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A multi-scale segmentation/object relationship modelling methodology for landscape analysis

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Abstract

Natural complexity can best be explored using spatial analysis tools based on concepts of landscape as process continuums that can be partially decomposed into objects or patches. We introduce a five-step methodology based on multi-scale segmentation and object relationship modelling. Hierarchical patch dynamics (HPD) is adopted as the theoretical framework to address issues of heterogeneity, scale, connectivity and quasi-equilibriums in landscapes. Remote sensing has emerged as the most useful data source for characterizing land use/land cover but a vast majority of applications rely on basic image processing concepts developed in the 1970s: one spatial scale, per-pixel classification of a multi-scale spectral feature space. We argue that this methodology does not make sufficient use of spatial concepts of neighbourhood, proximity or homogeneity. In contrast, the authors demonstrate in this article the utility of the HPD framework as a theoretical basis for landscape analysis in two different projects using alternative image processing methodologies, which try to overcome the 'pixel-centred' view.

The first project focuses on habitat mapping using a high dimension multi-scale GIS database. Focal patches are derived through aggregating automatically generated landscape segments using sub-patch information including dominant tree crown densities and species. The second project uses fractal-based segmentation to produce multiple candidate segmented agricultural scenes, and then develops a decision framework to choose the combination of segmentation levels best suited to identifying shrub encroachment. The challenge and flexibility of the *multi-scale segmentation/object relationship modelling* approach lies in the defining of the semantic rules which relate the lower level landscape units or holons to higher levels of organization. We seek to embrace the challenges of scale and hierarchy in landscapes and have tested two different ways to decompose complex natural environments into focal units utilising topological relations to model between the smallest units of differentiation and the focal level. We believe the use of a HPD theoretical framework will help development of better tools for characterizing the patterns and processes, acting through a range of scales, which make up landscapes.
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1. Introduction

Landscapes, patches and image objects are conceptual containers used by scientists to systematically assess dynamic continuums of ecologic process and flux. The continuums of flux that comprise ecological systems are a challenge to monitor and analyze because the underlying processes operate over a wide range of spatial, temporal and organizational scales, of which our observation techniques capture only a jittery kaleidoscope of pattern. Stated another way, human perception, including perception augmented with earth observation (EO) methods and tools, permits only a partial capturing of the flow of ecological events, and Levin (1992) has likened our observations

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of process (one moment of time and at a single scale) to a low-dimensional slice through a high dimensional cake. In some cases, the scale of these observations may have been chosen deliberately to elucidate key features of the natural system; more often, the scales are imposed on us by anthropocentic focus, perceptual deficiencies, or by technological or logistical constraints (Steele, 1978). Using the cake analogy, the challenge to increase the effectiveness of monitoring methodologies in ecological analysis can be decomposed into the following tasks: optimise the temporal and spatial resolution of slices, for target organisms or communities; maximize the amount of information extracted from each slice; and, intelligently combine information from slices of different temporal and spatial resolution. If there is no single "correct" scale with which to describe populations or ecosystems (Wiens, 1989), we conclude that our efforts should be focused on the second and third tasks. We concur with Levin (1992), who suggests that

> ... the problem is not to choose the correct scale of description, but rather to recognise that change is taking place on many scales at the same time, and that it is the interaction amongst phenomena on different scales that must accompany our attention. (p. 1947)

With this in mind, we focus on the information extraction and information combination tasks, suggesting a methodological framework drawn out of ecological theory, which should be applicable to a range of ecological analyses and management questions.

Landscape ecology is the study of the relationship between spatial pattern and (interconnected continuums of) ecological processes. A useful starting point for deriving process from pattern has been to explore landscape as groups of plant communities or ecosystems forming ecological units (patches) which have distinguishable structure, function, geo-morphology, and disturbance regimes (Forman and Godron, 1986). Central to this epistemology is the problem of properly distinguishing analysis units. Replacing arbitrary delineations of landscape units with ecologically sound ones is vital since ecological maps are increasingly being utilized outside the purely scientific sphere. This is largely driven by politicians, land managers and government statisticians who want to be able to apply pressure response models to landscape units. They want to have quantified answers and operational procedures in order to answer questions such as "What is the current level of landscape diversity and how does it compare with historic or sustainable levels?" and "What are the trends in habitats or populations of a particular species?" This trend of increased demand for applied landscape or spatial analysis is especially apparent within the European Community, where attempts to find operational, yet simplified procedures for the monitoring of landscape structure and landscape diversity are driven by needs of common agricultural policy formulation (see EC/EEA, 2000) and nature conservation strategies (see Blaschke, 2001).

Recent advances in geographic information (GI) tools and computer development offer the potential for a more dextrous handling of the mapping or decomposition of complex environments. We argue in this article that ecological theory points to there being multiple solutions for the decomposition of landscape, and that we should develop analysis tools that are flexible enough to embrace this ambiguity yet robust enough to support ecological science and sound management decision-making. We are seeking to address the fourth goal of ecosystem research as suggested by Müller (1997, p.142):

> to integrate ecosystem research and (environmental) ecosystem monitoring into an environmental information system [with] which [to] provide strategies for sustainable landscape management and for a holistic evaluation of ecosystem states.

Our paper begins with a brief examination of essential theoretical concepts of complexity, emergence, hierarchy, scale and non-linearity, and with a summation of a synthesis of theory designated hierarchical patch dynamics (HPD) by Wu (1999).

The robustness of landscape ecological analysis will increase by the degree to which subjectivity in drawing lines between landscape entities, or patches, is reduced. Thus, in the second section of the paper, we describe a novel methodological tool that is designed to map an HPD-defined reality. These tools are grouped into a methodology called *multi-scale segmentation/object relationship modelling*. The challenge for and flexibility of the *multi-scale segmentation/object relationship modelling* methodology lies in the defining of the hierarchy's object relationships. In the final section of the paper, we provide examples of two different methods to decompose complex natural environments into focal units utilising topological relations to model between the smallest units of differentiation, the focal level and the landscape level. The first project focuses on habitat mapping using a high dimension multi-scale GIS database. Focal patches are derived through aggregating automatically generated landscape segments using sub-patch information including dominant tree crown densities and species. The second project uses fractal-based segmentation to produce multiple candidate segmented agricultural scenes, and then develops a decision framework to choose the combination of segmentation levels best suited to identifying shrub encroachment.

2. Theoretical framework

A pre-requisite to developing landscape monitoring and analysis methodology is a theoretical comprehension of the structure and functioning of ecological systems (Müller, 1997). In the next sections, we outline some theoretical components, which we believe are the foundation for the methodology building that follows.

2.1. Theoretical components explaining landscape structure

2.1.1. Landscape heterogeneity and patches

The theory of self-organization suggests that dissipative self-organization results in the spontaneous creation of macroscopically ordered spatio-temporal and functional structures (Müller, 1997). These structures create local heterogeneity that may be defined as the uneven, non-random distribution of ecological units (Kolasa and Pickett, 1991). Farina (1998) describes three types of heterogeneity: temporal heterogeneity, functional heterogeneity and spatial heterogeneity. The interwoven patterns of heterogeneity and homogeneity have as their basic units the landscape element or patch. Patches may be defined as areas surrounded by a matrix, and may be connected by corridors (Forman, 1995) or as conceptual groupings of spatial heterogeneity, that are ubiquitous and which vary at different scales (Wu, 1999). It is important to emphasize that patches are ephemeral and to a degree arbitrary, gentle compartmentalisations of continuums of ecological processes that defy crisp boundary placement.

Various methods and measures have been developed to describe complex spatial patterns found in nature (Turner and Gardner, 1991; Wu and Marceau, 2002). Some success has been made based on the theory of fractal dimension (Mandelbrot, 1977), which seems to be appropriate for describing the irregular spatial structure of patchiness for various landscape properties (Milne, 1991). The fractal approach can be utilized in different ways, depending on whether it is used for a characterization of overarching landscape pattern or for a description of a set of patches in terms of a mosaic and its fractal structure. Alternatively, an exploration of the fractal dimension of individual patches (which create a mosaic of patches) may be made by measuring the fractal dimension of their shapes, for instance using perimeter-length relations or perimeter-area relations (see Nikora et al., 1999).

2.1.2. Scale

When exploring the multi-formity of patches and the ephemeral nature of boundaries an important defining concept is scale. Scale has been defined as the period of time and space over which signals are integrated or smoothed to give a message (Allen and Starr, 1982) and can be discussed in terms of grain and extent. Grain is the minimum area at which an organism perceives and responds to the patch structure of landscape (Kotliar and Wiens, 1990). Extent is the coarsest scale of spatial heterogeneity at which organisms react (Farina, 1998). Scale may be measured in absolute units or relative to the phenomenon under investigation, the 'focal scale'. Marceau (1999) provides a comprehensive review of the scale issue in the social and natural sciences, and Marceau and Hay (1999) provide a description of recent research into the issue of scale in remote sensing.

Scale is the spatial and temporal parameterization of our perceptive window on reality. It bounds the ecological phenomena that we can observe (for a comprehensive review, see Withers and Meentemeyer, 1999). We have made progress linking ecological pattern and process at a wide range of scales, with more success at the scale of individual organisms. However, techniques for extrapolating or translating information from one scale to another, including scaling up and scaling down, are poorly understood (King, 1997; van

Gardingen et al., 1997; Wu, 1999). Recent studies are addressing this gap (Hay et al., 2002).

A system functions across a variety of scales and when observed at one resolution we perceive certain characteristics filtering most of the noise, owing to the close layering (sub and upper layers) of the entire organization (Farina, 1998). However, when we observe landscape systems across a scale continuum, as a video camera attached to a rising balloon will record, we can identify sequences of images that contain roughly the same amount of information on the heterogeneity of the surface below (see, for example Fig. 1). Eventually, the information content changes and a spatial threshold passes. Scale thresholds are never crisp, since they mark the boundaries between scale continuums, but are made hard by *fiat*.

2.1.3. Scale and aggregation

Many of the explorations of scale in landscape analysis have been made in order to better understand the effect of arbitrarily grouped spatial phenomena on pattern-process relationships, known as the modifiable areal unit problem (MAUP) (Openshaw, 1984). The MAUP originates from the fact that a large number of ways exist in which a study area can be divided into non-overlapping areal units for the purpose of spatial analysis (Marceau et al., 1990). Fig. 2 demonstrates an example of the scale problem in remotely sensed data; in it, a range of resolutions of measurement are recorded in a single flight-line (i.e. one image) of airborne scanner data, but delivered to the user at a nominal scale (Burnett et al., 1999).

2.1.4. Hierarchy and quasi-equilibria

Self-organization and scale give us scale thresholds, explained using hierarchy theory as apparent changes originating from the filtering capacities of the superior levels of organization, which react as buffers to the signals that are sent out by the subunits of lower hierarchical levels (Müller, 1997). In hierarchy theory, objects are apparent as separable entities because of differences in flux rates, by gradients (Simon, 1962; Koestler, 1967). Relatively strong gradients will evoke more apparent boundaries, or local

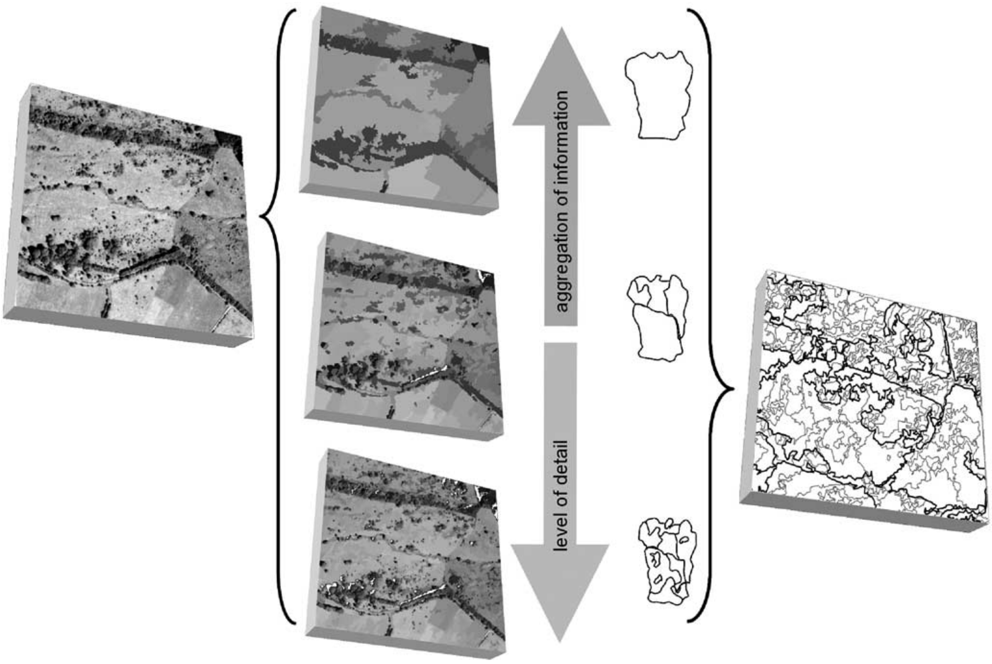

Fig. 1. The hierarchical structure of an open pasture and meadow test area are here captured through multiscale segmentation into 3 domains of scale. We can focus on a particular scale domain by examining the corresponding hierarchical network of image objects. The image-object database (right) encapsulates the landscape as a network of dissipative structures.

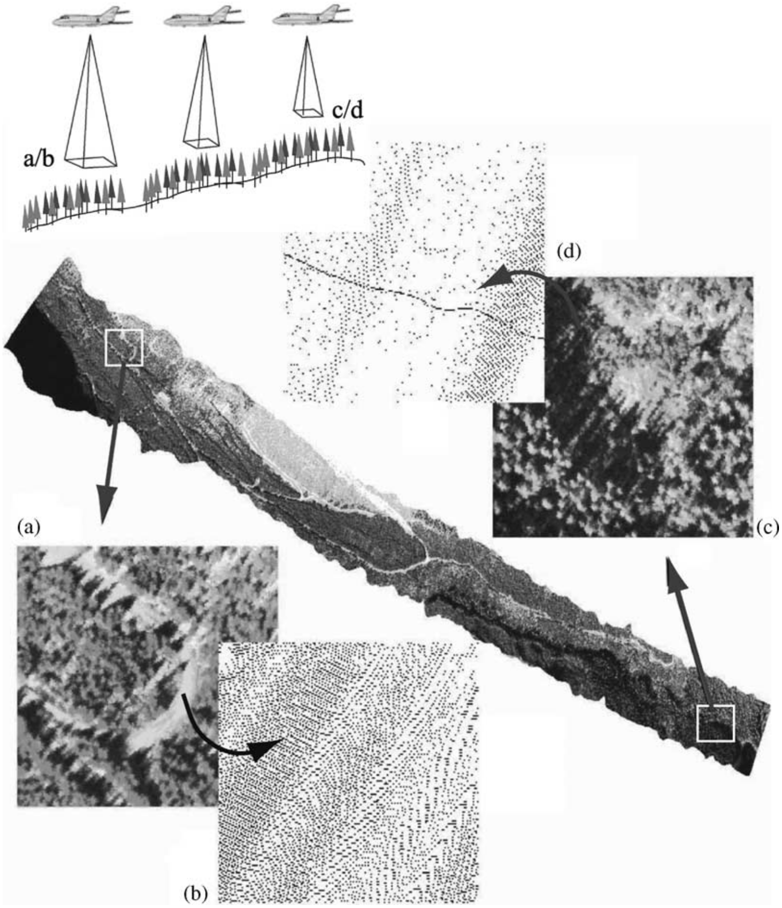

Fig. 2. For a single line of airborne multi-spectral scanner data, pixel size normalization of multiple resolutions of acquisition produces 'double' pixels when nearest neighbour resampling is used. The image swath has been resampled so that every pixel represents a nominal $1\,m^2$ of ground space. The topography of forested landscape imaged is severe (top left diagram), and over the course of this 4 km flight-line, the along-track resolution is constant (dotted line, top right diagram) while the across-track resolution varies (solid line). Distortion caused by pitching of the aircraft is observable throughout the flight-line (b and d). However, the acquisition scale differences have resulted in more 'double' pixels being added to the western end of the swatch (a and b) as compared to the eastern (c and d) (from Burnett et al., 1999).

heterogeneity. Boundaries manifest both between objects at the scale spatial (and temporal) scale and between objects at different scales. Decomposability and decomposition (i.e. the process of separating and ordering system components according to their temporal or spatial scales or both) are two of the base tenets of hierarchy theory. The decomposing of a landscape's hierarchical structure through multi-scale analysis is an important part of landscape analysis and O'Neill et al. (1986) recommends the use of three hierarchical levels as a minimum in analytical studies. Finally, landscapes are non-linear systems; systems that can exhibit instability at lower levels, but which exhibit complex meta-stability at broader scales. An analysis methodology should be flexible enough to account for quasi-equilibrium of landscapes.

2.2. Hierarchical patch dynamics

Patch dynamics provides a powerful way of dealing explicitly with spatial heterogeneity. Wu and Loucks (1995) suggest the integration between hierarchy theory and patch dynamics via the HPD paradigm and lay a theoretical framework for a theory-driven breaking down of ecological complexity through a hierarchical scaling strategy. Wu (1999), drawing on the Koestler's concepts of flux rates in hierarchy, suggests that ecological systems are nearly completely decomposable systems because of their loose vertical and horizontal coupling in structure and function. The term "loose" suggests "decomposable" and the word "coupling" implies resistance to decomposition.

When translating hierarchy theory to landscape ecology, holons are synonymous with patches: the ecological unit at a particular scale. Patches interact with other patches at the same and at higher and lower levels of organization through loose horizontal and vertical coupling. Fig. 3 shows a conceptual diagram of hierarchy with reference to a mixed forest/agriculture landscape. In it, the individual trees of level −1 are more tightly coupled with each other than with the level 0 patches above, yet there remains important inter-relationships. The varying strengths of interactions between holons produce surfaces or filters (Koestler, 1967). Levels and holons exhibit time–space separability, in that they are separated not only spatially by varying strengths of interaction but also temporally. The rates of interaction and process are key to building a hierarchical model of a complex system (Koestler, 1967; Wu, 1999) and thus central to our methodology.

Wu and Loucks (1995) and Wu (1999) suggest that the HPD theoretical framework can be used to perceive and model landscape as a hierarchical mosaic of patches although it is difficult in empirical studies to distinguish clearly between nested and non-nested hierarchies (Allen and Starr, 1982), at least prior to investigation. The list below is a digest of the HPD framework found in Wu (1999).

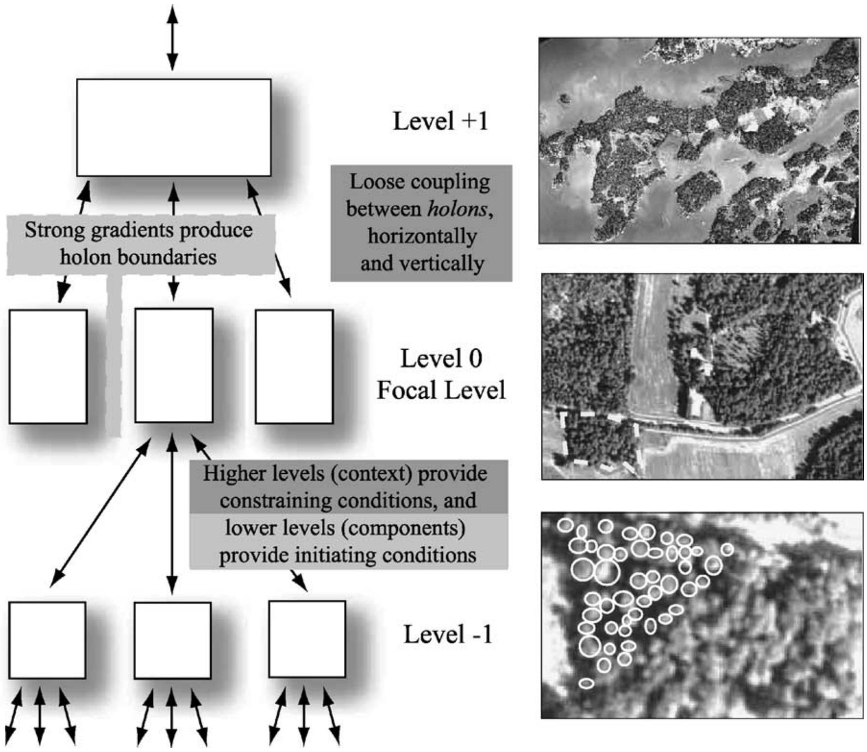

Fig. 3. A concept of the hierarchy concept (based on Wu, 1999). The left side of the diagram shows inter-holon structure. A range of gradients in ecosystem processes or flux produces 'loose coupling' and the generation of surfaces between holons. These surfaces vary in strength or contrast, resulting in a perceived independence of objects and scales of objects: scale thresholds. The right side of the figure shows a hypothetical decomposition of a forest and agricultural landscape into three hierarchical levels: the island patch in a sea matrix (holon +1), a forest patch (focal, holon 0), and individual trees as patches (holon −1).

1. Ecological systems can be perceived as spatially nested patch hierarchies, in which larger patches are made up of smaller, functioning patches.
2. The dynamics of a given ecological system can be derived from the dynamics of interacting patches at adjacent hierarchical levels. Patches at higher levels impose top-down constraints to those lower levels by having slower or less frequent processes, while lower levels provide initiating conditions and mechanistic explanations for, and give apparent identity to, higher levels through interactions among patches. Distinctive characteristic time scales of patches at lower versus higher levels are the fundamental reason for the near-decomposability of ecological systems.
3. Pattern and process have components that are reciprocally related, both pattern and process, as well as their relationship, change with scale.
4. Non-equilibrium and stochastic processes are common in ecological systems. In general, small scale processes tend to be more stochastic and less predictable. However, non-equilibrium and stochastic processes do not necessarily work against stability. They usually constitute mechanisms that underlie the apparent stability of systems.

We believe that a better landscape analysis methodology can be built upon a combination of HPD theoretical base, an object-orientated modeling environment and advanced GIS and RS methods.

3. Methodological framework

3.1. Critique of the pixel approach

Remote sensing has become an essential data source for landscape analysis. No other survey technique can operationally provide a regularized survey of landscape with which to assess *landscape level* patterns and change. However, remotely sensed images, like all observations of reality, are an imperfect capturing of patterns, which are themselves an imperfect mirror of ecosystem processes. Cracknell (1998) explores the question “What’s in a pixel?” and divides his critical examination of the ‘pixel’ into geometry, mixed pixels, point spread functions and resampling. He concludes that the ‘pixel’ is a more complicated entity than is generally acknowledged, and we must approach landscape analysis using EO data critically.

The sensor GIFOV is often imposed on us by technological or logistical constraints (Steele, 1978) and not solely based on the needs of the ecologist. The traditional method for analysis of EO data in landscape research is the classification of pixels based on pixels in the same land cover class being close in spectral feature space. This does not hold true for complex environments and their respective classifications. In addition, the pixel-centred view is usually uni-scale in methodology, exploring the pixels of only one scale of imagery and of only one scale within the image.

By ignoring concepts of hierarchy and scale in the landscape processes driving pattern creation, these approaches are still overly ‘pixel-centred’ (Townshend et al., 2000). They adhere to a concept of the pixel as a spatial entity (Fisher, 1997) that is assumed to have a de facto relationship to objects in the landscape. Uni-scale, pixel-based monitoring methodologies have difficulty providing useful information about complex multi-scale systems. If we accept that the reality we wish to monitor and understand is a mosaic of process continuums, then our landscape analysis must make use of methods which allow us to deal with multiple, yet related scales within the same image and with multiple images of landscape. Increasingly used multi-scale methods in landscape ecology include semivariance analysis (Faber and Förstner, 1999), wavelet analysis (Sheikholeslami et al., 2000), fractal analysis (Milne, 1991; Nikora et al., 1999), and lacunarity analysis (Plotnik et al., 1993). O’Neill et al. (1992) have also expanded percolation theory to hierarchically structured landscapes. Advances have been made in exploring hierarchy in image analysis, for example in the nested scene models and image segmentation of Hay et al. (2002). Landscape researchers now have the benefit of working with the next generation EO data sets, comprising (1) images of a significantly finer spatial resolution, and (2) multiple scales of data simultaneously, thus opening up the potential for analysis methodologies that are better adapted to the self-organized complexity of landscapes.

3.2. Partitioning an HPD-conceptualised reality

Our analysis methodology is designed to utilize information in the scales inherent in our spatial (image) data sets in addition to a range of auxiliary data sets. By scales in plural, we refer to the exercising of a multi-scale image data set, including for instance both airborne and satellite data, but also to the scales of information inherent in single images. The latter is possible because the *multi-scale segmentation/object relationship modelling* methodology is a move away from pixel-based analysis, to an object-based analysis, and multiple scales of objects can be explored within a single data set. In the following section, we articulate the methodological steps followed in the *multi-scale segmentation/object relationship modelling* approach including *GI database building*, *segmentation*, *object relationship model building*, *visualization*, and *quality assessment*. In Section 4, we provide more detailed information on the methods specific to the two example studies.

3.3. GIS building

The main prerequisite for our methodology is the collating of GI into database of geo-referenced survey, sample and auxiliary data. Survey data include any systematic and continuous assay of landscape. Surveys are often stored in raster format and include digital aerial photograph mosaics, scanning LIDAR data, airborne spectrometer swathes and satellite images. Sample data are higher resolution information on selected phenomenon of interest in the landscape, which are unfeasible to collect at the landscape level. For analysis of urban landscapes, such data may include spectral values, collected in situ with hand-held radiometers, of features such as vegetation, roofing material or sealed surfaces. For less anthropogenically modified landscapes, sample data may include distribution and habitat data from bird and insect investigations, or the distribution and species of dominant trees. Auxiliary data include other data sets which could be considered to be part of either category, for instance derived vector data such as topographic contours, road network and cadastral information, and raster digital elevation models (DEM). All three types of spatial data can now be managed (geo-referenced, stored and visualized) using any commercially available or open source geographic information systems (GIS). Fig. 4 presents some of the data layers available in a high dimension GIS built specifically for landscape analysis. By high dimension we refer to multiple temporal slices, spatial resolutions and sources.

3.4. Segmentation

Segmentation is, not surprisingly, the key to the *multi-scale segmentation/object relationship modelling* methodology. Technically, segmentation is not new (see Haralick et al., 1973), but it is as yet seldom used in image processing of remotely sensed data. Especially within the last two years, many new segmentation algorithms and applications have been tested in geoscience applications, but few of them lead to qualitatively convincing results while still being robust and operational (Blaschke and Strobl, 2001).

Central to our methodology, thus, is the issue of meaningful objects. As stated above, because we believe that ‘natural’ hard boundaries are antithesis to a view of landscapes as continuum mosaics, we turn to HPD theory for guidance. With *multi-scale segmentation*, we are searching for the gradient of flux zones between and within holons (patches): areas where the varying strengths of interactions between holons produce surfaces. To some extent these transitions are independent of the specific research question being addressed, but not completely. *Multi-scale segmentation* is often iterative, as discussed below. Methodologically, this equates to searching for changes in image object heterogeneity/homogeneity. The number of methods for segmenting an image is legion (for an overview, see Haralick and Shapiro, 1985; Ryherd and Woodcock, 1996; Kartikeyan et al., 1998; Baatz and Schäpe, 2000; Schiewe et al., 2001). Common approaches use region growing or thresholding algorithms, but many derivatives for specific applications such as grey scale, hyperspectral images or data fusion of different sensors exist.

3.5. Object relationship model building

Once a suite of segmentations has been derived from the image or images, it is necessary to build a model of the relationships between the segmented image objects. The building of the inter-object relationship model is described on the right side of Fig. 5. Some object relationships are automatically derived. For instance, the characteristics of level −1 objects (such as mean spectral values, spectral value

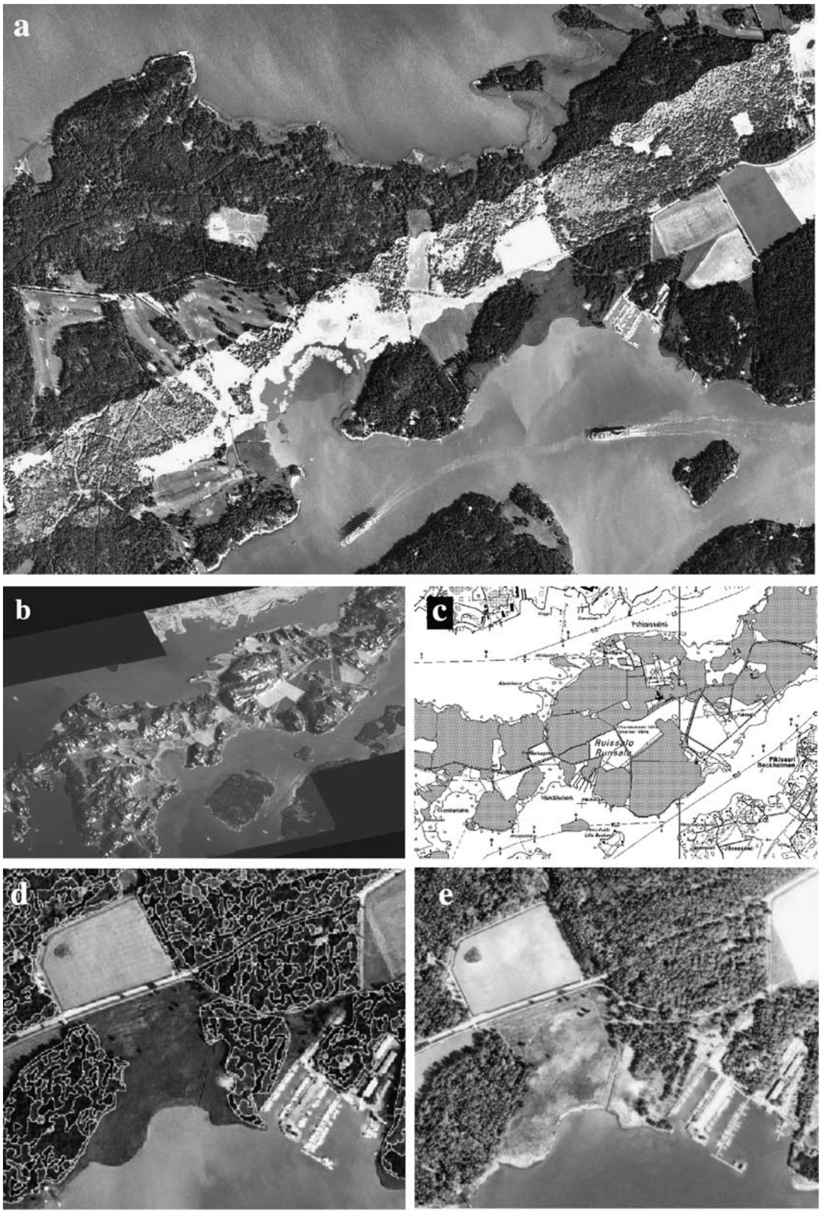

Fig. 4. Example of data layers from a high dimensional landscape analysis GIS. From top left to bottom right, the layers consist of Minolta digital camera mosaic (1 m GIFOV), a swath of AISA airborne spectrometer data (2 m GIFOV), Finnish base map (1:20,000), Landsat Tematic Mapper (30 m GIFOV), thematic map (1:10,000), digital elevation model derived from aerial photographs (resampled to 1 m resolution).

heterogeneity, and sub-object density, shape and distribution) can be automatically calculated and stored in the description of each level 0 object. On the other hand, other relationships are semantic, requiring the knowledge of the expert on the landscape in question, at least for training purposes. Relationships of this sort may include the defining of rules to collect segments with characteristics of a 'road' into a single linear

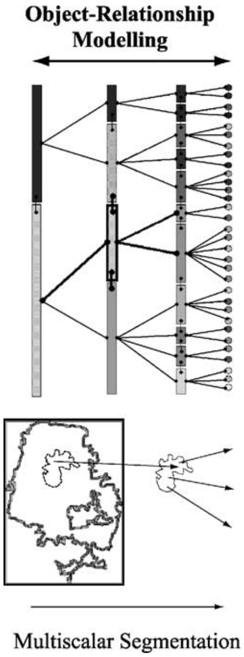

Fig. 5. Schematic showing *multi-scale segmentation and object relationship model building* steps. On the left, a single image of 0.4 m GIFOV is segmented into four layers of segments. All segments are stored in vector format in the database. On the right, the links between segmented objects are built up as part of the *object relationship model building* step in two ways. Some links (relationships, rules in the database system) at made automatically (light lines), as the characteristics of the segment are calculated and stored (e.g. mean spectral value, mean within patch heterogeneity), while other links (dark lines) are built by the expert based on knowledge of the hierarchical nature of the ecosystem.

level 0 object. This relationship model information can be stored in the system through a variety of mechanisms, for example as attributes in GIS vector objects or in a proprietary object-orientated database format.

The building of the relationship model links the holons in the hierarchy, and, we posit, surmounts the problem of MAUP. From a hierarchical point of view, MAUP is not really a "problem" per se; rather, it reflects the 'nature' of the real systems that are hierarchically structured (Jelinski and Wu, 1996).

3.6. Visualization

It is common in landscape analysis for a crystallization of our understanding of the patterns (our object relationship model) to be output. This visualization, a map or schematic (on paper or computer monitor), will necessarily emphasize some objects and relationships over others. The key to this step in the methodology is a solid understanding of the research question. For instance, in a urban forest example, the *visualization* rules can be designed to hide sub-objects below certain super objects, for instance having relationship rules that 'identify' it as anthropogenic objects (houses, roads), while showing deeper levels of object hierarchy within 'forest' and 'agriculture' super-objects. The derivation of a map may be accomplished through static modeling in GIS, via interactive GIS tools, or by firing a set of rules in a multi-scale segmentation system.

3.7. Quality assessment

Quality assessment is an essential component of the *multi-scale segmentation/object relationship modelling* methodology, both at the final stage when a visualization (map) has been derived from the system, and at each of the preceding stages. For example, at the *GIS database building* stage, quality assessment is the essential for tracking the accuracy of image to image registration. Derived data sets, such as those generated by algorithms that search for dominant tree crown positions, must also be assessed for error. This error assessment can be used in two ways: for information on how to improve data when new data ingestion is being considered and to carry forward into the object relationship building model for use when analysis is being conducted and results produced.

The five-component methodology described above can, on demand, produce a candidate discretization of space—a map. But more than that, the system can produce a variety of maps because the model and data that elucidates a map continues to exist behind the scene. The initial GIS database building stage can be considered as quasi-independent of specific research questions. With a modicum of change (in segmentation levels, relationship model and visualization rules), the same system can be tuned for a variety of different needs. This is the basis for our claim to *multi-scale segmentation/object relationship modelling* being flexible. The methodology is also relatively reproducible, compared to human interpretation. The methodology provides some feedback on uncertainty in the classification, and through its 'modeling nature' provides for an examination of what aspect of the system, whether data or heuristic, is weakest. Finally, the methodology is open in the sense that it is not difficult for new data sets to be added and for new relationships to be derived with which to strengthen the analysis.

4. Example studies

We take HPD as a theoretical starting point and evaluate the *multi-scale segmentation/object relationship modelling* methodology described above through the development of two landscape analysis projects.

4.1. Ruissalo Island: from individual trees to habitat units

The first example is taken from a study seeking to delineate habitat patches in a mixed hardwood and deciduous forest. The forests studied are located on the 11 km long island of Ruissalo, west of the city of Turku in SW Finland. The forest patches in the landscape differ in tree species, stem density, age and purity; ranging from dense immature birch (*Betula pendula*) plantations to mature stands of lime (*Tilia cordata*), Scots pine (*Pinus sylvestris*), Norway Spruce (*Picea abies*) and oak (*Quercus robar*) exhibiting early patch-phase dynamics. Due to natural characteristics and long term human management, the island is home to one of the richest species communities in Finland (Vuorella, 2000). The island is now managed as a recreation area but with a large proportion in nature reserves. The patchiness of the landscape, resulting from hundreds of years of use as meadows and pasture for grazing, wood production and scattered habitation, provides an intriguing environment to test new habitat mapping methodologies.

We adopted the five-step methodology described above to delineate patches (level 0 holons) of suitable habitat for the Three-toed woodpecker (*Picoides tridactylus*). Aspects of this study which are different from the later example are the reliance on semi-automated image processing for dominant tree crown detection and speciation, and heuristic-based aggregation of sub-patches using a purpose-built interactive GIS tool. In the *GIS building* phase, over a dozen spatial data sets were geo-referenced including aerial photography, digital camera and IR video mosaics, a digital elevation model, cadastral data and a Landsat TM scene (Fig. 4). Preliminary data processing was then applied. For instance, individual dominant tree crown detection and delineation algorithms were applied to the 1 m ground instantaneous field of view (GIFOV) digital camera data. The crown delineation by local maximum (LM) filtering (Fig. 6) was conducted using software and techniques described by Gougeon (1997). A raster density map was created from the results of this image processing. Crowns were also delineated as regions via a segmentation algorithm using a modified implementation of the method presented by Narendra and Goldberg (1980). Spectrally similar adjacent segments (using three colour channels) and segments smaller than a user-defined minimum size were merged with their neighbouring segment. The similarity of the segments was measured by means of *t*-ratio (Hagner, 1990). Using multi-spectral imagery at a lower resolution (airborne AISA at 2 m GIFOV), the delineated objects (LM and crowns) were separated spectrally using spectral signatures and a raster tree species layer was generated with pixel values corresponding to species codes. LM and crowns became, in effect, level −2 scene patches, with LM being patches at the theoretical lower limit in size: one pixel.

In the segmentation step, the digital camera image was again segmented using the algorithm described above. However, this time the scale of this segmentation was set to elicit clumps of crowns. This set of image objects was labeled level −1 patches. These segments were taken into the GIS database and in the *object relationship model building* step, attributes for each segment (i.e. characteristics of −2 patches) were populated through a semi-automated process of data layer mining. Finally, in the *visualization* step, the −1 patch vectors were aggregated to form focal (level 0) patches based on a model of nesting/foraging habitat. This aggregation was done in a semi-automated fashion, with both rules-based aggregation and aggregation by a user using a GIS tool developed for the project (Fig. 6). The result was a level +1 or landscape level map of candidate habitat for the three-toed woodpecker (*Picoides tridactylus*). At this time, a *quality assessment* step is being conducted. The over-all habitat map accuracy is being made with the cooperation of City of Turku ecologists and the sensitivity of the semi-automated methods is being tested.

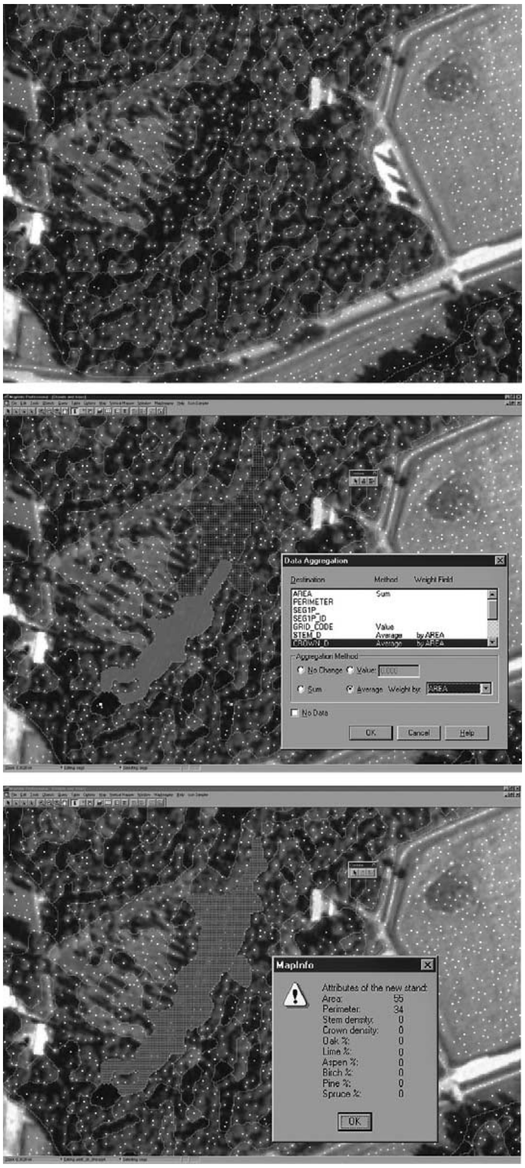

Fig. 6. Multi-scale patch delineation using GIS layers recording individual tree crown density and base holons which are aggregated to form ecological units. Aggregation is made using heuristics and based on differences in tree crown density, crown size and species using a specially designed GIS aggregation tool.

4.2. Biosphere Reserve Rhön: bush encroachment monitoring

In this example the *multi-scale segmentation/object relationship modelling* methodology was used to identify different stages of change within the Biosphere Reserve Rhön, a highland region in central Germany. For decades, the Rhön area was situated in a pronounced peripheral location: along the inner German border before reunification in 1989. For this reason the expansion and consolidation of infrastructure was hampered and agriculture remained of economic importance up until recently. In addition, unfavourable environmental conditions (wet, steep and stony) have restricted intensive land-use to the flood plains while the plateau and the slopes were grazed or cut less intensively. This history has maintained a diverse landscape with a high proportion of open area exhibiting both high conservation and cultural heritage values. The research question is to understand the spatial pattern of bush and shrub encroachment caused by reduced grazing intensity (Conradi and Plachter, 2001).

Pastures and meadows show an obviously different inner structure formed by trees, shrubs, basalt stone walls, and wet and fallow areas. Due to the regular mowing with modern machines and the inevitable additional maintenance, meadows are more homogenous than pastures, whereas livestock contribute to the spatial and temporal heterogeneity by grazing, trampling and defecation (Conradi and Plachter, 2001). In this research, we concentrated on the differentiation between types of pastures and different stages of encroachment. We were not aiming for a ‘complete’ land use classification.

In the *GIS building* step we collected 14 aerial photographs taken in 1993 for a biosphere reserve wide monitoring survey which cover the eastern slope of the Ulster valley in the municipality Ehrenberg (Hesse, Germany) at 1:10,000 scale. The photographs were scanned with a resolution of 600 dpi and ortho-rectified using Erdas Orthobase software. Finally, after conducting a colour alignment, a mosaic was created, and the image resolution was re-sampled to 0.4 m pixels. This high-resolution image mosaic allows us to identify single bushes and encroachments within the pastures and at the same time examine a large proportion of a landscape simultaneously. The mosaic is correspondingly large, comprising nearly one gigabyte of data.

In the *segmentation step*, a fractal-based multi-scale segmentation algorithm developed by Baatz and Schäpe (2000) was implemented. The fractal net evolution algorithm (FNEA) has already successfully been applied in other studies (see Blaschke and Strobl, 2001; Schiewe et al., 2001 for an overview) and is based on assessments of homogeneity and heterogeneity. In it, an iterative heuristic optimization procedure is programmed to get the lowest possible overall heterogeneity across an image. The basis for this is the degree of difference between two regions. As this difference decreases, the fit of the two regions is said to be closer. In the FNEA, these differences are optimized in a heuristic process by comparing the attributes of the regions (Baatz and Schäpe, 2000). That is, given a certain feature space, two image-objects are considered similar when they are near to each other in this feature space. For a d-dimensional feature space the heterogeneity h (or *degree of fitting* as named by Baatz and Schäpe, 2000) is described as:

$$h = \sqrt{\sum_d (f_{1d} - f_{2d})^2} \tag{1}$$

whereby f is a general term for any object feature used to determine heterogeneity. Examples for appropriate object features are, for instance, mean spectral values or texture features, such as the variance of spectral values. These distances can be further standardized by the standard deviation of the feature in each dimension using Eq. (2).

$$h = \sqrt{\sum_d \left(\frac{f_{1d} - f_{2d}}{\sigma_{fd}}\right)^2} \tag{2}$$

Eq. (3) defines the homogeneity of two adjacent regions by describing the difference of heterogeneity h of the two regions before (h_1 and h_2) and after a virtual merge (h_{m}). Given an appropriate definition of heterogeneity for a single region, the growth of heterogeneity in a merge should be minimized. There are different possibilities for describing the change of heterogeneity h_{diff} before and after a virtual merge—but they are beyond the scope of this paper.

$$h_{\mathrm{diff}} = \frac{h_{\mathrm{m}} - (h_1 + h_2)}{2} \tag{3}$$

It is important to note that these heuristics do not evaluate the absolute value of a region's heterogeneity but rather evaluate the change of the heterogeneity over a merge. This prevents, for instance, relatively homogenous image objects from being merged even if the mean values of the adjacent region are similar. This is crucial for the landscape used in this study and is one of the main reasons why FNEA was chosen, although many other segmentation algorithms have been tested (Blaschke et al., 2000). FNEA treats contrasts consistently and the resulting segmentation is nearly reproducible (because it uses heuristics, minor differences between several segmentation will appear) and universal, allowing for application to a large variety of data.

In the *object model relationship* step, the semantic links between image objects were established. According to the nomenclature in Section 3.2, we referred to the pasture and forest patches in the Rhön study area as the focal (level 0) patches. Single bushes, islands of intensively grazed grass and other homogeneous sub-areas comprise the −1 level. The level +1 is the landscape, consisting of a mosaic of pastures and meadows.

To aggregate the level −1 objects into level 0 objects, we assessed the 'between-objects heterogeneity' of the lower level objects. This is accomplished in part by measuring within each focal object (level 0) a parameter called '*mean spectral difference between all sub-objects*'. Note that an assessment of this parameter allows us to distinguish between two types of pastures with similar mean spectral characteristics but different 'within-patch heterogeneity'. The parameter 'mean spectral difference between all sub-objects' was collected for the level −1 patches, with values ranging between 11 (low spectral differences between sub-objects in all bands of the image) and 99 (very high spectral differences between sub-objects). The pastures fell into the range between 28 and 58.

In the *visualization* step, map output and a database containing the image mosaic can now be used as the foundation of a management plan. The methodology is currently being tested for accuracy and expanded to a much larger area. Using this technique, we have produced maps of grazing intensity.

Fig. 7 illustrates some results relevant to our research objective. With the *multi-scale segmentation/object relationship modelling*, we delineated different types of pasture according to their state of 'change'. While the grazing system is monitored seasonally and will be accompanied by ground-truth campaigns through 2003, the changes before 1995 can only be characterised indirectly using the methodology described above.

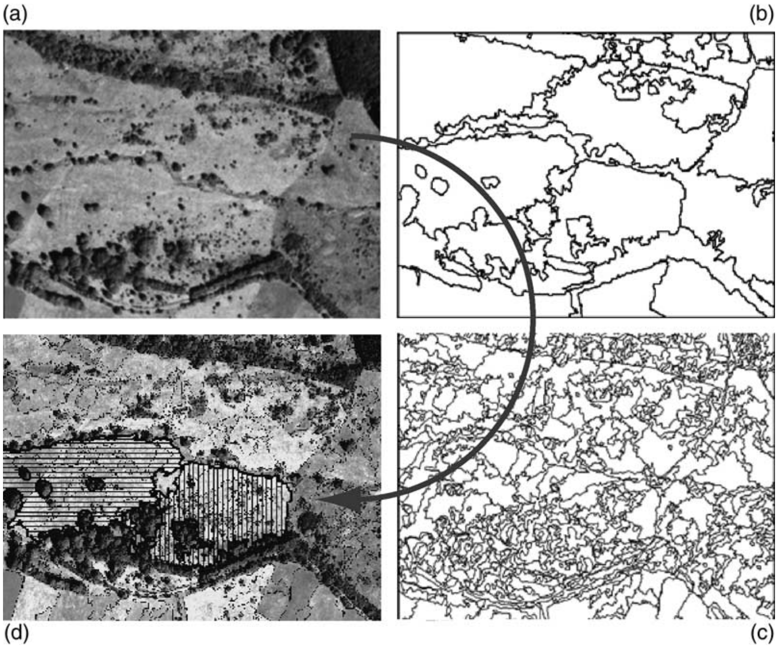

Fig. 7. The series of screen shots of the Rhön example, which was accomplished using eCognition software (Definiens AG): (a) initial image, (b) level -1 patches (50), (c) level 0 (300), (d) object relationship model building schematic shown in the resulting intensity analysis map (bottom).

5. Discussion

It is becoming more and more evident that levels of organization are not scalar but rather definitional—in that they come solely from the observer (or point of observation)—and at each user-defined level, phenomena exhibit properties that do not exist at other levels. This underscores the importance of a solid understanding of the ecology of the research question (species, community) at hand. Jelinski and Wu (1996) concluded from a thorough literature review that there was no suitable encompassing theory for indicating how sensitive results are to the scale of the analysis and to variations in the way in which data are represented. As Gardener (1998) states, the identification of appropriate scales for analysis and prediction is an interesting and challenging problem. Even if the factors producing scale-dependent patterns may not be clearly understood, accurate and reliable descriptions of scale-dependent patterns and processes are required to design data sampling procedures and test the accuracy and reliability of methods of the analysis and consequently modelling procedures. Some researchers currently elucidate alternative way towards the fuzzy delineation of objects or the delineation of fuzzy objects (e.g. Cheng, 1999) or a probability-based image segmentation approach (Abkar et al., 2000).

Although many scientists are aware that issues of heterogeneity, pattern, process, scale, scaling, and hierarchy are essential in developing robust methodologies of landscape analysis few make advantageous use of modern spatial tools such as remote sensing and GIS. While recent developments in complexity theory (e.g. complex adaptive systems, self-organized criticality) may help us understand how order and complexity evolve and are maintained in ecosystems and landscapes (Levin, 1999), empirical multi-scale analysis methodology must be developed to analyze, monitor and predict spatial heterogeneity in landscapes.

Wu (1999) provides a theoretical framework for this methodological development, using the metaphor of a scaling ladder. We have tried to embrace the challenges of scale and hierarchy in landscape by introducing and applying the *multi-scale image segmentation/object relationship modelling* methodology. In two different examples we decompose complex natural environments into focal units utilising topological relations to model between smaller units of differentiation and the focal level. Each example draws upon a synthesis of ecosystem theory as encapsulated in the HPD paradigm. This methodology generates 'candidate crisp' boundaries while theoretically and methodologically staying true to a hierarchical model of landscapes.

From the Ruissalo example, we can already identify some challenges. The MAUP problem is very much in evidence, and because we are using only one resolution of imagery to do the initial 'tree' delineation, we were successful at delineating crowns greater than 4 m in diameter and in forest patches with at least a 1-m gap between crowns. Crowns smaller than this or crowns that are much larger (especially large mature oaks) are either missed or divided. Further work on tree delineation algorithms is needed, and the use of multiple scales of imagery must also be incorporated into the initial delineation phase of the unit mapping. Further accuracy assessment is critical and will provide us with information on the resolution of potential data sets that would in the future improve the analysis. The heuristics we used to aggregate the patches also need refinement, and we are also currently working with biologists to improve our habitat model for the three-toed woodpecker (*Picoides tridactylus*).

The Rhön example demonstrates the applicability of the *multi-scale segmentation/object relationship modelling* methodology using FNEA segmentation. More specifically, we could produce visualizations of the landscape with discretization of roads, settlements, forest and pasture elements. Within the object relationship modelling step, the 'within patch heterogeneity' measure (mean spectral difference between all sub-objects) was successfully applied to characterize shrub encroachment on most pastures. However, it appeared that cultural landscape elements embedded within pastures, such as hedges, stone walls, and small islands of trees, were influencing the results. The next step will be to improve the object relationship modelling heuristics with which to distinguish between these structural elements, which are typical for the human-influenced landscape, and actual bush and shrub encroachment. In the next phase of the project we hope to use this more comprehensive set of heuristics to fully map the cultural and natural heritage of this visually appealing landscape.

We conclude that the *multi-scale segmentation/object relationship modelling* approach can be a vehicle for a theory-driven exploration of different types of landscape heterogeneity. The methodology will lead to a better understanding and characterization of the processes, operating through the broad range of scales that form landscape.

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