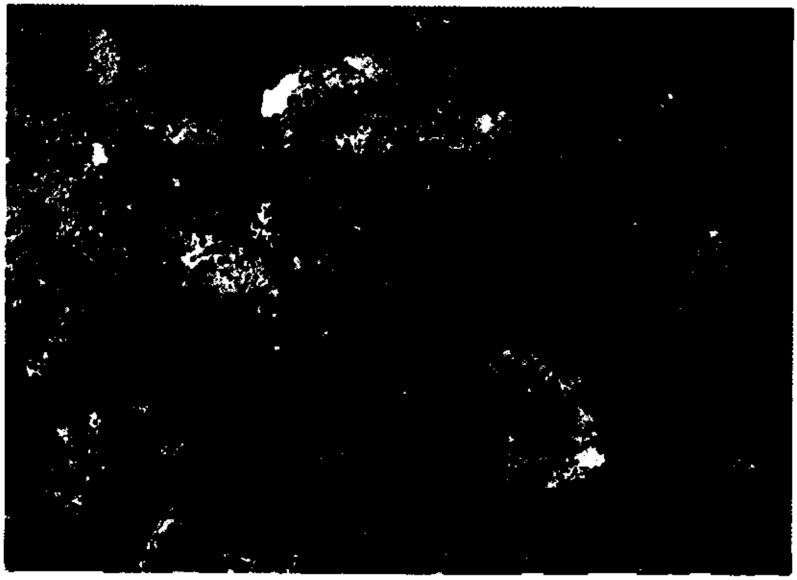
1990



1995

Plate 2 **Composite vegetation structural objects with the nested field of matrix subtype** hs2 **'Intermediate herb/moss cover with grey sand'** ***in*** **the test site** ***in*** **1990 and 1995 (scale 1:4000; legend on page 155).**

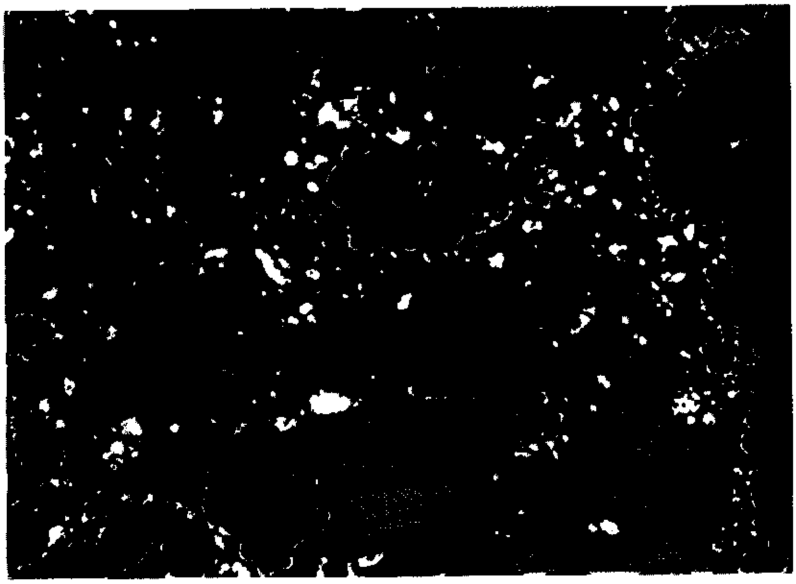
1990



1995

Plate 2 **Composite vegetation structural objects with the nested field of matrix subtype ´Sea buckthorn´ in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).**

1990



1995

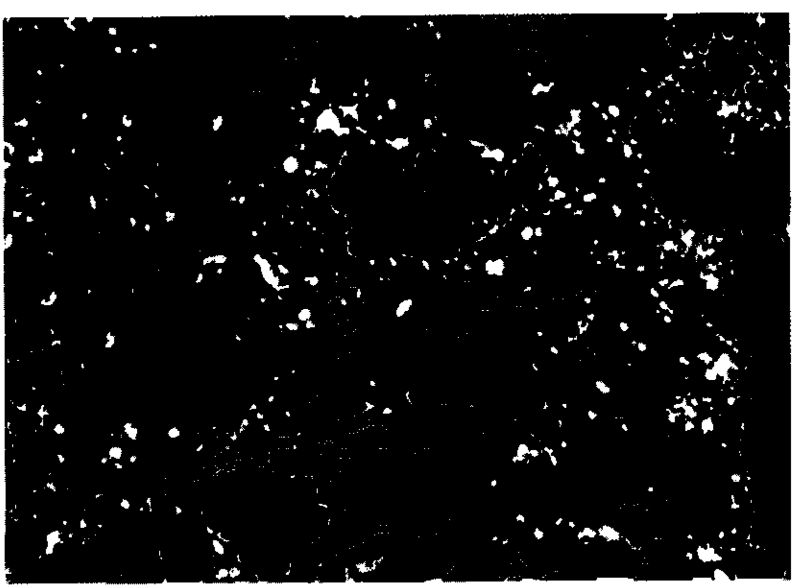


Plate 2 Composite vegetation structural objects with the nested field of matrix subtype ´Scrubs and trees´ in the test site in 1990 and 1995 (scale 1:4000; legend on page 155).

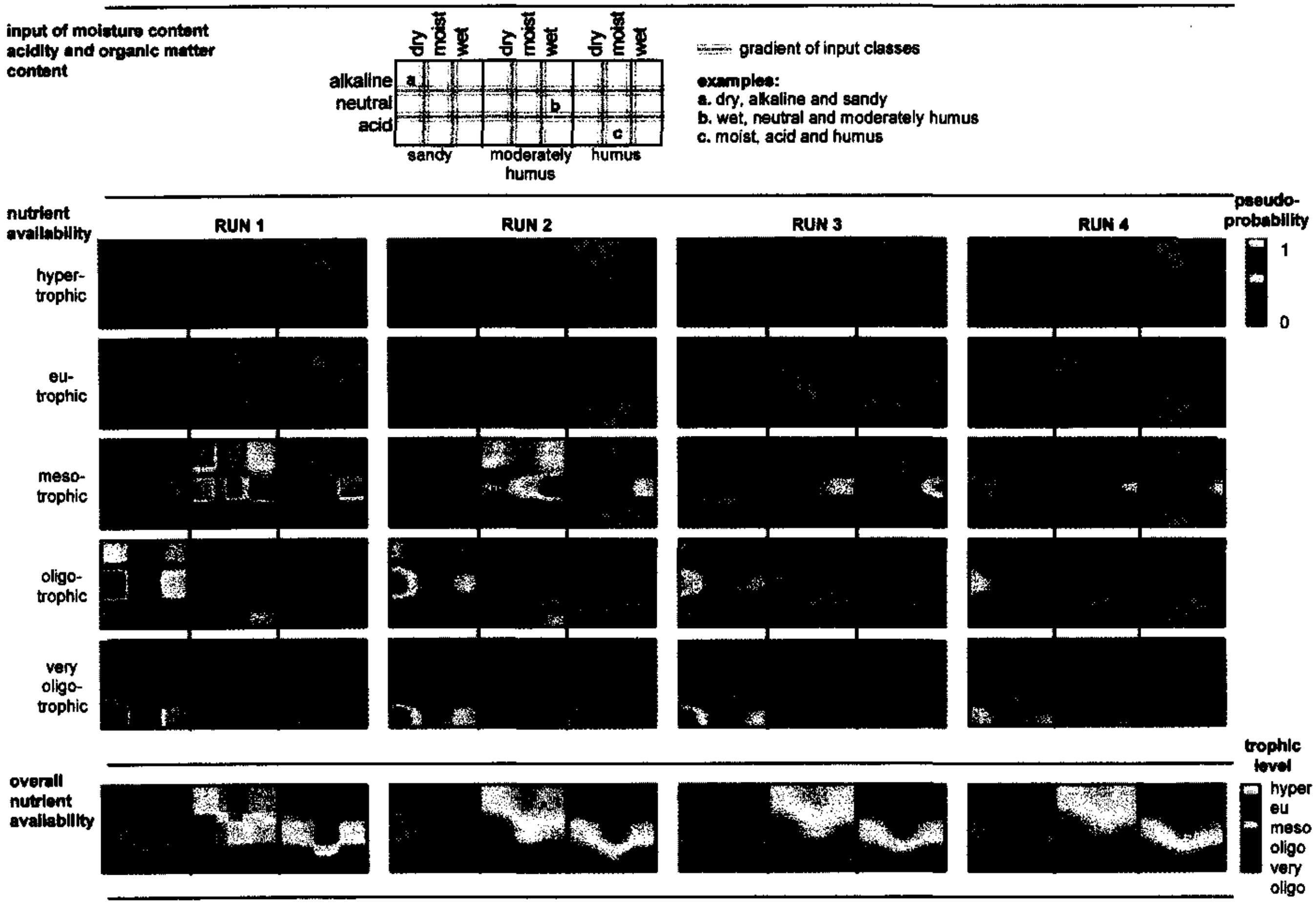


Plate 3. **Sensitivity of the estimated nutrient availability by ECOMOD with respect to uncertainty related to the model parameters and the input variables of a synthetic data set. See section 6.3 on page 101 for the specification of the model runs 1 to 4.**

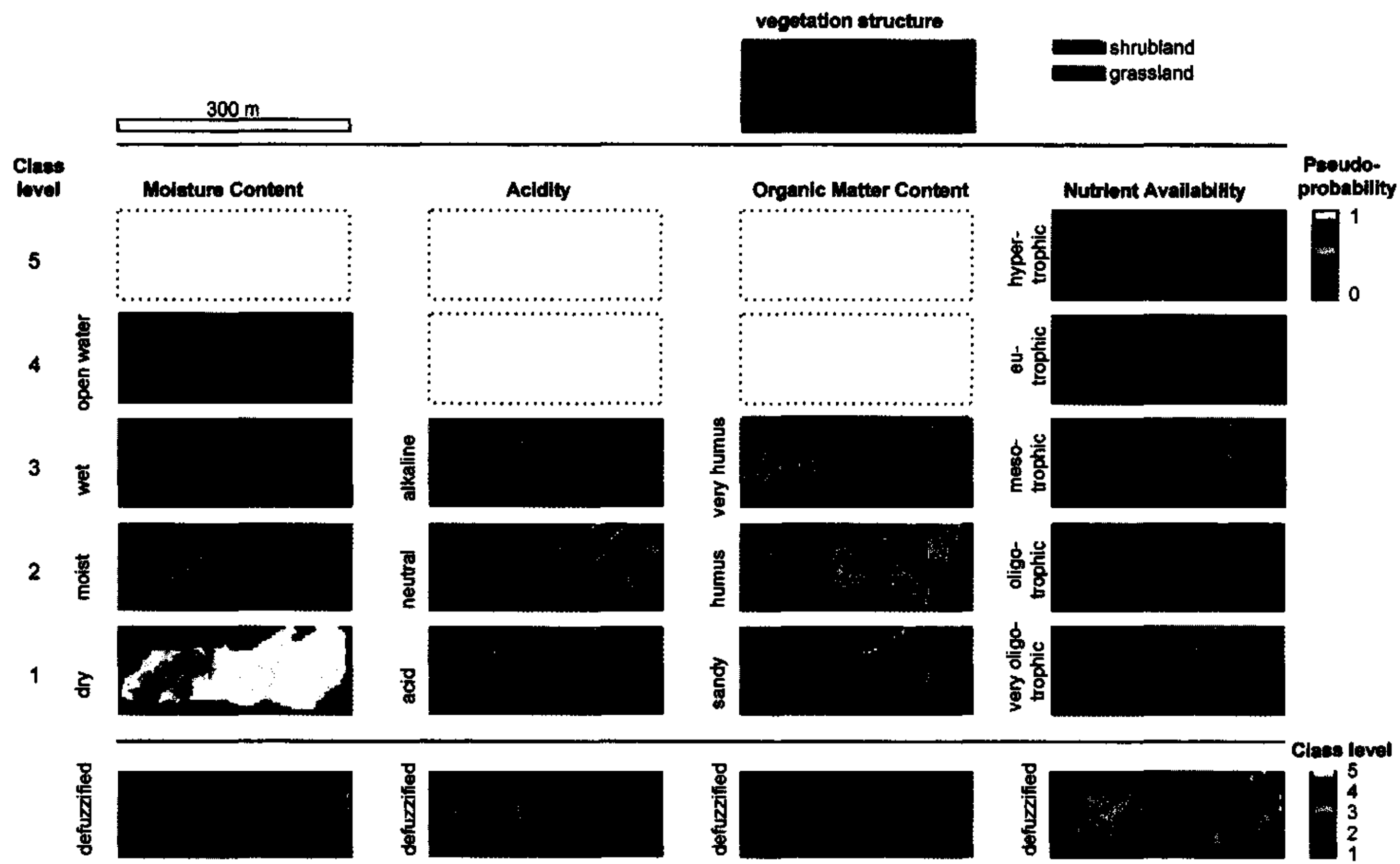


Plate 4a. Present (t_0) ecohydrological status of a dune slack estimated by ECOMOD. The estimated fuzzy variables, i.e. moisture content, acidity, organic matter content and nutrient availability, include the uncertainty related to the input variables and model parameters.

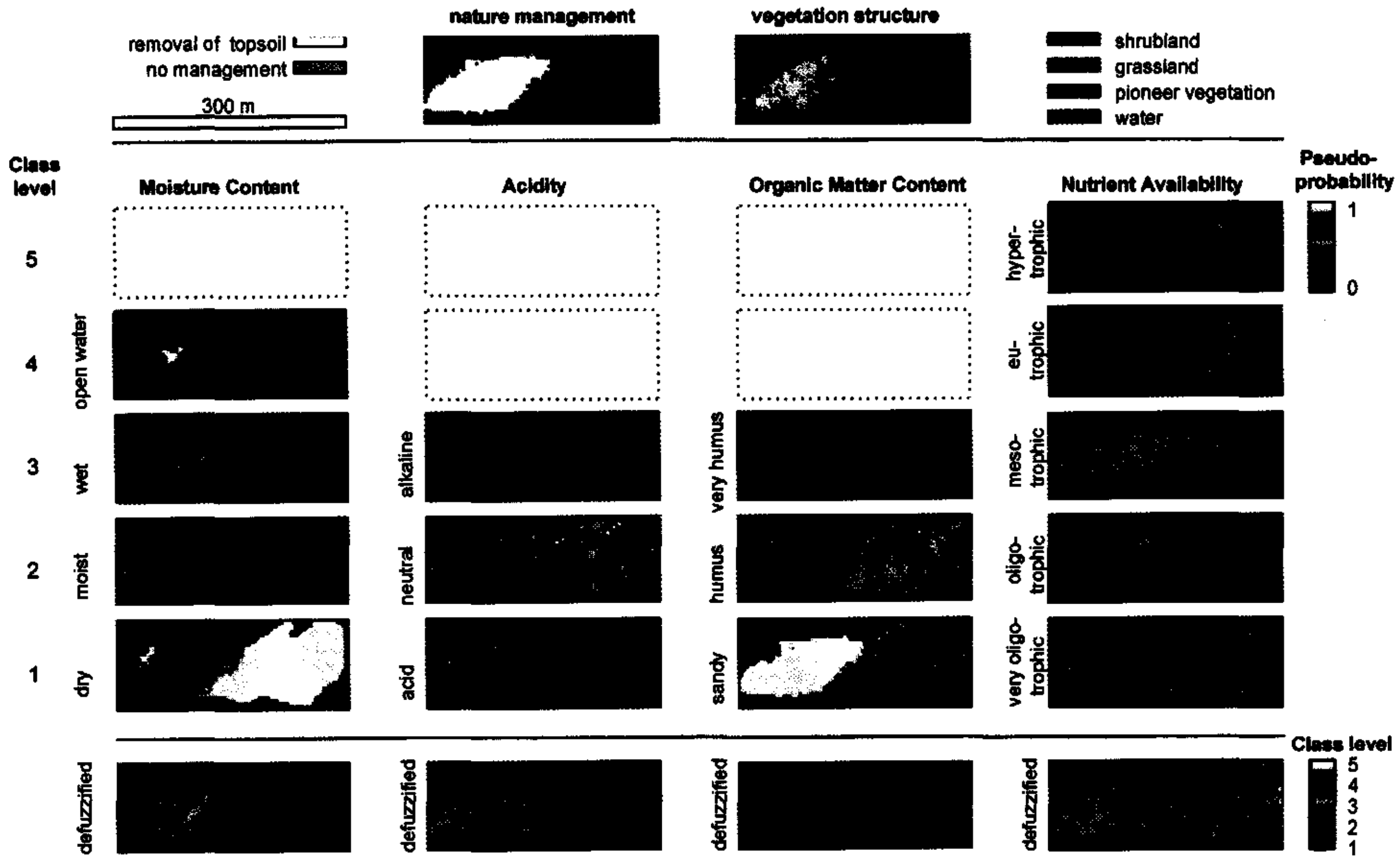


Plate 4b. Future (t_0+5year) ecohydrological status of a dune slack after raising the water table with 25 cm and the implementation of a nature management scenario, which involved the removal of 30cm topsoil in part of the slack. The output of ECOMOD includes the uncertainty related to the input variables and model parameters.