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Multiscale Object-Specific Analysis: An Integrated Hierarchical Approach For Landscape Ecology

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Résumé

L'écologie du paysage est une science transdisciplinaire qui a pour but fondamental de comprendre les interrelations entre les patrons spatiaux et les processus écologiques dans une optique d'application de stratégies d'aménagement appropriées. Cependant, l'atteinte de ce but constitue un défi de taille. Les paysages sont des systèmes complexes composés d'entités organisées de manière hiérarchique qui intéragissent à l'intérieur d'échelles spatiales et temporelles uniques. Ces intéractions génèrent des patrons spatiaux visiblement variables selon l'échelle d'observation. Les images de télédétection représentent une source de données primaires à partir desquelles les patrons du paysage peuvent être observés et évalués. Cependant, elles souffrent du problème des unités spatiales modifiables (MAUP). Une façon de contourner ce problème est d'utiliser les *objets*, ceux-ci constituant une représentation non-arbitraire de l'espace. Ainsi, leur agrégation et leur représentation lors de changements d'échelle contiennent une signification écologique implicite.

Pour être en mesure d'observer, de modéliser et de gérer nos interactions avec les paysages, les écologistes du paysage ont besoin d'une approche multi-échelle qui intègre de manière adéquate l'écologie, les données de télédétection et les capacités de vision par ordinateur pour la délinéation, la liaison hiérarchique, l'évaluation et la visualisation des objets dominants du paysage, et ce à travers les échelles. De plus, cette approche devrait être guidée par l'échelle intrinsèque des *objets-image* de taille, de forme et de distribution spatiale différentes qui composent une image de télédétection. Au moment où débutait cette thèse, une telle approche était inexistante.

La principale contribution de cette thèse est de proposer et développer une approche hiérarchique intégrée pour *l'analyse multi-échelle centrée sur l'objet* (MOSA) des paysages. L'approche MOSA intègre des concepts provenant de l'écologie du paysage et de la théorie des systèmes complexes ainsi que des solutions au MAUP (Chapitre 1). Elle incorpore aussi les données de télédétection et une structure itérative d'analyse et de changement d'échelle centrée sur les objets nouvellement créés (OSA/OSU – Chapitre 2); des concepts et des méthodes topologiques développés pour des analyses de « Scale-Space » qui permettent les liaisons hiérarchiques et l'analyse d'objets-image (Chapitre 3); et une adaptation d'une méthode de détection de caractéristiques de bassin versant résultant en une topologie multi-échelle centrée sur l'objet (MOST – Chapitre 4). Le résultat de cette intégration est une approche hiérarchique (MOSA) qui modélise automatiquement l'émergence d'objets-image dominants dans le paysage à travers les échelles et ce, à partir d'une seule image de télédétection. De plus, les objets-image résultants sont visuellement significatifs, hiérarchiquement localisables, topologiquement reliés et interrogeables et sont dérivés d'une approche minimisant les effets du MAUP.

Mots clés : *Écologie du paysage, analyse centrée sur l'objet (OSA), changement d'échelle centré sur l'objet (OSU), objets-image, analyse multi-échelle centrée sur l'objet (MOSA), topologie multi-échelle centrée sur l'objet (MOST), échelle, « Scale-Space » (SS), détection de « blob », analyse multi-échelle, problème des unités spatiales modifiables (MAUP), théorie de la hiérarchie, systèmes complexes, évolution fractale nette (FNEA).*

Abstract

Landscape Ecology is a transdisciplinary science with the fundamental goal to understand the interrelationship between spatial patterns and ecological processes, so that appropriate management strategies may be applied. However, achieving this is not a trivial exercise. Landscapes are complex systems composed of multiscale hierarchically organized entities that interact within unique spatial and temporal scales. These interactions result in scale-dependent spatial patterns that visually change, depending upon their scale of observation. Remote sensing platforms represent the primary data source from which such landscape patterns can be observed and assessed, but suffer from the modifiable areal unit problem (MAUP). The clearest way out of MAUP is by using *objects*, as objects constitute a non-arbitrary representation of space. Thus, their aggregation and scaling contains implicit ecological meaning.

In order to appropriately monitor, model, and manage our interaction within landscapes, Landscape Ecologists require a multiscale approach that judiciously integrates ecological theory, remote sensing data, and computer vision capabilities for the automatic delineation, hierarchical linking, evaluation, and visualization of dominant landscape objects through scale. Furthermore, this approach should be guided by the intrinsic scale of the varying sized, shaped, and spatially distributed *image-objects* that compose a remote sensing scene. At the time this thesis began, no such approach existed.

The principal contribution of this thesis is to propose and develop an integrated hierarchical approach for the *multiscale object-specific analysis* (MOSA) of landscapes. MOSA integrates concepts from Landscape Ecology, Complex Systems theory and solutions to MAUP (Chapter 1). It also incorporates remote sensing data and a newly created iterative *object-specific analysis* and *upscaling* framework (OSA/OSU - Chapter 2); concepts and topological methods developed for Scale-Space processing that allow for the hierarchical linking and analysis of explicit image-objects (Chapter 3); and a novel adaptation of a watershed feature detector resulting in *multiscale object-specific topology* (MOST - Chapter 4). The outcome of this integration is a hierarchical approach (MOSA) that automatically models the emergence of dominant landscape image-objects through scale, from a single scale of remote sensing imagery. Furthermore, the resulting image-objects are visually meaningful, hierarchically tractable, able to be topologically linked and queried, and are derived from an approach that minimizes the effects of MAUP.

Key Words: *Landscape Ecology, Object-Specific Analysis (OSA), Object-Specific Upscaling (OSU), Image-Objects, Multiscale Object-Specific Analysis (MOSA), Multiscale Object-Specific Topology (MOST), Scale, Scale-Space (SS), Blob-Feature Detection, Multiscale Analysis, The Modifiable Areal Unit Problem (MAUP), Hierarchy theory, Complex Systems, Fractal Net Evolution (FNEA)*

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Acknowledgements

One Indian-summer afternoon in 1997, I walked into a beautiful new geomatics lab, full of expensive toys and eager faces. As I passed by one of the rooms, I noticed a solidly built middle-aged gentleman with grey hair and beard, dressed as if he had just returned from the field. He was actively leaning over a cluttered grey desk, anxiously pointing to something on a large computer monitor with his right hand, and excitedly waving his left hand in the air. At the same time, he was enthusiastically immersed in conversation with an equally excited graduate student, whose nose appeared to be struggling for real-estate as it anxiously followed the gentleman's finger across the monitor. I still don't know exactly what it was about that moment that made me stop, but I do know that there was something magical about it. There was an essence, a quality of open, honest, intellectual exchange where each participant was student, and teacher. In that instant, I knew I needed to know who this gentleman was, because somehow – at that moment - I knew that he would play an important role in my life.

Always trust your feelings.... The Gentleman was Dr. André Bouchard, and six months latter we embarked upon a Ph.D. project together. The enthusiastic graduate student was Patrick Dubé, and the impressive new lab belonged to Dr. Danielle Marceau. To these three individuals I owe my deepest gratitude.

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Dedication

To my Dearest D: In this swirling, complex, and chaotic world... You are the most wonderful of strange attractors... To my favourite neural-net: Mr. Z. Daily, you teach me new dimensions of joy and laughter...

I am
a
smile junkie.

You
are
my drug.

Chapter 1: Introduction

"The significant problems we face

Cannot be solved

At the level of thinking we were at

When

We created them."

- Albert Einstein.

1. Context

Landscapes are complex systems, comprised of patch mosaics that differ in size, boundary condition, content, and successional age, with biotic and abiotic processes interacting in non-linear ways across a range of spatial and temporal scales. To understand, manage and forecast the consequences of 'natural' and 'human' interaction across such broad scales, an innovative transdisciplinary science is required. This science is Landscape Ecology; its primary goal is to understand the interrelationship between spatial patterns and ecological processes, so that appropriate management strategies may be implemented. To achieve these goals, landscape ecologists require theory and models to reduce the inherent complexity of nature, solutions to scaling problems, and innovative integrative approaches with which to evaluate and model the landscape at multiple scales.

To more fully appreciate these requirements, chapter one provides background information on Landscape Ecology, its evolution and goals, an introduction to Complex Systems theory, Hierarchy theory, scale and scaling, and hierarchical structure types. These concepts are followed by a discussion on the relationship between the modifiable areal unit problem (MAUP), remote sensing data and image-objects, and an overview of traditional multiscale image processing techniques. Based upon this information, a formalized problem is stated and a solution is proposed. Specifically, landscapes are complex systems that are composed of multiscale hierarchically organized entities that interact within unique spatial and temporal scales, and which produce correspondingly recognizable landscape patterns. Remote sensing platforms represent the primary data source from which landscape patterns can be assessed, but suffer from the modifiable areal unit problem (MAUP). The clearest way out of MAUP are objects. Thus, to model and manage our interaction within landscapes, we require the following:

- An integrated approach that is able to utilize remote sensing data and appropriate scaling techniques to generate meaningful representations of landscape patterns at multiple scales.
- Feature detectors that are able to automatically define dominant objects that compose these patterns at their respective scale(s) of expression.
- A topological mechanism for linking and evaluating object interaction and evolution through appropriate image hierarchies.

To meet these requirements, we propose that the analysis of multiscale landscape structure should be guided by the intrinsic scale of the varying sized, shaped, and spatially distributed *image-objects* that compose a scene, and present chapters two-four as three peer-reviewed articles, which demonstrate a logical progression of the authors' ideas towards developing a multiscale object-specific approach that satisfies this.

1.1 What is Landscape Ecology?

Forman (1995) describes a *landscape* as a kilometers wide mosaic over which local ecosystems[1] recur. He further describes *Ecology* (in general) as the study of the interactions among organisms and their environments. Therefore, *landscape ecology* is the ecology of landscapes. While this definition is simple and concise, Noble (1999) points out '...we live in landscapes; we manage landscapes. We often describe the environment around us in terms of landscapes. Yet landscapes have long been a scientific blind spot. The scientific description and classification of landscapes is weak and our understanding of their role in ecosystems functioning is poor.' As a result, different perceptions of landscapes have added to conceptually different descriptions of landscape ecology, which in turn have influenced the structure of this discipline, its acceptance and future in science[2], and its role in society.

The term *Landscape ecology* arose from the European traditions of regional geography and vegetation science (Naveh, 1982), and was first used by Carl Troll (1938, 1968; in Forman, 1995). Troll defined, '*Landscape ecology* [as] the study of the entire complex cause-effect network between the living communities and their environmental conditions which prevails in [a] specific section of the landscape...[and] becomes apparent in a specific landscape pattern or in a natural space classification of different orders of size'. As this discipline has evolved, the recognition of human interactions within the landscape, and a proactive perspective toward landscape management have entered more recent conceptual definitions. For example, Vink (1975) describes landscape ecology to be '...the study of the attributes of the land as objects and variables, including a special study of key variables to be controlled by human intelligence'. Zonneveld (1979) suggests that '... landscape ecology is an aspect of geographical study, which

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[1] Ecosystem: a relatively homogeneous area of organisms interacting with their environment – which has the potential to exist at essentially any scale (Forman, 1995).

[2] Pers Comm.: Dr. Richard Hobbs- President of the International Association of Landscape Ecologists (IALE), June 2000.

considers the (land) as a holistic entity, made up of different elements, all influencing each other'; and Risser *et al.* (1984) conclude that '...landscape ecology considers the development and dynamics of spatial heterogeneity, spatial and temporal interactions and exchanges across heterogeneous landscapes, influences of spatial heterogeneity on biotic and abiotic processes, and management of spatial heterogeneity.' Similarly, Naveh and Lieberman (1994) view landscape ecology as '...a transdisciplinary[3] ecosystem-education approach based on general systems theory, biocybernetics, and ecosystemology as a branch of total human ecosystem science'. In a less epistemological, more workable definition, the International Association of Landscape Ecology (IALE), defines landscape ecology as '...the study of spatial variation in landscapes at a variety of scales. It includes biophysical and societal causes and consequences of landscape heterogeneity. Above all it is interdisciplinary' (IALE, 1998).

From its origins in geography to its modern form, many disciplines including economics, land-use planning and decision-making, have significantly contributed to the development of landscape ecology (for excellent reviews see Turner, 1989 and Forman, 1995). In particular, a rich history of ecological research provides a basis for the study of vegetation patterns and landscape processes. For example, Clements (1916) stressed temporal dynamics but did not emphasize spatial patterning. Gleason (1917, 1926) argued that spatially heterogeneous patterns were important and should be interpreted as individualistic responses to environmental spatial gradients. With the development of gradient analysis (Whittaker, 1956; Curtis, 1959) the description of the continuous distribution of species along environmental gradients was made possible. Within this framework, abrupt discontinuities in vegetation patterns were believed to be associated with sharp discontinuities in the physical environment (Whittaker, 1975), while the spatial patterns of climax vegetation were thought to reflect localized intersections of species responding to complex environmental gradients. In 1947, Watt presented a revised concept of vegetation patterns in space and time, where the distribution of the entire temporal progression of successional stages was described as a pattern of patches[4] across a landscape. Similarly, the concept of the *shifting steady-state mosaic* (Bormann and Likens, 1979) incorporates natural disturbance processes and is related to Watt's conceptualization. However, many of these

[3] *Transdisciplinarity* exists where interaction involves not only the scientific and technological disciplines stated in goals, but also where planners and administrators become involved in the process (di Castri and Hadley, 1986)

[4] A relatively homogeneous non-linear area that differs from its surroundings. That is, the internal micro-heterogeneity present is repeated in similar form throughout the area of a patch (Forman, 1995).

ecological studies emphasize *describing the processes* that created the patterns observed in the biota. As a result, the explicit effects of spatial pattern on ecological processes have not been well studied. As Wiens (1995) reports, little work (to date) has focused on the structure of spatial mosaics and their effects on ecological systems. Yet many proponents in the field believe that this is (or should be) the focus of landscape ecology (Hobbs, 1997).

While an emphasis on pattern and process – and the required transdisciplinarity to understand these components - differentiates landscape ecology from other ('ecological') disciplines, several proponents in the field believe that emphasizing pattern and process alone is not enough. As Risser (1987) suggests, '...landscape ecology should not be regarded only as the synthetic intersection of many related disciplines which focus on spatial and temporal patterns of the landscape' – but rather, as Naveh (1991) suggests '...an innovative, transdisciplinary science of landscape appraisal and history, planning, management, conservation and restoration. As such it should be both a problem-inquiring and problem-solving oriented science'. This view is further supported by the IALE (1998) which encourages landscape ecologists '...to transcend boundaries, and to work together building theory and developing knowledge of landscape pattern and process, developing integrative tools, making them applicable to real landscape situations and applying them in solving problems.' While the word *'landscape'* intuitively possesses size limitations, some advocate that landscape ecology should also play a distinctive role in environmental problem solving at global scales (Naveh, 1991; Hobbs, 2000).

1.2 The Need for Appropriate Multiscale Theory

From the preceding discussion it is evident that the goals and expectations of Landscape Ecology are extremely broad and fall beyond the scope of a single individual, discipline, or lifetime. Therefore, I will draw upon a more narrow definition of landscape ecology from which to develop the remainder of this thesis:

> *'Landscape Ecology emphasizes broad spatial scales and the ecological effects of the spatial patterning of ecosystems. Specifically, it considers (a) the development and dynamics of spatial heterogeneity, (b) interactions and exchanges across heterogeneous landscapes, (c) the influences of spatial heterogeneity on biotic and abiotic processes, and (d) the management of heterogeneity'* (Turner, 1989).

To achieve these goals, it is imperative that landscape ecologists are fluent in the theory, methods, traditions, tools, data, and languages of the diverse fields they attempt to integrate; or they risk making the same mistakes each discipline has matured beyond. Ecological theory is not '*a simple guess*'[5]; ecological models are not '*video games*'[6]; satellite images are not merely '*pretty pictures*', and understanding '*scale*' holds the key to understanding landscape patterns (Levin, 1992). Therefore, landscape ecologists must have access to, and a working knowledge of, the following resources:

- Theories and models to reduce the complexity of the landscape so that understanding may be validated and appropriate management implemented.
- Innovative and integrative approaches with which to evaluate, describe, visualize, and manage landscapes at multiple scales that included appropriate solutions to scale and scaling problems.

To better understand these requirements the following sections briefly describe Complex Systems theory, Hierarchy theory, scale and scaling, hierarchical structure types, MAUP, remote sensing and image-objects, and multiscale image analysis approaches.

1.2.1 Complex Systems Theory

From a convergence of ideas developed primarily in economics, ecology, and computer sciences, *complex systems theory* has emerged with the goal of describing the behaviour of human and ecological systems (Kay, 1991; Schneider and Kay, 1995). In essence, complex systems are characterized by a large number of components that interact in a non-linear way and that exhibit adaptive properties through time (Waldrop, 1992; Coveney and Highfield, 1995). From this perspective, ecosystems can be regarded as open systems that extract high quality energy from the sun, and respond with the spontaneous emergence of organized behaviour so that their structure and function are maintained (Kay, 1991; Kay and Schneider, 1995). This mechanism is called *self-organization* and it is revealed in the form of spatial patterns and temporal rhythms at the macroscopic scale where we can observe them (Nicolis and Prigogine, 1989). An important characteristic of complex systems is that (intuitively) they take the form of a

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[5] A *theory* represents a coherent and unified body of knowledge that has been proven true, at least, against all the evidence available at the time (Wu and Levin, 1994).

[6] Levins (1968) defines a model as '...an abstraction, and therefore a simplification of reality.'

nested hierarchy i.e., leaf, branch, tree, etc. Thus, one way to explain and better understand natural processes is to use these natural scales and frequencies (i.e., hierarchies of spatial and temporal patterns) that emerge within a system.

1.2.2 Hierarchy Theory

Hierarchy theory[7] was developed in the framework of general systems theory, mathematics and philosophy in the 1960s and 1970s (Wu and Loucks, 1995) as a conceptual framework that built upon the idea of *natural scales*. In general terms, a hierarchy may be defined as 'a partial ordering of entities' (Simon, 1973). Thus hierarchies are composed of interrelated subsystems, each of which in turn is made of smaller subsystems until a lowest level is reached. More formally, a hierarchically organized system can be seen as a nested system (Figure 1.1) in which levels corresponding with progressively slower behaviour are at the top (Level +1), while those reflecting successively faster behaviour are seen as lower levels (Level -1). The level of interest is referred to as the *Focal Level* (Level 0).

The single most important consequence of such structuring is embodied in the concept of *constraint*. This concept emphasizes that the behaviour of an ecological system is limited (1) by the potential behaviours of its components and (2) by the environmental constraints imposed by higher levels. In a hierarchical system, interactions occur among and within subsystems in different orders of magnitude. Interactions are generally stronger and more frequent *within* a level of the hierarchy than *among* levels (Allen and Star, 1982). This important fact enables scientists to perceive and describe complex systems by decomposing them into their fundamental parts and interpreting their interactions. From a landscape ecology perspective, Hierarchy theory predicts that complex ecological systems, such as landscapes, are composed of relatively isolated levels (*scale domains)*, where each level operates at relatively distinct time and space scales. *Scale thresholds* separate such domains, and represent relatively sharp transitions or critical locations where a shift occurs in the relative importance of variables influencing a process (Meentemeyer, 1989; Wiens, 1989).

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[7] Hierarchy theory is generally regarded as formally being introduced into ecology by Allen and Starr (1982); though it should be noted that early work by Watt (1947), Whittaker (1953), and others embrace ideas that are implicitly hierarchical (Urban et al. 1987).

1.2.3 Scale and Scaling

Scale is *the* fundamental determinant of hierarchical structure (Levin, 1992). Furthermore, if something is not hierarchically structured it is beyond our understanding (Simon, 1962). Thus the key to understanding the hierarchical structuring/patterning of complex systems first lies in understanding the 'nature' of scale. In general, the term *scale* represents the 'window of perception'. More specifically, scale refers to the spatial dimensions at which entities, patterns, and processes can be observed and characterized. Thus if one changes the scale at which a scene is viewed, one effectively changes (perceived) reality.

Ecologists define scale as having two components: *grain* and *extent*. Grain corresponds to the smallest spatial sampling units used to gather a series of observations. Extent is the total area over which observations of a particular grain are made (O'Neill and King, 1998). In cartography, scale represents the ratio of a distance on a map to the corresponding distance on the ground. While in remote sensing, the spatial resolution of an image represents the surface on the ground or the spatial sampling increment from which (integrated) values are collected and registered by the sensor. In this thesis, the term *small scale* refers to small extents with a fine grain, while *large scale*, refers to a large area with a coarse grain. The term *scaling* is often associated with multiscale analysis, and refers to translating information from one scale to another. This is typically conducted in one of two ways. *Upscaling* is a 'bottom-up' approach that consists of using information at a small scale to derive information at a coarser scale; thus information tends to be lost in the upscaled representation due to generalization. *Downscaling* is a 'top-down' approach that refers to decomposing information at one scale into its constituents at smaller scales. This often results in information redundancy and – without an appropriate compression procedure - increased storage requirements.

Due to the non-linearity inherent to complex systems, scaling poses a serious challenge, as significant errors can result when data are arbitrarily scaled across domains (Gardner et al. 1982; King, 1990). Thus, scaling is part of what is referred to as the 'scale problem'. In the natural sciences (Marceau, 1999), this problem essentially encompasses two complementary components that may be expressed by the following questions:

- What is the appropriate spatial scale for the study of a particular (geographically based) entity or process?
- How can we adequately transfer information from one spatial scale to another?

1.2.4 Hierarchical Structure Types

To better understand the scale problem, we need to distinguish between different hierarchical components and their structural relationships. For example, while conceptually appealing, Hierarchy theory quickly runs into problems related to scale. To accurately characterize a constraint envelope (or triad) the analyst must (1) clearly identify the scale and level of the study and their appropriateness for the phenomenon (i.e., object) of interest; (2) know the important variables influencing the object at different scales and levels; (3) know when one is translating levels or scales, and recognize issues involved in top-down or bottom up thinking; and (4) sample and experiment across scales and levels (Gibson et al, 2000). None of these are trivial considerations, especially when the phenomenon of interest is seldom a single entity. More often it is a class of objects that vary in size, shape, distribution and temporal evolution even when observed with a fixed grain and extent, i.e., cities, agricultural fields, fallow lands, hedge rows, forest stands, tree species, and specific habitat types.

To apply Hierarchy theory to landscape problems, Cousins (1993) suggests two fundamental requirements. The first allows for the quasi-independence of objects at different hierarchical levels. This is outlined in the explanation of hierarchically organized systems (i.e., interactions *within* vs. *among* levels). However, to achieve this, objects need to be clearly defined and clearly separated from non-objects such as aggregates. Rowe (1961) makes this distinction by stating that *objects* contain structurally organized parts, while *aggregates* occupy a common area, but have no structural organization. Furthermore, objects have *intrinsic scale*, whereas aggregates do not. Thus according to Rowe, a forest may appear as a solid object when viewed from a distance, but it is not an object itself. Instead, it is an aggregate of objects (i.e., vegetation, soils, gaps, etc). This is because a 'forest' is a conceptual human construct; whereas a tree – a necessary forest component - has a characteristic size predicated by specific environmental and biological constraints, and is itself physically composed of structural parts (i.e., bole, bark, and branches).

When landscape components are defined as either objects or non-objects, the result is two fundamentally different types of hierarchies. Those composed of *aggregate objects*, and those composed of *integrated objects*. Cousins (1993) final requirement for hierarchical analysis incorporates the ability to distinguish between these different hierarchical types, with the warning that such hierarchies should not be mixed. If mixed then their interpretation becomes subject to generalization errors due to aggregation and scaling problems. To better understand the importance of different hierarchical structures and the need to keep them separate, the Object-Oriented (OO) paradigm (Graham, 2001) defines two kinds of hierarchical structures, each of which describes different types of relationships between classes. A *class* refers to a group of objects with similar attributes and behaviours, and an *object* is any physical or conceptual entity. The first type of OO hierarchy describes the '*aggregation relationship*' by asking if a focal object (e.g. tree) is *'a part of'* a higher-level object (e.g. forest), or reciprocally if it is *'composed of' a* lower level object (e.g. bole, branches, leaves). True responses to both questions typically result in a nested hierarchy (Figure 1.2).

The second type of OO-hierarchy describes the '*generalization/specialization relationship'* and asks whether an object at the lower levels is *'a kind of'* the focal object. This results in generalization: e.g., a pine is a kind of tree. Conversely, the upper level class *'can be'* the object at the focal level e.g., vegetation can be a tree, grass, or flowers. This represents specialization. True responses typically result in both nested[8] and unseated[9] hierarchies (Figure 1.3). The important point to appreciate is that while both kinds of hierarchies may contain the same focal object (i.e., tree), their relationships are completely different, thus the questions that can be posed, and the information resulting from each type of hierarchy will be very different.

We suggest that recognizing this distinction between hierarchy types, and the warning against mixing them has not been fully understood or heeded across a broad range of disciplines. For example, the biological hierarchy of cell-organ-organism-ecosystem[10] (which is a hierarchy of objects composed of parts within parts within parts) has been imprudently extrapolated to include psychological and social/cultural phenomena (Rowe, 2001); and object and aggregate hierarchies are also routinely mixed. For example, Wu, (1999) states that *"...levels in the traditional hierarchy of ecological organization (i.e., individual-population-community-ecosystem-landscape-biome-biosphere) are definitional and do not necessarily meet scalar[11] criteria. Yet,*

[8] For example: pine, tree, and vegetation are each *a kind of* the class above, and *can be* the class beneath, thus they are hierarchically nested.

[9] For example: maple and flowers are a *kind of* vegetation, however both cannot be a kind of tree. Thus, flowers are unseated with regards to tree, but nested with regards to vegetation.

[10] Cousins (1993) notes that the concept of 'ecosystem' is also a subjectively determined aggregate with boundaries given by an observer, yet it is possible to define an ecological object which substitutes for ecosystem in a hierarchy of functional objects (pp. 77-78).

[11] (i.e., scale-related, albeit spatial or temporal).

the concepts and principles of Hierarchy theory usually apply only to scalar, not prescribed or definitional hierarchies". While we agree with Wu and others (Allen and Hoekstra, 1991; Ahl and Allen, 1996) regarding this scaling criterion, the described 'traditional hierarchy' is a mix of both integrated objects (i.e., individual, ecosystem, biosphere) and conceptual aggregate objects (i.e., population, community, landscape[12]).

The real problem is that few recognize that any mixing has occurred. As Rowe, (2001) states '...the fallacy of mixing different categories, and treating them as isomorphic, traps many otherwise-clever minds.' When we consider this information, it is no wonder that O'Neill and King (1998) state that '...as yet we have been unable to determine whether landscape hierarchies are truly nested, unseated, or completely at the arbitrariness of the evaluator.' In many cases this may be because we have been evaluating mixed hierarchies, thus inadvertently participating in the modifiable areal unit problem (MAUP).

1.2.5 MAUP, Remote Sensing, and Image-Objects

The *Modifiable Areal Unit Problem* (MAUP) as first defined by Openshaw and Taylor (1979; 1981) represents the sensitivity of analytical results based on the definition of data collection units. In essence, MAUP arises from the fact that areal units are usually arbitrarily determined and 'modifiable', in the sense that they can be aggregated to form spatial units of different sizes. Consequently, the value of any work based upon them may not possess any validity independent of the units that are being studied (Marceau, 1999). The MAUP is composed of two related but distinct components: the *scale problem*, and the *aggregation problem* (Marceau et al, 1994a). The scale problem results from changing the number of spatial units under analysis within a fixed spatial extent or area, i.e., observing the landscape at a 1.0 meter spatial resolution, versus a 100 meter spatial resolution. The observable area is constant, but the visual information we perceive within that area is different. In the aggregation problem, the number of spatial units under analysis is held constant (i.e., all 1.0 m pixels), but how they are aggregated (i.e., which individual 1.0 m pixels are coalesced into groups of 100 m pixels) produces very different results.

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[12] Grene (1987) indicates that the taxonomic hierarchies of species to kingdoms are linked by the history of evolutionary descent and are not, at each or any level functioning objects today. Furthermore, the components of population, community, and landscape are conceptual rather than real world, thus their boundaries are subjectively chosen by the observer (Cousins, 1993).

To overcome the potential for error resulting from MAUP, Fotheringham (1989) describes five potential solutions:

- the derivation of optimal zoning systems,
- the identification of basic entities,
- abandonment of traditional statistics,
- sensitivity analysis, and
- the search for fluctuations in variables and relationships with scale.

In particular, Fotheringham suggests that the identification of basic geographical entities provide the clearest way out of the MAUP. Furthermore, if entities and relationships between variables (i.e., the spatial primitives that model the entities) emerge at specific scales, there must also be a way to define them and to relate them across discrete levels of organization (Marceau, 1999). To test this we require data with a coarse enough extent, and fine enough grain to capture landscape patterns over a wide range of scales. Fortunately, remote sensing platforms satisfy this requirement by providing relatively contiguous, ubiquitous, and inexpensive access to landscape-sized data at a variety of spatial, spectral, and temporal scales[13] (Marceau and Hay, 1999a). However, it has only recently been recognized (Marceau, 1992; Marceau, et al, 1994a; Arbia et al, 1996; Jelinski and Wu, 1996), that remote sensing is a particular case of the MAUP; which may explain many of the inconsistencies in results when remote sensing data are used to produce thematic maps or used as inputs into physical models, without explicitly taking into account the impact of scale (Marceau and Hay, 1999a). Furthermore, the fundamental primitive of a remotely sensed image is typically a square pixel, which is neither a real world object, nor a topologically discrete digital model of a real world object.

Thus to overcome (or at least reduce) the effects of MAUP when using remote sensing data, we require innovative approaches capable of converting pixels into meaningful *image-objects* that

[13] An important ecology-based goal and incentive for using remote sensing data is if local field measurements can be inferred either directly or indirectly from remotely sensed variables, then spatially comprehensive remote sensing coverage can be exploited to estimate variables at landscape to regional scales within ecosystem models (Wessman, 1999). In addition, remote sensing simplifies field-sampling strategies for model parameterization/validation because it, as the scaling tool, can delineate landscape structural or functional units for optimal sampling design (Prince and Steininger, 1999).

correspond to ecologically meaningful integrated objects. An image-object is a 'basic entity', located within an image that is perceptually generated from high-resolutions pixel groupings or clusters (Hay et al. 1996; 2001). That is, objects that 'automatically' appear in an image when viewed for the first time[14]. High-resolution (H-res) refers to the situation where a real world object is modeled by the sensor as being composed of many pixels. Conversely, low-resolution (L-res) refers to the integrated signal from many (smaller) real-world objects being modeled as a single pixel (larger pixel).

1.3 Multiscale Image Analysis Approaches

Humans have evolved sophisticated biological responses that allow them to automatically sense, and cognitively manipulate their environment at a range of spatial, spectral, temporal, optical, haptic, gustative, olfactory and acoustic scales. Similarly, during the last three decades, a number of computational multiscale approaches i.e., pyramids, quadtrees, wavelets, fractals and others have been developed in an effort to emulate, enhance, and improve upon these innate multiscale capabilities[15]. In general terms, multiscale analysis comprises two fundamental components: the generation of a multiscale data set, and the delineation of objects within these data by using feature detectors. The proceeding sections briefly outline a number of these techniques and their applications.

1.3.1 Pyramids

Early methods for the multiscale representation of images fall under the heading of *hierarchical data structures*, which has two basic roots. The first began in the late 1960s and early 70s in computer graphics, and was developed for data compression (Klinger and Dyer, 1976) and image segmentation (Haralick and Shapiro, 1981). The other was for the handling of geographic data in Geographic Information Systems (GIS) (Mark, 1986). The basic concept of defining hierarchical data structures was initiated by using *pyramids*. A pyramid of an image is a description of its data contents generated by a recursive decomposition of space. An early

[14] These correspond to what David Marr (1982) refers to as the most elementary elements of the primal sketch i.e., tokens (or primitives) consisting of edges, lines segments, and blobs.

[15] The ability to portray and evaluate a digital signal (such as a remote sensing image of a landscape) at multiple scales represents both a technology driven extension, and what some consider as the natural evolution of our innate abilities (Kurzweil, 1999).

approach was to successively apply linear filtering to a fine resolution image and then subsample the image recursively. Subtracting from each level an interpolated version of the next coarser level derived a detailed pyramid. However, linear filtering is not always consistent with real-world features, which has resulted in the development of non-linear pyramidal approaches, e.g. the *pyramidal median transform* (Starck et al. 1998) or *morphological pyramids* (Serra, 1988). Numerous planar pyramid decomposition methods exist (Samet, 1990), however, using squares is unique and results in the generation of quadtrees.

1.3.2 Quadtrees

The quadtree was introduced by Klinger (1976) and represents a multiresolution approximation by local averages on tiles of varying size. In this hierarchical approach, an image is recursively divided into four equal sized smaller regions (or tiles)[16]. Decomposition halts when a homogeneity criterion is reached based on the pixel values within the corresponding image region[17]. Visually, the sequence of decomposed representations can be illustrated as a tree structure, where each branch defines a new level of detail, and the leaves represent the level where further division is not possible or required. The quadtree construction algorithm is sensitive to pattern/spatial structure, thus at heterogeneous locations it further decomposes the scene into finer resolution tiles. Decomposition is based on the concept of minimizing the total heterogeneity (using measures such as variance, or entropy) between the current partition and a finer, or coarser resolution partition. Quadtree decomposition results in data redundancy, thus by incorporating a 'pruning' condition, redundant information can be removed, resulting in a more efficient storage/compression strategy. However, quadtrees are limited to a square representation of space, which contains inherent spatial bias along the diagonal. Furthermore, they have difficulty with grid data (i.e., remote sensing imagery) when neighbouring cells do not have the same value (Csillag, 1997).

1.3.3 Wavelets

Wavelets are functions that satisfy certain mathematical requirements and are used to represent data (or other functions) by conducting analysis at different scales or resolutions. Wavelet analysis is similar to Fourier analysis in the sense that it breaks a signal down into its constituent

[16] Hence the reference to 'quad' in its name.

[17] What this criterion is depends upon what the user defines as 'interesting'.

parts for analysis. Whereas the Fourier transform breaks the signal into a series of sine and cosine waves (its 'basis functions') of different frequencies, the wavelet transform breaks the signal into its 'wavelets' (i.e., small waves) – which are scaled and shifted versions of the 'analyzing wavelet' or 'mother wavelet' (Valens, 1999). In simple terms, the mother wavelet is an approximating function used to assess the structure of the signal that is contained neatly in a finite domain[18]. Thus in practice, a mother wavelet is defined within a fully scalable modulated window that is shifted along the signal, and for every position the spectrum is calculated. This process is then repeated many times with a slightly shorter (or longer) window for every new cycle[19]. In the end, the result will be a collection of time-scale representations[20] of the signal, all with different resolutions.

In comparison to sine and cosine waves, which are smooth, and of infinite length, the wavelet is irregular in shape and compactly supported. It is these properties of being irregular in shape and compactly supported that makes wavelets an ideal tool for analysing signals of a non-stationary nature[21]. Their irregular shape lends them to analysing signals with discontinuities or sharp changes, while their compactly supported nature enables temporal localization of the signals' features (Altmann, 1996). Furthermore, unlike the single set of Fourier basis functions, wavelet transforms have an infinite set of possible basis functions, thus providing immediate access to information that can be obscured by other time-frequency methods. This allows both flexibility, where the scientist can choose the wavelet, but it also requires an understanding of what one expects in the signal, the ability to define an appropriate mother wavelet, and the recognition that wavelets can introduce artifacts within a multiscale representation (Starck et al, 1998).

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[18] i.e., compact support within a specified window.

[19] Scaling and shifting of the mother wavelet – or more correctly, *dilation* and *translation* – consists of two basic forms: the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT). In DWT, the signal is broken into dyadic blocks (i.e., shifting and scaling is based on the power of 2). In CWT, discretely sampled data are still used, however the shifting process is a smooth operation across the length of the sampled data, and the scaling can be defined from the minimum (original signal scale) to a maximum chosen by the user, thus giving a much finer resolution. The trade off for this improved resolution is an increase in computational time and memory required to calculate the wavelet coefficient (Altmann, 1996)

[20] In the case of wavelets we normally do not speak about time-frequency representations but about *time-scale representations*. The term *frequency* is reserved for the Fourier transform.

[21] The vast majority of biological signals are non-stationary (Polikar, 2001).

In addition, since the original signal or function can be represented in terms of a wavelet expansion (that is, using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients. Thus, if wavelets are chosen that are best adapted to the data, or if coefficients below a defined threshold are truncated, then the data are sparsely represented; which makes wavelets an excellent tool in the field of data compression (Starck et al, 1998).

1.3.4 Fractals

The term 'Fractal' was coined by Mandelbrot (1967) to represent a *fractional representation of space* that is more complex than can be represented by the traditional three dimensions of Euclid. In essence, a fractal is a shape made of parts similar to the whole in some way. While fractals can be used to generate spatial representations, such as realistically appearing topographic features and vegetation, they are more commonly used as a measure of surface or structural complexity (Xia and Clarke, 1997). The biggest limitation with fractals is that they can be calculated in many different ways, i.e., using walking dividers (Mandelbrot, 1967), variograms (Mark and Aronson, 1984), box-counting (Goodchild, 1982), the power spectrum method (Turcotte, 1987) and others (Xia and Clarke, 1997), each of which generates a different value for the same surface, thus making comparison difficult, and somewhat meaningless.

1.3.5 Variance, Spatial Extent, and Optimal Resolution

In Landscape Ecology, one of the first steps in multiscale analysis is often an empirical description of changes in pattern with changes in scale (Schneider, 1997). One of the simplest (and surprisingly effective) quantitative methods to achieve this is to plot the change in variance with changes in spatial extent (Gardner, 1998). Plotted results often reveal breaks in slope, which have been interpreted to demonstrate phenomena ranging from discrete levels of spatial organization within the image (O'Neill et al, 1991), to the defining optimal spatial resolution for object classes. For example, Marceau et al., (1994b) identified optimal spatial resolutions[22] for the detection and discrimination of coniferous classes in a remote sensing image by calculating the internal variance of each forest class in relation to increasing spatial resolution. Minimum

[22] *Optimal spatial resolution* was defined as the spatial sampling unit corresponding to the scale and aggregation level characteristic of the geographical entity of interest.

variance was used as the indicator of the spatial resolution best capturing the intrinsic characteristics of each forest class. Hyppänen (1996) also conducted a study to identify the optimal spatial resolution in a forested landscape. He used a similar approach to Woodcock and Strahler (1987) and reported a clear peak of local variance for different tree species. In comparable studies, Atkinson (1997) determined a suitable spatial resolution for agricultural mapping; Franklin *et al.* (1996) derived semivariograms to generate *geographic windows* corresponding to the scale of observation to provide forest inventory, forest structure characteristics, and land-cover classes; and Atkinson and Curran (1995) used semivariograms and kriging to define an optimal-sized resolution for various remote sensing applications. Costanza and Maxwell (1994) also conducted a study to find the optimal resolution for a particular modeling problem that balanced the benefit of increasing data predictability with the cost of decreasing model predictability due to changes in scale.

1.3.6 Feature Detectors

Regardless of how a multiscale representation is generated, once achieved, feature detectors are required to isolate entities of interest within either individual layer/scales, or within all scales of the multiscale output. Describing all such techniques is beyond the scope of this thesis. However, several feature detectors that are typically used include edge detectors, thresholding techniques, template matching, and morphological operators. In basic terms:

- Edge detectors are high pass filters that enhance areas of high contrast in an image i.e., sharp changes in brightness values between two adjacent pixels. Numerous linear and non-linear techniques exist (Jensen, 1996).
- Template matching is the seeking of patterns, that match a query pattern. A catalogue or inventory of all objects may be used to facilitate later queries (Starck et al., 1998)
- Thresholding traditionally requires defining either a specific grey-level value, or a range of values within the image or within a frequency histogram that corresponds to the area of interest within the image. From the specified value(s) a threshold or cut-off value is defined resulting in a binary representation. Values of interest correspond to 1's, and non-important values to 0's. The resulting binary mask represents the spatial location of spectral elements within the threshold set. These binary areas or *blobs* can then be individually defined with region labelling techniques.
- Mathematical morphology (MM) is both a theory and method of processing digital images on the basis of shape. Morphological operators are a MM technique that represent a

class of non-linear neighbourhood operators that aim at extracting relevant structures from an image. Erosions and dilations are the two fundamental operators. A morphological approach to image segmentation typically combines region growing and edge detection techniques. In essence, it groups image pixels around a regional minimum and creates boundaries around the edges of these pixel groupings. A typical application is a watershed transformation – of which many versions exist (Soille, 1999).

While numerous multiscale image-processing approaches exist, the important concepts to note are that in Landscape Ecology (to the best of our knowledge):

- multiscale analysis is seldom (if ever) used to evaluate how an image-object evolves and or is hierarchically linked through scale;
- few approaches exist that are capable of automatically defining the varying sized, shaped and spatially distributed image-objects within a scene at their characteristic scales of expression; and
- few approaches exist for topologically querying ecologically based image-objects at either a single or multiple scales.

1.4 Thesis Objectives and Overview

A synopsis of the preceding sections reveals the following challenges. Landscapes are complex systems composed of multiscale hierarchically organized entities that interact within unique spatial and temporal scales, and which produce correspondingly recognizable landscape patterns. However, these patterns change depending upon their scale of observation. Furthermore, there is no single or 'optimal' scale of observation for defining objects of significantly different size and shape. Remote sensing platforms represent the primary data source from which (multiscale) landscape patterns can be assessed, but suffer from the MAUP. The clearest way out of MAUP is by using objects, as objects constitute a non-arbitrary representation of space. Therefore, to appropriately model and manage our interaction within landscapes, Landscape Ecologists need an integrated multiscale approach that judiciously combines ecological theory and computer vision methods to satisfy three key requirements. First, the ability to use remote sensing data and appropriate scale and scaling approaches to generate meaningful representations of landscape patterns at multiple scales. Second, appropriate feature detectors, capable of automatically defining ecologically meaningful image-objects that compose these patterns at their respective scale(s) of expression. Third, topological mechanisms for automatically linking and evaluating image-object interaction and evolution through appropriate scales.

When we consider that humans define different sized, shaped and spatially distributed objects by using varying sized operators that are specific to the structural characteristics of these objects, we propose that the analysis of multiscale landscape structure should be guided by the intrinsic scale of the varying sized, shaped, and spatially distributed *image-objects* that compose a scene. Therefore, the primary objective of this thesis is to fulfill the previously stated (three) requirements, by developing an integrated hierarchical approach for the *Multiscale Object-Specific Analysis* (MOSA) of landscapes. The development and evolution of this object-specific approach is presented in chapters two-four, where each chapter constitutes a peer-reviewed article that builds upon the author's previous work. Thus, as a whole, they represent a logical progression towards achieving the stated objective.

Chapter 2 is titled *'A Multiscale Framework for Landscape Analysis: Object-Specific Analysis and Upscaling'.* This work is co-authored by G. J. Hay, D. J. Marceau, P. Dubé, and A. Bouchard, and published in *Landscape Ecology* in June 2001, as Vol.16, No.6: 471 – 490. This paper fulfills the first requirement by introducing an iterative object-specific framework that reduces MAUP, incorporates concepts from complex systems theory, and uses remote sensing data for generating a meaningful multiscale representation of the dominant image-objects composing a scene.

To meet the second requirement, a more in depth understanding of feature detectors and topological mechanisms for isolating and querying individual image-objects was necessary. As a result, the author ventured into Computer Vision to evaluate the applicability of Scale-Space theory and its' associated methods. The results of this work are presented in Chapter 3, which is titled *'A Scale-Space Primer for Exploring and Quantifying Complex Landscapes.'* This paper has been accepted without changes and was published in *Ecological Modelling* in July 2002, as Vol.153, Issue 1-2: 27-49. The contributing authors are G. J. Hay, P. Dubé, A. Bouchard and D. J. Marceau. To the best of our knowledge, this paper represents the first introduction of linear scale-space and blob feature detection within landscape ecology[23]. It provides important insight

[23] As no commercial Scale-Space and Blob-Feature detection software existed to evaluate this combination of techniques, the first two authors (Hay and Dubé) developed - in house - all applications for testing and analysis.

and understanding into how multiscale feature detectors, and topological mechanisms could be integrated within a multiscale object-specific approach.

To meet the third criteria, additional understanding of different hierarchical and topological structures was required. To achieve this, several different multiscale techniques were evaluated, and advantageous capabilities were integrated. This work is discussed in Chapter 4, and is titled *'A comparison of three image-object methods for the multiscale analysis of landscape structure.'* This work entered the peer-review[24] process in March 2002, and was accepted for publication in August 2002. It is co-authored by G. J. Hay, T. Blaschke, D. J. Marceau, and A. Bouchard. In particular, it describes three recent multiscale image-processing approaches that focus on image-objects, discusses the importance of appropriate object-hierarchies, and illustrates how image-objects allow for the hierarchical linking of pattern components. In addition, it introduces *MOST* (multiscale object-specific topology) as a synergistic combination of concepts from Object-Specific Analysis and Mathematical Morphology, and further outlines how an integration of iterative OSA/OSU (Chapter 2), the topological methods developed for Scale-Space (Chapter 3), and the feature detectors in MOST (Chapter 4), together constitute a unique hierarchical approach capable of multiscale object-specific analysis (MOSA).

Chapter 5 represents the thesis conclusion. It summarizes the entire thesis, emphasizes its original contribution, and outlines future work.

[24] This paper represents an invited submission to a special issue of the ISPRS Journal of Photogrammetry and Remote Sensing (ISPRS - International Society of Photogrammetry and Remote Sensing), theme: Challenges in Geospatial Analysis, Integration and Visualization.

Chapter 2: A Multiscale Framework for Landscape Analysis: Object-Specific Analysis and Upscaling[⊗]

"The world is both richly strange and deeply simple.
That is the truth spelled out in the graininess of reality;
that is the consequence of modularity.
Neither gods nor men mould clay freely;
rather they form bricks."

- Philip Morrison (1966)

[⊗] This work is co-authored by G. J. Hay, D. J. Marceau, P. Dubé, and A. Bouchard, and published in *Landscape Ecology* in June 2001, as Vol.16, No.6: 471 – 490.

2. Abstract

Landscapes are complex systems that require a multiscale approach to fully understand, manage, and predict their behaviour. Remote sensing technologies represent the primary data source for landscape analysis, but suffer from the modifiable areal unit problem (MAUP). To reduce the effects of MAUP when using remote sensing data for multiscale analysis, we present a novel analytical and upscaling framework based on the spatial influence of the dominant objects composing a scene. By considering landscapes as hierarchical in nature, we theorize how a multiscale extension of this object-specific framework may assist in automatically defining critical landscape thresholds, domains of scale, ecotone boundaries, and the grain and extent at which scale-dependent ecological models could be developed and applied through scale.

Keywords: *object-specific analysis, scale, multiscale, upscaling, MAUP, landscape thresholds, domains of scale, remote sensing, OSA, OSU, image-objects.*

2.1 Introduction

To better understand, manage, and predict the behaviour of the complex systems that provide life on earth, we require an improved understanding of the scale-specific interactions responsible for landscape metabolism (Levin, 1992), robust techniques for visualizing and deciphering multiscale processes from patterns (Turner et al. 1991), and appropriate scaling strategies for linking and modelling data at multiple scales (King, 1990; Ehleringer and Field, 1993). To assist landscape ecologists in these tasks, modern remote sensing technologies provide multi-resolution data sources for analysis and hypothesis testing over both large and small areas, and Hierarchy theory provides a useful analytical framework for describing the landscape's composition within these scenes.

According to Hierarchy theory, ecological systems are considered as 'nearly decomposable' hierarchically organized entities resulting from (different) structuring processes exerting their influence over defined ranges or domains of scale (Allen and Starr, 1982; O'Neill et al. 1986; Holling, 1992). Conceptually, the decomposability of these systems implies that their analysis and understanding can be enhanced by organizing their numerous components into fewer discrete, interactive units at different levels based on differences in process rates (O'Neill et al. 1989, King 1999). When these ideas are considered in relation to the spatial, spectral, temporal, and radiometric properties inherent to remote sensing data (Marceau and Hay, 1999a), the keys to fully unlock the complex relationships between scale-specific landscape patterns and processes appear close at hand. For example, Moody and Woodcock (1995), Benson and MacKenzie (1995), O'Neill et al. (1996), and Pax-Lenney and Woodcock (1997) describe the influence of remote sensing resolution on detecting landscape patterns and processes. Bian and Walsh (1993), Souriau (1994) and Walsh et al. (1997) discuss the identification of landscape scale-thresholds and domains of scale as viewed in remotely sensed data, and Caldwell et al. (1993), Ustin et al. (1993), Friedl et al. (1995), Cullinan et al. (1997), DeFries et al. (1997), and Stewart et al. (1998) describe the challenges of scaling remote sensing data and the implementation of multiscale approaches for ecosystem models.

In addition to the remote sensing platforms more familiar to landscape ecologists such as AVHRR[⊗], TM[⊗] and SPOT[⊗], lesser-known hyperspectral airborne sensors like CASI[⊗] and AVIRIS[⊗] have been in operation for over a decade providing unique opportunities to diagnostically examine landscape patterns and processes at very fine spatial and spectral scales (Wessman et al. 1989). These sensors allow for the discrimination of landscape structures that are absent in coarser imagery, thus providing opportunities to link field data with patterns at much coarser scales (Treitz and Howarth, 2000). They also serve as excellent test-beds for conducting fine-scale landscape analysis in preparation for data available from the new high-resolution satellites such as Ikonos (with its commercially available 1 m^2 panchromatic and 4 m^2 multispectral channels), MODIS[⊗] (with its 36 co-registered channels ranging from 250 m^2 – 1.0 km^2), and Hyperion (launched in November 2000, with a capacity to acquire 220 spectral bands (from 0.4 to 2.5 μm) at a 30 m^2 spatial resolution).

It is becoming increasingly apparent, that in order to fully understand the complexity of landscape dynamics, we require the ability to recognize broad-scale patterns and processes, and relate them to those at finer scales where we are most familiar (Wu and Qi, 2002). These high-resolution sensors provide critical data and perspectives that will assist in bridging this knowledge gap.

While remote sensing data holds great promise, it is also important to recognize its limitations. In particular, all remote sensing data represent a unique form of the modifiable unit areal problem or the MAUP (for a comprehensive review see Marceau, 1999). Though the importance of MAUP has previously been noted in landscape ecology (Jelinski and Wu, 1996), its relationship

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[⊗] See Table 2.2

to remote sensing data remains poorly recognized and understood (Wu et al. 2002). In particular, the effects of MAUP can be especially devastating during scaling, where arbitrarily extrapolating site-specific measurements to coarser scales can result in substantial error (Gardner et al. 1982; King, 1990). Thus the ramifications for inappropriately using remote sensing data to understand multiscale landscape patterns/processes are profound. This is especially relevant in landscape ecology, where multiscale studies are increasingly conducted (Wu and Qi, 2002), and where land-cover classifications generated from satellite imagery are frequently used to characterize the ecology of large areas and to make generalizations about the distribution of species and communities (Townsend, 2000).

The primary objectives of this paper are to describe a novel approach for analyzing and upscaling remotely sensed data, and a multiscale extension to this approach, both of which are based on the spatial influence of the dominant objects composing the scene, rather than relying solely on user bias. These novel approaches incorporate object-specific analysis and solutions to the MAUP. Together they represent a framework for spatially defining critical landscape thresholds and domains of scale, ecotone boundaries, and the grain and extent at which scale-dependent ecological models could be developed and applied.

2.1.1 Theoretical Background

The following two sections briefly provide a theoretical background on scale, scaling, the relationship between remote sensing imagery and MAUP, and the fundamentals of object-specific analysis and object-specific upscaling, and their relationship with other scaling techniques.

2.1.2 Scale, Scaling, Remote Sensing Imagery and MAUP

Conceptually, scale represents the 'window of perception', the filter, or measuring tool with which a system is viewed and quantified. As scale changes, so do the associated patterns of reality, which has obvious implications for understanding any organism, place, or system. An important characteristic of scale lies in the distinction between grain and extent. Grain refers to the smallest intervals in an observation set, while extent refers to the range over which observations at a particular grain are made (O'Neill and King, 1998). Within a remote sensing context, grain is equivalent to the spatial resolution of the pixels composing an image, while extent represents the total area that an image covers.

Associated with multiscale analysis is the term domain of scale (or scale domain). This refers to a region of the scale spectrum over which, for a particular phenomenon, patterns do not change or change monotonically with changes in scale. Such domains are separated by scale thresholds - relatively sharp transitions or critical points along the spatial scale continuum where a shift in the relative importance of variables influencing a process occur (Meentemeyer, 1989; Wiens, 1989).

To analyze objects or entire scenes at different scales, and to utilize information between these scales, appropriate scaling methods are required. Scaling refers to transferring data or information from one scale to another. It requires the identification of the factors operational at a given scale of observation, their congruency with those on the lower and higher scales, and the constraints and feedbacks on those factors (Caldwell et al. 1993). As noted by Jarvis (1995), scaling represents a real challenge because of the non-linearity between processes and variables, and heterogeneity in properties that determines the rates of processes. In practice, scaling can be performed from a 'bottom-up' or a 'top-down' approach: upscaling consists of using information at smaller scales to derive information at larger scales, while downscaling consists of decomposing information at one scale into its constituents at smaller scales.

Allen and Hoekstra (1991) suggest that scale is not a property of nature alone but rather is something associated with observation and analysis, and that the scale of a process is fixed only once the observer has specified the actors in the system. So what happens when the scale of observation is arbitrarily derived, as is the case with remote sensing data? Quantification problems resulting from such arbitrariness are known as the modifiable unit areal problem or the MAUP (Openshaw and Taylor, 1979; Openshaw, 1981).

The MAUP originates from the fact that a significant number of different - often arbitrary - ways exist by which a study area can be divided into non-overlapping areal units for the purpose of spatial analysis. In essence, MAUP represents the sensitivity of analytical results to the definition of data collection units, and is illustrated by two related but distinct components: the scale problem and the aggregation problem. The former is the variation in results that can be obtained when areal units are progressively aggregated into fewer, larger units for analysis; the latter represents the variation in results generated by the use of alternative aggregation schemes at equal or similar resolutions (Openshaw, 1984). Consequently, the potential for error in the analysis of spatial data resulting from MAUP is significant, and has been recognized in a number of studies (Dudley, 1991; Fotheringham and Wong, 1991; Hunt and Boots, 1996).

Marceau (1992) was among the first to demonstrate that remote sensing data represent a particular case of the MAUP. In a remote sensing scene, an image may be envisioned as a regular net arbitrarily thrown over a study area where the grain and extent of the mesh define the areal units measured (Figure 2.1). More correctly, each pixel represents an integrated radiance measure corresponding to the spectral, spatial, temporal, and radiometric influence of the real-world objects within the area delineated by the instantaneous field of view (IFOV) of the sensor (Duggin and Robinove, 1990). IFOV determines how much of the ground area the sensor 'sees' at any given instant in time. This results in three general situations: the ground features of interest are smaller than, approximately equal to, or larger than the spatial sampling unit. It should be noted that within a single image, each of these sampling combinations are possible, and in fact very probable. In the first situation, this type of image is referred to as low resolution or L-res, in the second and third cases, as high resolution or H-res (Woodcock and Strahler, 1987). Consequently, every image is characterized by a scale and aggregation level, which determines its structure and information content. Recognizing this is critical for determining what information can be extracted from an image, and how reliable it is (Marceau et al. 1994a).

Fortunately, several solutions to MAUP have been suggested (Fotheringham, 1989). In particular we note two important concepts related to these solutions. First, the MAUP does not exist if analysis is performed with basic entities. The term basic entity refers to an object composed of similar parts that are different from itself. For example, if we consider a tree-crown as a basic entity, conceptually it may be composed of, or is an aggregate of leaves and branches, each of which individually belongs to classes that are themselves, basic entities. Thus, identifying basic entities provides the clearest way out of the MAUP, as a user works with spatially discrete entities rather than arbitrarily defined areal units (for additional information see Fotheringham, 1989). Second, while MAUP certainly poses significant challenges, it can also reveal critical information for understanding the structure, function, and dynamics of complex real world systems if it is recognized and dealt with explicitly (Jelinski and Wu, 1996). Part of the challenge in recognizing MAUP is that there is no unique 'MAUP statistic' to quantify its influence, though correlation analysis and other techniques have been used (Amrhein and Reynolds, 1996; Hunt and Boots, 1996). Instead, users of spatial data must be cognizant of the fact that spatial analysis of arbitrarily defined areal units can produce results that may not necessarily represent the content of the original units, but rather, the associations between them (i.e., aggregation problem) and the scale at which they were assessed (i.e., scale problem).

2.1.3 The Fundamentals of Object-Specific Analysis (OSA) and Upscaling (OSU)

Object-Specific Analysis (OSA) is a multiscale technique that defines unique spatial measures, specific to the individual objects composing a remote sensing scene. These object-specific measures are then used in weighting functions for upscaling an image to a coarser resolution. The resolution of the upscaled image can either be defined manually by the user (see section 2.2), or automatically by statistical properties of the objects composing the image (see section 2.3 and 2.4). Both forms of upscaling are referred to as Object-Specific Upscaling (OSU) because they incorporate object-specific weights. Thus, MAUP effects are minimized in both OSA and OSU, as object-specific spatial information is incorporated throughout the analysis.

An underlying premise of OSU is that H-res image-objects should have more influence on an upscaled signal than a single L-res pixel – which signal is already regularized[25]. The term 'image-objects' refers to basic entities, located within an image that are perceptually generated from H-res pixel groups, where each pixel group is composed of similar digital values, and possesses an intrinsic size, shape, and geographic relationship with the real-world scene component it models [e.g., a tree crown (Figure 2.2)].

The heuristics determining this threshold of 'similarity' are based on the novel concept that all pixels within an image are explicitly considered H-res samples of the scene-objects they model, even though (as previously described) each pixel many represent both H- and L-res object information. The importance of this rule is that by biasing for H-res samples only, we explicitly seek for objects that exist at, or over, a larger spatial extent than the area covered by the individual pixels that compose them. Essentially, we are using parts of objects (grain) to define the extent of objects that exist at their next (coarser) scales. The spatial extents defined are then used as weights to representatively upscale the image to a coarser resolution.

Similar to Mandelbrot's famous question concerning the length of a coastline, the answer is dependent on the precision of the measuring tool (Mandelbrot, 1967). In the case of OSA, the maximum sized object that can be defined is represented by the relationship between the spatial resolution of pixels composing the objects within a scene, and the ability of the heuristics to

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[25] *Regularization* is a signal-processing term describing the integration of signals generated by objects that are no longer individually discernable (thus L-res), due to the physical limitations of the sensing device in relation to the size of the objects being assessed.

define this object's edges. As a result, this technique can be applied to any type of remote sensing data from H-res data such as the CASI (airborne), and Ikonos (satellite), to medium resolution TM and low-resolution AVHRR. The only difference in each case is to appreciate the relationship between the pixel size and the geographic size of the object the pixel is a component of. In a CASI data set, pixels could be considered parts of individual trees, trees being the object of analysis. In TM data, individual pixels may be considered parts of a particular forest stand, and in AVHRR data, individual pixels may represent parts of a larger extent, more general landscape entity such as a deciduous broad-leaf forest class.

Though sharing similarities with other scaling and scale detecting techniques (Turner et al. 1991; Gardner, 1998), OSA is unique, in that it incorporates an explicit multi-resolution (i.e., hierarchical) sampling and evaluation of each pixel in relation to the (different sized) coarser grain objects of which it is a nested constituent. For example, while scale variance analysis (Moellering and Tobler, 1972) is also a hierarchical approach, there is no consideration of pixels as parts of individual objects composing a scene. Instead, pixels composing the image are aggregated by systematically increasing grain size (for the entire image), resulting in a nested hierarchy of images with the same extent, but with different spatial resolutions. A measure of the total scene variance is then evaluated for each image in the hierarchy, and the results are plotted illustrating potential scale thresholds at specific resolutions within the entire scene. A similar approach is described by Woodcock and Strahler (1987), where local scene variance is graphed as a function of increasing spatial resolution, and also by Marceau et al. (1994b) where a minimum spectral variance threshold is used to define the optimal spatial resolution of different forest classes.

In OSA, a ubiquitous 'optimal' resolution is never found, as none exist in images representing complex heterogeneous environments (Hay et al. 1997). Instead, different 'optimal' resolutions or thresholds are defined based on the different objects being assessed (Hay et al. 1996). In the previous examples, the described techniques are used for scale exploration only. They do not explicitly consider individual pixels as parts of variably sized, shaped, and spatially distributed objects, and they do not include facility for upscaling, or provide information indicating where in the image such spatial thresholds exist. OSA does not have these limitations.

2.2 Materials and Methods

We begin the Methods section by describing the study site and data used. We then describe OSA and user-defined OSU. This is followed by an introduction to a multiscale extension to these techniques within the context of a new methodological framework.

2.2.1 Study Site

Our initial interest in scale issues was based on understanding the spatial evolution of individual trees and forest gaps through scale (Marceau and Hay, 1999b), particularly as it relates to changes in landscape fragmentation. To facilitate this we applied OSA and OSU to H-res CASI data, which allowed us to follow the evolution of familiar image/site structures through scale. The CASI (Compact Airborne Spectrographic Imager) is a pushbroom sensor designed to operate from light aircraft and helicopters, with data capture capabilities based on a two-dimensional frame transfer CCD array. 16 bit signed data were collected during 20:10 - 21:40 hours (GMT) over the Sooke Watershed, Vancouver Island, British Columbia, Canada on August 1, 1993 (Figure 2.3). The data were radiometrically corrected to 1.5 m^2 pixels, and a study site (Figure 2.4a) was located along Rithet Creek and extracted from a channel centred at 0.66 µm (+/- 0.05 µm)[26]. This scene was then corrected for geometry and atmosphere, and all subsequent analyses were performed on it. Ancillary data include 1:10,000 forest inventory maps, numerous field surveys, and 1:12,000 colour near-infrared (NIR) aerial photography (1993). In this area, the very dry maritime Coastal Western Hemlock biogeoclimatic subzone dominates, though a small component of moist maritime Coastal Douglas-Fir subzone also exists.

In Figure 2.4a, three principal stand types are visible, each of which illustrates the dominant seral tree species - Coastal Douglas-Fir [(Pseudotsuga menziesii) (Mirb.) Franco var. menziesii]. Located in the centre of this image is a mature stand (141-250 yrs) with a crown-closure of 56-65%. Below it (bottom centre) is a dense young stand (21-30 yrs) with a crown-closure of 76-85%. Surrounding these two, notably on the image left, is a stand of mixed-immature and mixed-young individuals (1-20 yrs), with crown closures ranging from 0-45%. Three gravel roads transect the scene and are represented as bright linear features. An exposed, sparsely vegetated clear-cut (C.Cut) lies adjacent to a gravel road at the upper right quadrant of the

[26] We note that the selection of bandwidths and locations was limited to those predetermined for a prior mission (Hay et al. 1997).

scene, and a small, partially vegetated marsh is located at the bottom right. Throughout the site, many exposed soil, and soil-grass patches are visible. In the Thematic Map (Figure 2.4b), these patches have been classified as C.Cut.

2.2.2 OSA and User-Defined OSU

This section briefly describes the basic methodology underlying OSA, and how to apply OSU within a user-defined resolution. In the earth sciences it is generally observed that objects closer to each other are more alike than those further apart (Curran and Atkinson, 1998). Similarly, in a remotely sensed image, spatially near pixels tend to elicit a strong degree of spectral autocorrelation. Therefore, plotting the digital variance of samples (pixels) located within increasingly larger kernels, while centred on an image-object of known size tends to produce a distinct break, or threshold in variance as increasingly sized kernels contact the image-object's edges. The unique window size (VT_w) defined at this variance threshold location (VT_{ij}) corresponds explicitly to the object's known size, and is a key component for determining object-specific weighting values [i and j represent row and column within the original CASI image (O_I)]. Conceptually, VT_w may be considered similar to lag as described when using semivariance. For example, the window size at location (A) in Figure 2.5 represents the maximum scale for defining the (inset) tree-crown[27]. Locations B-C, D-E, and F-G, represent an object-specific range of 'optimal' window sizes for defining the nested image-objects, of which the centre tree-crown pixel (white dot) is a member. Locations B, D, and F represent the local variance minima corresponding to the scales where the next set of 'nested' objects are first manifest. Minimum variance indicates that the pixels composing this measure are locally the most spectrally similar, thus they are the most 'object-like', while variance maxima located at C, E, and G respectively, represent the maximum spatial extents of these nested objects. Locations A-B, C-D, and E-F are explained in the Discussion section.

The window size at one-iteration prior to VT_{ij} is used to define the maximum area (A_{ij}) at which the central pixel under analysis is spectrally and spatially related to its neighbours. At the same time that A_{ij} is defined, the corresponding mean (M_{ij}) and variance (V_{ij}) values are also defined for the central pixel within VT_w. These procedures are then applied to all remaining pixels in O_I, resulting in corresponding variance (V_I), area (A_I), and mean (M_I) images.

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[27] The inset image has been extracted from the mature-stand in O_I, and the corresponding curve represents the actual variance values determined at each incremented window size.

Once V_I, A_I, and M_I have been generated, two steps are required to complete user-defined OSU. The first involves determining an object-specific weight (W_{ij}) for each ($\forall$) pixel (P_{ij}) in O_I, which is represented by W_{ijK}.

Equation 1

$$\forall P_{ij} \in O_I$$

$$W_{ij}K = (A_{ij}K / S_K)$$

W_{ijK} defines the object-specific weight for each A_{ij} within an upscaling kernel (K) [of a (k x k) user-defined dimension], where S_K is the sum of all A_{ij} within K (see equation 2).

Equation 2

$$S_K = \sum_{i}^{k} \sum_{j}^{k} A_{ij}$$

The second step is to apply the object-specific weight to produce a new upscaled image.

Equation 3

$$\forall UP_{LM} \in U_I$$

$$UP_{LM} = \left[\sum_{L}^{k} \sum_{M}^{k} \left(O_{ij} * W_{ij} \right) \right]$$

UP_{LM} represents an upscaled pixel located at row L, column M, in the resultant upscaled image U_I. O_{ij} is the DN (digital number) of the pixel located in the original image at row i, column j, that is evaluated within the upscaled kernel. UP_{LM} and the pixels within rows (i-k, j+k) and columns (i+k, j-k) represent the same real-world extent. Thus, U_I is composed of fewer pixels than O_I, though both represent the same geographic area. Resampling within the upscaling kernel is represented by the double summation of all DNs to a single object-weighted pixel value that is located within the new upscaled image. The non-overlapping kernel is then moved a distance of K pixels across O_I, and the process is iterated until a new upscaled image U_I is generated.

2.2.3 A Multiscale Extension: Iterative OSA and OSU

Although a single remote sensing scene represents a unique instance of all discernible objects within its extent, we hypothesize that it also contains additional information related to image-objects (IOs) that exist over a "limited" range of coarser, non-immediately discernible spatial scales, located within the same extent. Support for this comes from three sources:

- Appreciating that both H- and L-res information exists within an image collected at a single resolution (Woodcock and Strahler, 1987)
- Understanding the intimate relationship between IFOV and object size (Slater, 1980)
- Recognizing that previous work illustrates the ability of OSU methods to reveal patterns that consistently model the spatial extent of differently sized objects existing at coarser scales (i.e., tree crowns, canopy gaps, etc, Hay et al. 1997).

To exploit this range of multiscale information within a single image, we hypothesize that by iteratively applying OSA to define object-specific (maximum and minimum) variance-thresholds within M_l, dominant landscape objects will emerge through the iteration process. In essence, we are applying principles of non-linear feedback to ascertain if self-organization (Kay and Schneider, 1995) - in the form of patterns corresponding to the spatial extent of dominant landscape objects - will 'emerge' at each new scale. We note that our goal in developing and applying object-specific techniques is to allow for previously existing self-organized patterns (i.e., image-objects) to be detected within the image/landscape at different scales. It is not to generate new self-organizing patterns. This subtle difference is important to clarify, because a strict requirement of self-organization includes temporal evolution (Nicolis and Prigogine, 1989; Coveney and Highfield, 1991), while a single remote sensing image - and all analysis performed on it - can only represent an instant in time.

The result of this iterative approach is a nested hierarchy of image-sets (IS_t) at a specific scale (t), composed of V_l, A_l and M_l that have membership ($\in$) in a uniquely numbered (n) scale domain (SD_n). Within this SD_n, each image has the same grain and extent, and represents the results of multiscale analysis specific to the individual image-objects composing it. Following this logic, each SD_n is a member of a scale-domain super set (SDS) that represents the entire range of object-specific multiscale analysis (OSA) and scaling results (OSU) evaluated within the fixed spatial extent of a unique digital landscape (O_l). This hierarchical structure (outlined in Figure 2.6) may be described in the following manner:

Equation 4

$$P_{ij} \in IO_s \in IS_t \in SD_n \in SDS$$

A digital landscape is composed of pixels (P_{ij}) that are parts of (s) many unique image-objects (IO_s), that are defined within a specific image-set (IS_t), that is a member of a scale-domain (SD_n), which populates a scale-domain set (SDS).

To operationalize this framework with minimal user-bias, we apply object-specific concepts to select the most appropriate images for upscaling. To minimize the scale problem resulting from arbitrary scaling, we apply a resampling heuristic (R_h) based on the relationship between image-objects and pixel size, and apply OSU as our upscaling algorithm (Hay et al. 1997). This combination of iterative OSA and OSU constitutes an object-specific multiscale framework for landscape analysis that is further discussed in the following sections.

2.2.4 Selecting an iterated Mean image (M_I) to upscale

Through the iteration process, M_I pixels increasingly become parts of objects existing over larger and larger extents, yet the spatial resolution of the pixels representing each new image-object remains constant. To reduce unnecessary computation, an appropriate M_I must be evaluated within each IS_t to determine if upscaling is necessary. In the first OSA iteration, the exact process described in section 2.2 is applied. That is, each P_{ij} is assessed within larger windows until a local maximum variance threshold ($VT_{w(max)}$) is reached that corresponds to a 'peak' location as illustrated by (A) in Figure 2.5. When applied to the entire image, this process generates the first image-set (i.e., V_1, A_1, M_1).

In the second iteration, each P_{ij} (in the newly generated M_1) is assessed within larger windows until a local minimum variance threshold ($VT_{w(min)}$) is reached. This results in the generation of a second image-set (i.e., V_2, A_2, M_2) that represents the beginning scales of all newly emergent image-objects. Conceptually, each pixel in M_2 will be represented by a local variance saddle or pit, as illustrated by (B) in Figure 2.5. Therefore, odd-numbered OSA iterations define scales representing the 'end' of objects, while even-numbered OSA iterations define the beginning scale of the next emergent object(s). As a result, all M_I generated from even-numbered OSA iterations will be selected for upscaling.

2.2.5 Defining an upscale resolution (R_h)

Once an appropriate image has been selected for scaling, the upscale resolution will be defined by a resampling heuristic (R_h) that is based on the relationship between pixel size, and the size of the minimum discernible image-object for which VT_w was initially developed. R_h is similar to recommendations by O'Neill et al. (1996), who suggest a grain size 2 to 5 times smaller than the spatial features of interest, and a sample area 2 to 5 times larger than the patches assessed. We note that this grain size recommendation corresponds to a reference by Slater (1980) regarding the point-spread function (PSF)[28] of the sensor. Essentially, if an object is less than ¼ the size of the sensor's IFOV, its influence in the corresponding pixel is equal to the sensor PSF. In modern sensors this value is exceptionally small, though it can be defined for each sensor, and included within the model. For the purpose of this study, R_h equals the resampling resolution where the minimum area (A_{min}) of all pixels composing the image-objects defined in A_i must be four times larger than the spatial resolution of the current image. This ensures not only detection (as implied by the ¼ PSF rule), but also identification (Jensen, 1986). By adopting this 4:1 relationship, we are again erring on the side of caution (i.e., under-sampling).

We also note that if ¼ represents detection, and 4:1 represents identification, then a fuzzy i.e., not specifically defined, range of scales (a maximum of) 16 times an object's minimum detectable size exists, where part of an object's spatial influence is potentially discernible within a single image. This further supports the hypothesis in section 2.3 regarding a limited range of object-specific spatial information within a single image.

2.2.6 Upscaling Strategy

In a previous study, Hay et al. (1997) evaluated OSU against four resampling or scaling techniques traditionally included in remote sensing image-analysis software. Over a gigabyte of data were analyzed and upscaled from 1.5 m to 3 m, 5 m, and 10 m respectively, using nearest neighbour, bilinear interpolation, cubic convolution, non-overlapping averaging, and OSU. All upscaled images were evaluated against (non-upscaled) data of the same scene originally collected at a 10 m spatial resolution. The technique producing an upscaled image most visually and statistically similar to the original 10 m image was considered the most appropriate upscaling technique. Six thousand samples representing six different forest classes were evaluated using the smallest root-mean-square-error (RMSE) results to represent the best technique. Results indicate that OSU produced the most visually and statistically accurate upscaled images of those tested, with the lowest RMSE in 10 out of 18 classes over all forest

[28] The PSF defines the spatial influence or 'spread' of a zero-dimensional point of light resulting from lens aberrations in the sensor.

types and ranges of scale tested. In the eight times it did not obtain the lowest RMSE, it produced six values with the second lowest errors. Based upon these results OSU is considered the most appropriate upscaling technique, thus it is used to resample the selected M_l to a resolution specified by R_h. To accomplish this, R_h is applied to Equation 1, replacing the user-defined upscaling kernel size (K). This iterative OSA and OSU strategy is then applied until VT_w is larger than the image dimensions.

2.3 Results

The original CASI image (O_l) spatially represents a complex forest scene spanning a geographic extent of 600 x 600 m. Spectrally it represents both the minimum chlorophyll a reflectance signal[29], and the absorption maximum of solvated chlorophyll a (Kirk et al. 1978). In this study, it is also considered a surrogate measure of vegetative 'greenness'. When the multiscale extension described in Section 2.3 is applied to O_l, the result is a hierarchy of image-sets (SD_n), each consisting of variance (V_l), area (A_l), and mean images (M_l), with the same spatial resolution. As upscaling occurs, the spatial resolution of the newly generated image-sets increase as do their scale domain subscripts i.e., SD_{n+1}. The iteration where OSU first takes place is referred to as SD_1. The image-set prior to this is SD_0 - as upscaling is not applied. Figure 2.7 illustrates image-sets within the first four scale-domains (SD_{0-3}), generated from automatically applying 10 iterations of OSA, and 4 iterations of OSU to the original CASI image. The procedures for producing these results are outlined in Table 2.1 and Figure 2.7a, and are summarized as follows.

OSA was applied to the O_l where object-specific measures of maximum local variance were assessed for every pixel resulting in the first image-set (V_1, A_1, and M_1). OSA was then applied to the newly generated M_1, where object-specific measures of minimum local variance were similarly assessed, resulting in the second image-set (V_2, A_2, and M_2). Together, these image-sets and O_l represent the first scale domain (SD_0), of which V_2, A_2, and M_2 are illustrated in Figure 2.7. Based on the concepts described in section 2.3.1, M_2 was automatically selected for upscaling to a resolution defined by R_h. This resulted in a grain change from 1.5 m to 2.4 m and the generation of the first upscaled image (U_1) (Figure 2.8). These procedures were then repeated for the next 8 iterations, substituting in the appropriately defined M_l, R_h, and U_l

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[29] Though radiometrically 'close', the low trough in spectra associated with plants is nearer to 675 nm, than to the spectral band location (655-665 nm) defined in this data set.

variables. In all cases, the resulting upscale images ($U_{2\text{-}4}$) were used as the 'seed' images for OSA, from which new image-sets ($IS_{3\text{-}10}$) composing the additional scale-domains ($SD_{1\text{-}4}$) were generated. To facilitate visual comparisons[30] between the image-sets illustrated in Figure 2.7, each upscaled image was resampled to 400 x 400 pixels. Resampling was performed using nearest neighbour so that original DN values were not changed. As a result, images in latter scale-domains appear more 'blocky' than those in SD_0.

As the grain size increased through the upscaling process from 1.5 m to 9.83 m, the total number of pixels in the image was reduced from 160000, to 3721. Object-specific analysis was stopped at OSA_{10}, as analyzing kernels contacted the borders of the image. Throughout the scaling process, the scene extent remained constant at 600 x 600 m, but the physical dimensions of the generated images were systematically reduced from 400 x 400, to 61 x 61 pixels. The visual differences in information content resulting from these procedures are illustrated in Figure 2.8, where $U_{1\text{-}4}$ is illustrated against the background of O_I. We note that OSU was applied to $M_{2, 4, 6, 8}$ to generate this upscale composite.

Within each SD_n, the V_I represents a threshold-image resulting from OSA. Essentially it illustrates where the edges of differently sized objects have been reached. Bright tones define areas of high variance (object edges), while darker tones define areas of low variance (object interiors) e.g. bright road edges vs. dark young forest (image bottom) in V_2. Similarly, each A_I models the maximum spatial extent - or area of influence - of its constituent objects at a specific grain defined within the variance threshold kernel. This important measure represents the unique (scale-specific) areas over which dominant landscape objects exist, thus it is used to determine object-specific-weights for scaling. Because image-objects are composed of similar pixels, they tend to be assessed within smaller kernels, as their accompanying variance measures are small. This results in correspondingly small area values, which are visually represented by dark areas. In A_2, dark tones within the mature stand (image centre) clearly correspond to individual tree crowns, while the brighter surrounding values correspond to edges composed of shadow and or understory pixels. Visually, these results strongly support the validity of objects-specific heuristics (at least over fine scales), as individual trees illicit complex illumination/shade effects on either side of their crown, yet both sides are considered part of a single object (i.e., a dark tone).

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[30] All figures are 8 bit linearly scaled versions of 16 bit data that have been enhanced for illustration. In the original images, far greater visual clarity is achieved than in print.

In each M_l every pixel represents a H-res member of a newly detected image-object that exists at its next (coarser) scale i.e., branches and leaves now become part of a tree crown. Because these images are generated from average values calculated within specific threshold kernels, they represent the dominant image structure defined at a specific spatial resolution within a unique scale-domain. To enhance interpretation of the overall structural evolution of each M_l composing SD_{1-4}, we have applied a simple linear color table, as printed gray-tone gradations are more difficult to distinguish. In each M_l, black and purple represent high-density vegetation, dark blue represents low-density vegetation, and light blue-green represents the gradient between sparsely vegetated and non-vegetated areas. Clear-cut areas with varying amounts of vegetation range from green-yellow, where colors represent low-density invading grasses and shrubs on partially exposed soils, to orange-red, representing the maximum scene brightness resulting from fully exposed soils.

As the spatial resolution of each SD_n changes, each V_l, A_l, and M_l visually delineate newly defined scale-specific structures that represent the dominant objects emergent at these scales. In SD_0 a large amount of recognizable object structure is explicitly defined. In particular, individual tree crowns, their shadows, canopy gaps, patches of exposed soil and vegetation, road edges, and vegetation along roads are highly discernible in both V_2 and A_2. In SD_1 we see an obvious evolution from individual crown structures within the mature stand (as defined in V_2 and A_2), to larger sized objects (dark patches) that correspond to areas of high stand densities and include reflective characteristics from crowns, shadows, and understory. At this scale, the (highly reflective central) gravel road is influenced by the spectral characteristics of the surrounding vegetation, causing it to change from green-yellow (as depicted in M_2) to a light blue (in M_4). It is also important to note the increasing spatial effect (i.e., larger areas of bright tones in A_4) appearing along the edge of vegetated and non-vegetated areas. In V_4, this is represented by bright linear features around (darker) objects, and will be referred to further in the Discussion section.

In SD_{2-3} we see a dramatic change in the overall scene composition from the previous scale-domain sets. Here, the images clearly illustrate a distinct evolution within three dominant object groups: C.Cut (including roads, grasses, and bare soil depicted), young-forest (which includes young and juvenile classes), and mature forest. The net result is an increasing spatial and spectral encroachment of clear-cut, and low vegetation density areas within locations that were initially densely vegetated. This is most apparent in the upper right quadrant of each image, where the spatial influence of C.Cut, and lower density vegetation (i.e., young forest) increase at the expense of mature forest.

2.4 Discussion

2.4.1 What exists between the end of one image-object and the beginning of another?

We suggest that multiscale image-object thresholds are often far more 'fuzzy' or less discrete than the term threshold commonly implies. This is because the pixels used to evaluate image-thresholds are themselves a hemispherical integration of reflected light, which represents the non-linear interaction of entities existing over different scales. For example, a single 'threshold' pixel defining the extent of a tree-crown may share its composition with a portion of this crown's edge, the neighbouring crown shadow, understory, and partial reflectance from near-by exposed soil. Therefore, rather than a pixel being part of a nested hierarchy of discrete image-objects that spatially lie adjacent to each other through scale, there exists instead a unique range of scales between the end of one image-object and the beginning of another, which is composed of integrated 'edge' pixels. We refer to the species of objects that populate this 'edge-space' as edge-objects (EOs), and suggest that an example of their signal is illustrated in Figure 2.5, between A-B, C-D, and E-F.

Conceptually, EOs exist within a varying range of scales located on the 'other-side' of discrete image-object frontiers or boundaries, but due to their digital nature[31] they actually share part of their spectral composition with a non-linear integrated fraction of the edge pixels they abut. As a consequence, EOs will always be L-res which means they will be represented by relatively large V_I and A_I measures, as they are unable to be defined within the range of scales commonly used to assess image-objects (see Figure 2.7). For example, during OSA_1, visual and statistical output generated at each increment in window size indicated that 99% of O_I was processed within a window size of 29 x 29. Yet, the remaining 1% required analysis up to a window size of 63 x 63. In addition, this 1% of pixels did not visually correspond to spatially meaningful image-objects within O_I. Instead, they represented edge locations between recognizable IOs. A similar trend was found in all additional iterations throughout the OSA process.

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[31] Within a digital scene, an image-edge or threshold is not a 1D-line composed of zero-dimensional points lying between two or more pixels, but rather a 3D pixel (i.e., x, y, DN) that must exist in the same location as one of the points it is trying to segregate.

To ensure that spatially dominant image-objects will emerge through multiscale analysis, rather than EOs, we confirm that inverse area values (which favour image-objects) are used to define all OSU weights. And yet, EOs appear to spatially dominate at coarser grain sizes, rather than recognizable image-objects (see Figure 2.7). We suggest two plausible solutions for this condition. Either EOs represent real landscape structure(s) or they are artifacts resulting from inappropriate OSA heuristics.

Strong support that OSA heuristics work well on recognizable image-objects is provided by SD_0 in Figure 2.7, where individual tree crowns, road edges, canopy gaps, and barren areas have been explicitly delineated. When these results are considered in relation to the evaluation conducted during heuristic development, we are confident that the heuristics work well. The second solution is that EOs are actually image-objects that represent real multiscale landscape structure that we may not be familiar with from a single-scale perspective.

2.4.2 If edge-objects (EOs) are real, what landscape phenomenon do they model?

As Wu and Qi (2002) point out, it is not always clear whether the effect of changing scale is an artifact due to the improper use of analytical methods, an indication of the scale multiplicity of ecological systems, or neither of the two. If for a moment, we consider that EOs are real landscape entities rather than image artifacts, what do they structurally represent? By their very nature, we know that they are not image-objects with obvious real-world counterparts; if they were, we would recognize them. Obviously, we need to evaluate EOs with a different conceptual perspective. What we do know is that EOs exist in the 'edge-space' between image-objects. Visual analysis of Figure 2.7 reveals a spatial evolution of increasing perimeter for C.Cut, gravel-road, and barren-ground, that extends far beyond their initial physical boundaries (see Figure 2.4a). When these changes are considered in relation to the scale-dependent manner in which OSA functions, it is highly plausible that the evolution of EOs models the scale-dependent change(s) occurring at, or within, ecotones.

Although the study of ecotones is complicated by the diversity of interpretation regarding their nature, we adopt the definition of Holland (1988), where the transition zone between adjacent patches is recognized as an ecotone. In OSA, image-objects correspond to scale-dependent patches within a landscape mosaic, thus EOs correspond to their ecotones. A serious challenge with ecotone detection is the subjectivity inherent with identifying boundaries along gradually changing ecolines. Here the difficulty involves dividing a zone of 'continuous' variation into compartments. As Johnston et al. (1992) indicate, even when statistically significant differences exist between individual compartments, the boundaries between them may not represent true ecotones. Instead, ecotones span the range between these two extremes. In addition, boundary distinctness is scale dependent, thus users are also faced with the subjectivity of determining the most appropriate scale to assess the scene, which in turn affects the delineation of ecotones.

One of the true benefits of imaging spectrometry is the ability to explicitly link specific spectral characteristics with physiological properties (Wessman et al. 1989). If the idea of EOs as ecotones is linked with the spectral characteristics of the original CASI image (i.e., a surrogate measure of vegetative 'greenness'), it is further plausible to hypothesize that EOs defined in O_I may be a visual analogue of what is referred to as 'depth-of-edge influence', or 'edge width' (Chen et al. 1999). Depth-of-edge influence is associated with microclimatic zones across abrupt edges in the landscape, and can result in broad areas of edge influence, which constitute a significant portion of (unaccounted) fragmentation in a landscape. The phenomenon varies over time and with edge characteristics, and can extend four to six tree heights into the forest from a recent clear-cut edge. Notably, edge-width value varies according to different tree species, ranging from 60 m in Eastern Red Pine / White Pine to over 400 m in Pacific N.W. Douglas-fir forests (Chen et al. 1999). This 'EO = edge-width' hypothesis is further supported by the fact that O_I is a high-resolution scene of a (then) recently clear-cut site on southern Vancouver Island, where the dominant tree species in all three forest classes (Mature, Young and Juvenile) are Pacific N.W. (Coastal) Douglas Fir. However, it is important to note that no microclimate data were available to corroborate this hypothesis. Nevertheless, this provides an excellent example of how object-specific analysis offers new insight into linking and questioning the relationships between landscape processes and multiscale landscape patterns, that may not have been possible without such a multiscale perspective.

2.4.3 Can an OSA perspective be used to define landscape-scale thresholds?

Through the iterative OSA and OSU process, the patterns generated within a SDS represent an evolution of image-objects from small-scale entities such as individual tree-crowns, to larger 'landscape' sized objects that will eventually dominate the entire image. From the results in Figure 2.7, it is clear that between SD_1 and SD_2, recognizable image-objects stopped being generated, and unfamiliar EOs began to emerge and dominate the scene. We suggest that this change in spatial dominance, from image-objects to EOs, corresponds to crossing a landscape-scale threshold, and that it can be defined in a similar fashion as individual image-object thresholds.

Recall that when applying OSA to detect object-specific thresholds, each pixel is evaluated as part of an individual image-object. Therefore, to detect a landscape-scale threshold within an OSA framework, all image-objects and EOs within a scene are evaluated as being part of a larger scene-object (i.e., a landscape-scale threshold-object) that spatially dominates the entire image/landscape being assessed. This is operationalized by evaluating the total scene variance (TSV) for each image in a nested hierarchy, where each image represents the same study area, but at a different grain size. The resulting signal is then plotted and modeled, revealing distinct saddles and peaks that correspond to the beginning and end scales of landscape-scale threshold-objects. Essentially this is scale variance analysis as described in section 1.2.2, except that within an OSA framework, the nested hierarchy corresponds to image-sets generated at each OSA iteration, and images representing different grain sizes are generated only at odd-numbered iterations (except for OSA_1). In addition, TSV is defined for each variance-image rather than each mean-image as object-specific structures are explicitly defined in V_I, while in M_I such structures are smoothed. In simple terms, these procedures correspond to evaluating the total difference in the variation resulting from the individual image-objects composing a scene through all possible object-specific scales of analysis.

To better understand the total scene variance and corresponding scene/landscape structure through scale, TSV values generated for each V_I at odd numbered iterations[32] are modeled with a high order polynomial ($R^2 = 0.999$), and the resulting curve [Poly. (TSV)] is illustrated in Figure 2.9. We note that while the shape of this cure is similar to that found in Figure 2.5, it must be assessed with caution past iteration 8, as OSA_{8-10} kernels required analysis over larger window sizes than the available image dimensions. This indicates that the pixels being assessed were part of a larger-scale image-object that existed beyond the extent defined by the image. Visual analysis of Poly. (TSV) reveals a saddle at iteration 3 and a peak at iteration 6 indicating the beginning and end range of the first landscape-scale threshold-object. It is also possible that another landscape scale threshold begins at or after OSA_{11}. Recall from Table 1, that OSA_{3-4} are members of SD_1. When compared with the results in Figure 2.7, the first landscape-sized threshold corresponds explicitly to the visual changes between SD_1 and SD_2, supporting the idea

[32] We note that values generated at even-numbered iterations produced a very similar curve, transposed by one iteration in the x-axis.

that OSA can be used to evaluate a full-range of landscape thresholds ranging from small-scale image-objects to large-scale landscape structures.

2.5 Conclusion

From a multiscale perspective a scale-domain set may be visualized as a hierarchical scaling ladder (Wu, 1999), and each SD_n may be visualized as an individual rung, separated by unequal spaces that are specific to the range of scales assessed within the IS_t that composes it. Alternatively, since Figure 2.9 supports the detection of landscape-thresholds between adjacent SD_n, it may be more reasonable to include SD_n as a subset of a higher-order set we refer to as a landscape-threshold-domain (LTD_v), where the subscript (v) represents the number of different landscape thresholds defined by TSV within the SDS. Thus equation 4 should be augmented as follows:

Equation 5

$$P_{ij} \in IO_s \in IS_t \in SD_n \in LTD_v \in SDS$$

As a result, it may be more appropriate to consider the landscape represented by a linked group of differently-sized scaling ladders, where each ladder corresponds to a specific LTD_v, rather than a single hierarchical scaling ladder as Wu (1999) suggests. Though originating from different starting points, we suggest that a multiscale OSA and OSU approach provides a methodological framework that is complementary to the described theory, and techniques required by the Hierarchical Patch Dynamics Paradigm (HPDP) (Wu and Loucks, 1995). HPDP provides a link between the patch dynamic perspectives and hierarchy theory that emphasizes multiscale properties of pattern and process dynamics in ecological systems. In this paradigm, individual patches are considered the fundamental structural and functional units. In OSA these primitives correspond to image-objects, whose spatial dimensions and influence can be defined and aggregated to unique coarser scales (i.e., OSU), specified by the dominant entities (A_l) composing a scene.

If at multiple image scales, the spatial extent of dominant A_l patterns strongly corresponds to geographic areas over which known processes are dominant (i.e., soils, slope, aspect), these areas may be selected as locations over which scale-dependent ecological models could be developed, or data explicitly translated to and from (Holling, 1992). King (1990) identifies four general methods of translating ecological models to larger scales: (1) lumping, (2) direct extrapolation, (3) extrapolation by expected value, and (4) explicit integration. In particular, direct extrapolation could benefit from OSA because it involves explicitly running a small-scale model for a set of discrete elements, scaling the output of each element by the area represented, then combining the outputs to represent the large-scale system.

If we consider that the OSA and OSU heuristics are sufficiently robust, and that MAUP effects are minimized - through adopting an entity, or object-specific approach - then the complex patterns forming at each OSA iteration represent the emergence of real world structures existing, or imbedded at different scales within a single scale of imagery. Good reason exists to consider this a sound supposition, as (V_I) and (A_I) strongly correspond to real world scene-components, thus the heuristics defining image-object thresholds are being met. As threshold patterns emerge at each iteration, and their specific resolutions and extents are defined, the ideal situation would be for remote sensing data - representing surrogate ecological measures [such as leaf area index (LAI), or fraction of photosynthetically active radiation, (FPAR)] – to be scaled with OSU and used as inputs into unique ecological models operating over the spatial extents defined by the corresponding A_I (Freidl, 1997). Alternatively, model development and data type selection could be guided by the OSA scale-domains and landscape threshold patterns generated. If iterated OSA and OSU results correspond to field data over a range of known scales, precedent exists upon which to assess OSA and OSU results at coarser, unverifiable image scales. At present, object topology is not embedded within the analyzing routines, but it is envisioned in subsequent versions, which will provide multiscale image-object output for use in geographic information systems.

In this paper we introduce a multiscale framework for analysis and upscaling that, when applied to remote sensing imagery, reduces the effects of MAUP by incorporating an object-specific approach. By considering landscapes as hierarchical structures and adopting this multiscale framework, the patterns of landscape objects operating at, and over, unique spatial scales may be thematically and numerically quantified by their spatial dominance. While aware that the entities that emerge in a data set are scaled by virtue of the observation protocol and the filters applied to the data during analysis, we suggest that multiscale OSA and OSU offers a potentially powerful framework for improved understanding of scale-specific landscape patterns. In particular, multiscale OSA may assist in defining critical landscape thresholds, domains of scale, ecotone boundaries, and the grain and extent at which scale-dependent ecological models could be developed and applied.

This paper provides only a small sample of the potential of multiscale OSA tested over a relatively fine geographic area. However, the methodology is applicable to any resolution (i.e., grain and extent) of remotely sensed data The next step is to apply these ideas over a larger-extent fine-grained scene, where sufficient ancillary data exist so that results may be fully verified over numerous spatial scales. To facilitate this, analysis is presently underway in the complex agro-forested Haut-Saint-Laurent region of Quebec to examine how landscape fragmentation and connectedness change through scale, and what their implications are for landscape management (Bouchard and Domon, 1997; Pan et al. 2001). Our primary objective will be to apply the described object-specific framework to H-res Ikonos satellite data (acquired in September, 2000) that represents an 11 km x 11 km scene, and evaluate the multiscale results against a database representing more than 15 consecutive years of intensive field studies and research.

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Linking Chapters 2 and 3

In Chapter 1, we introduced landscapes as Complex Systems, which by their very nature necessitate a multiscale approach towards their monitoring, modeling, and management. To achieve this, we determined that Landscape Ecologists require an integrated multiscale framework that combines appropriate ecological theory, computer vision methods, and remote sensing data to meet three defined criteria. Chapter 2 described how the first of these criteria was met by introducing an iterative object-specific framework that reduces MAUP, incorporates concepts from Complex Systems theory, and uses remote-sensing data for generating a multiscale representation of the dominant image-objects composing a scene.

To meet the second criterion, we require appropriate feature detectors that are able to automatically define ecologically meaningful objects that compose specific patterns at their unique scales of expression. To achieve this, Chapter 3 represents an in-depth investigation of Linear Scale-Space theory and Blob Feature Detection. Due to the non-trivial nature of these computer vision techniques, this paper has been adapted within the context of Complex Systems and written as a non-mathematical primer that emphasises the historical, conceptual, and utilitarian characteristics of this approach. Methodology has been described in a pseudo code approach to provide a guide for interested users. We also describe key strengths, limitations, and a number of potential ecological applications for these techniques. Most importantly, this chapter provides important insight and understanding into multiscale feature detectors, and how topological mechanisms could be integrated within a multiscale object-specific approach.

Chapter 3: A Scale-Space Primer for Exploring and Quantifying Complex Landscapes[⊗]

"We shall not cease from exploration
And the end of all our exploring
Will be to arrive where we started
And know the place for the first time"

- T.S. Eliot

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3. Abstract

Over the last two decades, the scale-space community has developed into a reputable field in computer vision, yet its nontrivial mathematics (i.e., group invariance, differential geometry and tensor analysis) limit its adoption by a larger body of researchers and scientists, whose interests in multiscale analysis range from biomedical imaging to landscape ecology. In an effort to disseminate the ideas of this community to a wider audience, we present this non-mathematical primer, which introduces the theory, methods, and utility of scale-space for exploring and quantifying multi-scale landscape patterns within the context of Complex Systems theory. In addition, we suggest that Scale-Space theory, combined with remote sensing imagery and blob-feature detection techniques, satisfy many of the requirements of an idealized multiscale framework for landscape analysis.

Key Words: *Scale-Space, Multiscale Analysis, Complex Systems, Landscape Patterns, Blob-Feature Detection*

3.1 Introduction

Landscapes are complex systems, which by their very nature necessitate a multiscale or hierarchical approach in their analysis, monitoring, modelling and management. In the following section, we describe Complex Systems theory, Hierarchy theory, the importance of scale and remote sensing data when evaluating landscape patterns, and suggest that Scale-Space theory, combined with remote sensing imagery and blob-feature detection techniques, satisfy many of the requirements of an idealized multiscale framework for landscape analysis.

Complex Systems theory evolved within the framework of General Systems theory (von Bertalanffy, 1976), mathematics and philosophy in the 1960s and 1970s. It represents a convergence of ideas developed primarily in economics, ecology, and computer sciences that aim at describing the behaviour of human and ecological systems characterized by a large number of components that interact in a non-linear way and exhibit adaptive properties through time (Kay, 1991; Waldrop, 1992; Coveney and Highfield, 1995). Such systems are referred to as complex systems (Nicolis and Prigogine, 1989). To quantify their behaviour, Complex Systems theory integrates concepts from Catastrophe theory (Saunders, 1980), Chaos theory (Gleick, 1987), Hierarchy theory (Allen and Starr, 1982), Non-Equilibrium Thermodynamics (Schneider, 1988), and Self-Organization theory (Nicolis and Prigogine, 1977). When applied within an ecological context, landscapes/ecosystems may be regarded as open systems that extract high quality energy from the sun, and respond with the spontaneous emergence of organized behaviour so that their structure and function are maintained (Kay and Schneider, 1995; Kay and Regier, 2000). This response is characterized by rates of energy dissipation that increase as the system moves from equilibrium to a newly organized/emergent state. As a consequence, complex systems are referred to as *dissipative structures*, and their mechanism of emergence is called *self-organization* (Bak et al. 1988). The key to recognizing self-organization is that it is revealed in the form of spatial patterns and temporal rhythms at the macroscopic scale where we can observe them (Nicolis and Prigogine, 1989). In this sense, defining spatial patterns and the scales where they emerge is an important step towards comprehending their underlying processes (Phillips, 1999).

An important characteristic of complex systems is that (intuitively) they take the form of a nested hierarchy (e.g., leaf, branch, tree, stand, canopy, forest, etc). In general terms, a hierarchy may be defined as 'a partial ordering of entities' (Simon, 1962); thus hierarchies are composed of interrelated subsystems, each of which are made of smaller subsystems until a lowest level is reached. Within the formal framework of Hierarchy theory[33], a hierarchically organized entity can be seen as a three-tiered nested system in which levels corresponding to slower behaviour are at the top (Level +1), while those reflecting successively faster behaviour are seen as a lower level in the hierarchy (Level -1). The level of interest is referred to as the Focal level (Level 0). From a landscape ecology perspective, Hierarchy theory predicts that complex ecological systems, such as landscapes, are composed of relatively isolated levels (*scale domains)*, where each level operates at relatively distinct time and space scales. *Scale thresholds* separate these domains, and represent relatively sharp transitions or critical locations where a shift occurs in the relative importance of variables influencing a process (Meentemeyer, 1989; Wiens, 1989). In general, interactions tend to be stronger and more frequent *within* a domain than *among* domains (Allen and Star, 1982).

Conceptually, these ideas enable the perception and description of complex systems by decomposing them into their fundamental parts and interpreting their interactions (Simon, 1962). But the ability to define exactly what constitutes the most appropriate hierarchical components,

[33] Many generally regard Hierarchy theory as being introduced into (Landscape) Ecology by Allen and Starr (1982); though it should be noted that early work by Watt (1947), Whittaker (1953), and others embrace ideas that are implicitly hierarchical in nature (Urban et al., 1987).

where such thresholds between hierarchical components exist in space and time, and how information should be appropriately transferred between levels in the hierarchy are non-trivial tasks[34]. In addition, the concepts and principles of Hierarchy theory usually apply only to scalar (i.e., scale-related, albeit spatial or temporal), not prescribed or definitional hierarchies (Wu, 1999); yet the traditional hierarchical levels of ecological organization are definitional (i.e., individual-population-community-ecosystem-landscape-biome-biosphere) (Allen and Hoekstra, 1992; Ahl and Allen, 1996). Thus, complex systems exhibit hierarchical structures that are manifest as unique patterns emerging at specific scales. We assign meaning to these patterns, but as it turns out, this meaning may be completely inappropriate for describing the underlying processes, or understanding the 'system' as a whole, because we have been trying to coax from these landscape patterns a hierarchical mirror of our own definitional classes/organizations, which inadvertently may have also been defined at the 'wrong' - or inappropriate – scale(s).

Levin (1992) states that scale is *the* fundamental determinant of hierarchical structure, thus the key to understanding complex systems and the patterns they generate first lies in understanding the 'nature' of scale. An important characteristic of scale is the distinction between grain and extent. *Grain* refers to the smallest intervals in an observation set, while *extent* refers to the range over which observations at a particular grain are made (O'Neill and King, 1998). Within a remote-sensing context, grain is equivalent to the spatial, spectral, and temporal resolution of the pixels composing an image, while extent represents the total area, combined bandwidths (i.e., wavelengths), and temporal-duration covered by the entire image(s). Conceptually, scale represents the 'window of perception', the filter, or measuring tool, with which a system is viewed and quantified; consequently real-world objects only exist as meaningful entities over a specific range of scales. More specifically, the type of information obtained is largely determined by the relationship between the actual size of objects in the scene/data, and the size (i.e., resolution) of the operators (i.e., filters) used to extract information. This simple, and often overlooked fact is critical for understanding and interpreting all patterns. For a more in-depth treatment of scale in the natural sciences and remote sensing see Marceau (1999), and Marceau and Hay (1999a,b).

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[34] As yet, we have been unable to determine whether landscape hierarchies are truly nested, unseated, or completely at the arbitrariness of the evaluator. In fact, there is nothing about the levels extracted from an observation set that requires them to be nested, and several studies conducted to date seem to suggest unseated hierarchies (O'Neill and King, 1998).

When landscapes are considered as complex systems, remote sensing technology represents the principal tool and data source for obtaining meaningful large-extent information. While such technology provides a plethora of multi-spatial, multi-spectral, and multi-temporal resolution data, our ability to define spatial patterns within this data – and thus enhance our understanding of the underlying processes – is still largely determined by the relationship between the objects in the scene, and the scales at which we observe them. It is also important to note that while modern sensors incorporate sophisticated multi-resolution capabilities[35], the data they generate essentially represents an arbitrary spatial sampling (i.e., a 'snap-shot') of a scene.

To truly understand the hierarchical nature of landscapes requires an ability to provide a multiscale (data) representation of such scenes, as well as multiscale analytical techniques for assessing the patterns that emerge through scale. Humans (also complex systems) daily exploit an inherent capacity to extract a vast amount of multiscale information from their local environment i.e., sight, smell, sound, etc. In particular, the lens of the eye changes shape to focus on objects of interest over a range of scales. From a remote sensing perspective, a similar solution may be to build a sensor that allows us to image the whole planet contiguously (i.e., from very fine spatial, spectral, and temporal resolutions to very coarse resolutions) so that no patterns/structures are missed. Obviously, current technology limits this notion, but the idea is intriguing. Are there multiresolution frameworks that incorporate scaling[36] techniques for resampling data to multiple scales, which can also be used to explore and quantify complex landscape structures at multiple scales? Ideally, such a framework should contain the following abilities:

- the capacity to generate a multiscale representation of a scene from a single scale of fine-resolution remote-sensing data;
- exhibit hierarchical (i.e., multiscale) processing and evaluation capabilities;

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[35] For example MODIS has 36 co-registered channels ranging from 250 m^2 – 1 km^2, while Hyperion (launched in November, 2000) has the capacity to acquire 220 spectral bands (from 0.4 to 2.5 μm) at a 30 x 30 m spatial resolution (http://eo1.gsfc.nasa.gov/miscPages/home.html).

[36] Scaling refers to transferring data or information from one scale to another. In practice, it can be performed from a 'bottom-up' or a 'top-down' approach: *upscaling* consists of using information at smaller scales to derive information at larger scales, while *downscaling* consists of decomposing information at one scale into its constituents at smaller scales.

- be spatially tractable through all scales [i.e., object-oriented or object-specific (Hay et al. 1997)];
- be mathematically sound and computationally feasible;
- be capable of automatically defining (dominant) multiscale patterns within the scene that are not biased by class definitional constraints (thus allowing for scaling between defined patterns);
- be able to produce results that are spatially explicit and ecologically meaningful (i.e., usable within geographic information systems and spatial models).

Obviously this is no small task. Hay et al. (2001) present *Object-Specific Analysis (OSA) and Upscaling (OSU)* as an innovative and potentially powerful framework for the multiscale analysis and scaling of landscape components based on the concept of *image-objects* (Hay et al. 1997). By considering landscapes as hierarchical in nature, they describe how a multiscale object-specific framework may assist in automatically defining critical landscape thresholds, domains of scale, ecotone boundaries, and the grain and extent at which scale-dependent ecological models could be developed and applied through scale. While this framework satisfies nearly all of the (previously described) idealized attributes, its principal limitation is that it is empirically based. In computer vision, several multiresolution methods such as quad-trees, pyramids, multigrids, wavelets, and scale-space are well known (Jähne, 1999, Weickert, 1999), but for several of these techniques, their use of nontrivial mathematics tends to prevent their adoption by more physiologically and ecologically oriented disciplines. In addition, they were not specifically developed for landscape analysis. However, Scale-Space theory in particular exhibits some very unique multiresolution characteristics which lead us to suggest that as an uncommitted vision system, Scale-Space theory combined with blob-feature detection and remote-sensing imagery satisfy many of the requirements of an idealized multiscale framework for landscape analysis. In particular, they exhibit the potential to fulfill the non-definitional scaling requirements of hierarchical organizations. In the remainder of this paper we will evaluate these ideas by providing a non-mathematical introduction to the theory, methods, and utility of scale-space and blob-feature detection for exploring and quantifying multiscale landscape patterns.

3.1.1 Background: Scale-Space theory

This section describes the purpose, and historical context of Scale-Space theory and the important role played by Gaussian kernels. Scale-Space theory is an uncommitted framework for early visual operations that has been developed by the computer vision community to automatically analyze real-world structures at multiple scales when there exists no *a priori* information about such structures or the appropriate scale(s) for their analysis. In other words, this is a system for determining the scale of an object and where to search for it before knowing what kind of object we are studying and before knowing where it is located (Lindeberg, 1994b). The term *uncommitted framework* refers to observations made by a *front-end vision system* (i.e., an initial-stage measuring device) such as the retina or a camera that involves 'no knowledge', and 'no preference' for anything.

Such a framework does not provide definitive results regarding scene content (i.e., object delineation, or classes), but rather provides a derived representation that can support, or guide later stage visual processes. Typical applications include dealing with texture, contours, and autonomous robotic vision (Weickert, 1999). For example if a robotic probe was sent to another planet to find alien life, biasing (or committing) the probe to search for life-forms similar to our own may result in overlooking alien forms that exist in a different manner than we had expected. Similarly, when exploring image patterns to obtain process understanding it is important not to bias the pattern defining tool unless we are certain we know exactly what we are looking for. When one considers that modern remote sensing technology is capable of providing spectral and spatial data beyond our innate capacities, or experience (e.g., x-ray, ultraviolet, infra-red, thermal, and microwave data, at continental, global, planetary, even galaxy scales), the ability to recognize 'important' scene patterns, or their 'optimal' scale(s) of expression *a priori* are not always possible.

When scale information is unavailable, the only reasonable approach for an uncommitted vision system is to represent the input data at (all) multiple scales. Consequently, the basic premise of linear scale-space is that a multi-scale representation of a signal (such as a remote-sensing image of a landscape) is an ordered set of derived[37] signals showing structures at coarser scales that constitute simplifications of corresponding structures at finer scales. In this context,

[37] *Derivatives* represent the relationships between the rates of change of continuously varying quantities. The solution of a differential equation is, in general, an algebraic equation expressing the functional dependence of one variable upon one or more others. If, on the other hand, the function depends upon several independent variables, so that its derivatives are partial derivatives, then the differential equation is classed as a *partial differential* equation.

simplification' refers to *smoothed* structures resulting from convolution[38] with Gaussian kernels of various widths (i.e., scales).

In the English literature, the earliest scale-space accounts are attributed to Witkin (1983) who is credited with coining the term, and to the well-developed framework written by Koenderink (1984). Since this time, the Western scale-space community has developed into a serious field of computer vision (Nielsen et al. 1999) with international conferences (ter Haar Romeny, 1997) and several comprehensive published texts (Lindeberg, 1994b; Florack, 1997; Sporring et al. 1997). Yet despite this success, its non-trivial mathematics (i.e., group invariance, differential geometry and tensor analysis) has limited its adoption outside of computer vision, and until recently (Weickert et al. 1997; Florack and Kuijper, 1998), cultural differences had obscured the fact that earlier Scale-Space theory and applications were actually pioneered in Japan by Iijima (1959) more than two decades prior to their Western counterparts. It is interesting to note that while early Japanese scale-space research[39] was based on determining solutions for optical character recognition, there was also an underlying philosophical motivation behind its evolution. Its principles go back to Zen Buddhism, and may be captured by the phrase "Anything is nothing, and nothing is anything." This suggests that to obtain the desired information, it is necessary to control the unwanted information. Thus, 'smoothed' scale-space structures may be interpreted as a kind of unwanted information, which helps to understand the semantical content of the original image (Weickert et al. 1997).

3.1.2 Uniqueness of the Gaussian Kernel

Gaussian operators (kernels) are fundamental to Scale-Space theory. In one dimension, a Gaussian distribution[40] - also called a 'normal distribution' - may be characterized by its familiar 'bell shaped curve'. In two dimensions, its distribution represents a circular area that radially diffuses outwards from a bright centre towards darker edges, while in three dimensions, it appears as a single mountain peak, that grades smoothly to its base (Figure 3.1). Their use in

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[38] *Convolution* involves the passing of a moving window (or kernel) over an image to create a new image where each pixel in the new image is a function of the original pixel values within the moving window and the coefficients of the moving window as specified by the user.

[39] Which even today is still considered mathematically elegant and up-to-date (Florack and Kuijper, 1998)

[40] For computational reasons, we represent the asymptotic distribution of a Gaussian with four standard deviations (which approximates 99.999% of the theoretical distribution).

Scale-Space theory is not by chance, but instead reflects strict purpose, design, and evaluation. In the following section, we discuss these concepts in greater detail.

All biological or artificial vision systems require the ability to measure samples from a (real world) scene. This is done through a sampling aperture, which must consist of a finite size in order to integrate the entity to be measured (i.e., light intensity). In an uncommitted framework, there is no information regarding the size to make this aperture, therefore the obvious solution is to leave the aperture size (scale) as a free parameter. In addition, the description of any physical system within an uncommitted framework must be independent of the particular choice of coordinate system, so that if coordinates are changed, the description will still describe the same system. These requirements and others can be stated as *axioms*, or postulates for an uncommitted visual front end. In essence, they represent the mathematical formulation for "we know nothing, and we have no preference whatsoever" (ter Haar Romeny and Florack, 2000).

Weickert et al. (1997) provides an overview of more than ten axiomatics for an uncommitted framework that is satisfied by the Gaussian kernel within a linear scale-space framework. In the list below, we describe four of the most important axioms:

- *Linearity* (i.e., no knowledge, no model, no memory): measurement should proceed in a linear fashion, as non-linearities require the incorporation of *a priori* knowledge.
- *Spatial shift invariance* (i.e., no preferred location): all scene locations should be measured in the same fashion, i.e., with the same aperture function.
- *Isotropy* (i.e., no preferred orientation): scene structures with a specific orientation like a horizontal horizon, or vertical trees, should have no measurement preference. This necessitates an aperture with a circular integration area.
- *Scale invariance* (i.e., no preferred size/scale): any size of structure at this stage of acquisition is just as likely as any other, and there is no reason to acquire information with only the smallest-sized apertures.

Just as scale represents the free parameter in an uncommitted framework, scale is also the free parameter in biological vision systems. That is, scale is not fixed, but instead is variable. Neuropsychological studies indicate that the retina, and related processing layers, measure input with receptive fields at a wide range of sizes (scales) and at all orientations. The importance of these findings, as noted by Young (1985) and Koenderink (1984), is that the receptive fields in the mammalian retina and visual cortex can be well modeled by Gaussian derivatives up to order four. A zero-th order Gaussian kernel is illustrated in Figure 3.1B, and a first-order Gaussian derivate and its biological equivalent is illustrated in Figure 3.2. For a more explicit description of Gaussian derivative kernels, see Lindeberg (1994a). In this paper, we will deal exclusively with the zero-th order Gaussian derivative.

Another important quality is that all partial derivatives of the Gaussian kernel are solutions of the *linear, isotropic diffusion equation*[41]. The diffusion equation describes the physical process that equilibrates concentration differences without creating or destroying mass. This process is governed by well-defined laws relating the rate of flow of the diffusing substance with the concentration gradient causing the flow. Within a scale-space framework, this means that the effect of Gaussian smoothing can be considered as the diffusion gradient of the grey-level intensity of an image over scale (t)[42]. Thus, not only does the Gaussian kernel and all its partial derivates satisfy the linear diffusion equation, they also exhibit a similarity with biological visual operators, and they satisfy the axioms for an uncommitted vision system, namely that of linearity, and no preference for location, orientation and scale. They also represent a family of kernels, where scale - defined as the standard deviation of the Gaussian distribution (t) - is the free parameter (ter Haar Romeny and Florack, 2000).

3.2 Scale-Space Methodology Part I: Generating a Multi-Scale Representation

There are two principal components required for any multiscale analysis: the generation of a multi-scale representation and techniques for feature extraction. In the following section, we outline the methodology for applying scale-space to generate a multi-scale representation from a scanned airphoto and describe the results.

3.2.1 The Scale-Space Primal Sketch

Recall that a linear scale-space representation of a signal (i.e., an image) is an embedding of the original data into a derived one-parameter family of successively smoothed signals that represent the original data at multiple scales. In simple terms, an image is convolved with a Gaussian filter of a specific scale, which results in a derived image. This process is iterated. At

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[41] Together with the zero-th order Gaussian, they form a complete family of scaled differential operators.

[42] In the diffusion equation, time is the free variable. However, in scale-space, scale is considered equivalent; consequently, scale is represented by (*t*).

each iteration the 'scale' of the filter increases (by a fixed amount) resulting in a group of successively smoothed images, each of which are composed of the same grain size and extent. More explicitly, each derived signal (i.e., each new 'smoothed' image) is created by convolving the n^{th}-order derivative of a Gaussian (DOG) function with an original signal, where the scale (*t*) of each derived signal is defined by selecting a different standard deviation for the DOG function (at each new iteration). This results in a 'scale-space cube', or 'stack' of increasingly 'smoothed' images that illustrates the evolution of the original image through scale. Each hierarchical layer in a stack represents convolution at a fixed scale, with the smallest scale at the bottom (t_{min}), and the largest at the top (t_{max}) (Figure 3.3). In practice, a user defines a range of scales, along with a constant scale increment. Thus, (t) is incremented at each iteration by a user-defined constant, where a mathematical function automatically specifies the size of the convolution window (i.e., the number of pixels) necessary to determine the new scale.

Witkin (1983) and Koenderink (1984) refer to this stack of images as a *linear scale-space*, while Lindeberg (1993) refers to it as a *scale-space primal sketch* because it bears similarity to the *primal sketch* proposed by Marr (1982). Marr's primal sketch represents the most elementary level in a computer-vision framework developed to derive shape information from images. It involves defining primitives consisting of edges, line segments, and blobs, and then grouping these primitives based on their first-order statistics. Appropriately, the main features that arise within any scale-space stack are smooth regions which are brighter or darker than the background, and which stand out from their surrounding. These features are referred to as 'grey-level blobs' (Figure 3.4).

3.2.2 Dataset

In this paper, linear scale-space is applied to an 8-bit scanned panchromatic airphoto through scales ranging from $t_{0\text{-}100}$, with a scale increment of two. Thus the first 'smoothed' image in the stack (t_1) results from convolving the airphoto (t_0) and a Gaussian kernel with a standard deviation (i.e., scale) of three, the second smoothed image (t_2) with a standard deviation of five, etc. These scale variables were chosen based on computational convenience and the assumption they would provide a representative sample of the multiscale structure inherent within the image/scene. The scanned airphoto has a spatial resolution of 2.0 x 2.0 m an extent of 500 x 500 pixels, and was acquired during the late summer of 1997. Geographically, it represents a portion of the highly fragmented agro-forested landscape typical of the Haut Saint-Laurent region of southwestern Québec. The vegetation in this area is dominated by beechmaple climax forest (*Fagus grandifolia* Ehrh - *Acer saccharum* Marsh.) situated on uncultivated moraine islets, with cereal crops grown in the rich lowland marine clay deposits of the Champlain Sea (Meilleur et al. 1994). In this image (Figure 3.4), stone hedgerows (dark diagonal linear features) separate bright toned agricultural fields, resulting in rectangular field structures. The high contrast grey-tones of the fields are related to different soil moisture regimes. Dark tones represent a relatively high content of soil moisture and organics, while bright tones represent increased clay content and reduced soil moisture. The 'rough' grey-tone forest-texture (image top) represents a mixed-age deciduous forest resulting from extensive harvesting during the early 19th century (Simard and Bouchard, 1996; Bouchard and Domon, 1997). Large mature deciduous tree crowns dominate the scene, interspersed with early successional species. A bright narrow gravel road winds horizontally across the scene segmenting forest and fields. For the remainder of this paper, the stack derived from the Haut Saint-Laurent airphoto will be referred to as the *HSL-stack*.

3.2.3 Perceptual Volumetric Scale-Space Structure

One of the most unique characteristics of a scale-space primal sketch is the potential to exploit the spatial association implicit to 2-D grey-level blobs with the perceptual volumetric structures that populate each stack, and which 'appear' to link grey-level blobs through scale. For example, the two graphics in Figure 3.5 illustrate the perceptually implicit multiscale structure contained within the HSL-stack. Specialized 'in-house' colour and opacity palettes have been applied at two different ranges of scale, and are intended for visualization purposes only (see Figure 3.5a). The upper scene represents scales ranging from $t_{0\text{-}100}$, the lower scene from $t_{0\text{-}50}$. An important, though subtle concept to appreciate when evaluating these images is that visually distinct volumetric structures of varying sizes and shapes persist only within a specific range of scales, even though smoothing is applied over every part of the image, and through *all* scales. In addition, it is critical to recognize that, while these illustrations are populated by impressive volumetric structures, they exist perceptually only. That is, there is no topology delineating or relating 2-D structures, i.e., grey-level blobs at a specific scale, to uniquely labeled 3-D objects. To facilitate the description (and eventual quantification) of these perceptual structures we will briefly explain the notion of *blob events*.

To quantify the perceptual structures located within a stack first requires applying feature detectors[43] to the grey-level primal sketch (which is discussed in greater detail in Part II of the Methodology section). This results in the generation of simplified geometrical structures that can be linked through scale based on the notion of 'scale-space events'. A unique sub-set of these structures is referred to as *blob events*, the description of which provides a formal grammar or syntax that we will use to describe the perceptual structures in the HSL-stack. Lindeberg (1993) specifies four generic blob event cases:

- Annihilation – one blob disappears
- Merge – two blobs merge into one
- Split – one blob splits into two
- Creation – one new blob appears

It is important to note that while the perceptual structures in the HSL-stack appear as volumes through multiple scales their corresponding blob events are discrete in scale. That is, identifying blob events actually requires defining a single pixel location within a corresponding perceptual volumetric structure. In the literature, this location is referred to as either a 'bifurcation' and/or a 'singularity' (Figure 3.6). For example, in the upper image of Figure 3.5, a small 'floating' dark blue oval structure, located just to the left of the image centre is visible. In the parlance of blob events, the pixel representing the base of this oval structure would be considered the location (x, y) in scale (t) where a unique blob *creation* bifurcation occurs. Similarly, in both upper and lower images in Figure 3.5, numerous arch shaped structures (depicted in light blue tones) represent *merge* events. The pixel location (x, y, t) where each 'arm' of these structures joins to form an arch would be considered a merge bifurcation. When these merge structures are visually evaluated in greater detail, it takes little effort to interpret their evolution through scale as the joining of individual tree crowns into stands, and then into larger forest components.

For a more complete evaluation of these and other structures, Figure 3.7 provides rotated perspectives of both scenes. Depending on the range of visible scales assessed (i.e., $t_{0\text{-}50}$, or $t_{0\text{-}100}$), some 'forest'-merge structures appear to evolve into *annihilation* events. In both figures, *annihilation* events also appear as red mound-like structures that spatially coincide with dry-soil areas within the agricultural fields. In both figures, *split* events are less visually obvious.

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[43] (i.e., differential geometry operators composed of Gaussian kernels of different orders).

When one considers that this family of perceptually distinct multiscale structures result from diffusive or *dissipative* principles (i.e., Gaussian), it is possible to obtain a clearer appreciation for the concept of hierarchical systems as *nearly decomposable systems* (Simon, 1962). That is, while distinct hierarchical structures exist as individual image planes or layers in the HSL-stack, the results of the Gaussian filter show how structures interact and diffusively persist through scale, but not through all scales. We also note the impressive vertical structures surrounding high contrast features such as roads, and hedgerows. While it is possible to associate ecological importance to these edges, it is necessary to recognize that one of the limitations of scale-space is that high contrast features tend to persist in scale, regardless of whether or not such features have ecological meaning.

3.3 Scale-Space Methodology Part II: Scale-Space-Blob Feature Detection

The second component of any multiscale analysis consists of feature detection. Four techniques may typically be applied to a linear scale-space: edge, ridge, corner, and blob detection (Lindeberg, 1996; 1999). While the first three techniques have found useful applications in computer vision, edge detection also represents an active body of research in ecological studies where it is used to evaluate landscape fragmentation and connectedness (Hansen and di Castri, 1992). An increasingly important body of ecological research also involves developing theory and methods for the detection and linking of dominant scene-structures through scale i.e., image-objects (Hay et al. 2001) or patches (Wu and Levin, 1997). From a scale-space perspective, these dominant scene-structures spatially correspond to significant blobs that have been extracted from a scale-space primal sketch. In the proceeding section, we describe blob-feature detection as introduced by Lindeberg (1993, 1994b[44]). In some instances, our descriptions do not satisfy the exact order as described by Lindeberg; this is because we outline how such steps may be computationally achieved. We note that while the following represents a simplified description of a mathematically dense method, even this simplified description is not trivial.

[44] In particular, chapters 7-9 provide an in-depth discussion on the scale-space primal sketch, image-structure, and algorithms for generating scale-space blobs.

3.3.1 Step 1:

- *The first step of scale-space blob detection is to generate the scale-space primal sketch (explained in Part I). From this, blobs are extracted at all levels of scale.*

The fundamental objective of scale-space blob detection is to link grey-level blob features at different scales in scale-space to higher order volumetric objects called *scale-space blobs*, and to extract significant image features based on the level of their appearance and persistence over scales. This is premised on the underlying heuristic that volumetric blob-like structures, which persist in scale-space, are likely candidates to correspond to significant structures in the image/scene. To quantify the qualitative structures illustrated in Figures 3.5 and 3.7, scale-space blobs are first defined using a technique that for descriptive purposes is analogous to applying 'watershed analysis' over a grey-scale 'landscape'[45]. To achieve this, 2-D grey-level blobs (Figure 3.4) at each scale (t) in the stack are treated as 3-D objects with extent both in space (x, y) and in grey-level intensity (z). Thus, a scale-space blob begins its life with (at least) one local grey-level maxima (i.e., a peak) then analysis proceeds by defining its surrounding region (or watershed). This can be visualized in the following manner.

Imagine an image layer from the primal sketch as a flooded 3-D grey-level landscape (Figure 3.8). As the water level gradually sinks, peaks will appear. At some instance, two different peaks become connected. The corresponding elevation levels (grey-levels) are called *base levels* of the blob. Since these base levels are defined on a 2-D image plane (i.e., an image layer at a specific scale), they represent unique areas, which define the *support region* of a *grey-level blob*.

- These areas are converted to a binary mask (i.e., all base level areas are white, the remainder are black) (Figure 3.9).
- This process is then applied to each scale (t) of the grey-level stack resulting in corresponding binary blob masks for each scale.

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[45] The actual technique involves convolving the 2-D image with the Laplacian of a Gaussian function (see Figure 3.2d) at different standard deviations, then defining the zero-crossings in the resulting images. In practice, zero-crossings are identified by thresholding each image within a tight range of near zero floating point grey-values i.e., ± 0.005. This results in images populated by binary blobs (Figure 3.9). When these 'threshold' binary blob images are evaluated through scale, the behaviour of their constituent blobs is defined as 'created', 'merged', 'split', or 'annihilated' (refer to section 3.2.3 and section 3.3.2).

- Each binary mask is then applied to its corresponding grey-level layer, and (z) values are extracted under the mask, resulting in a *grey-level blob layer*.
- The extracted z values are integrated to produce a single value that represents the raw grey-level blob volume (x, y, z) for each blob. This is done for each grey-level blob layer.

3.3.2 Step II:

- *The next step is to compute the normalized scale-space volume for each scale-space blob based on the concepts of effective grey-level blob volume and scale-space lifetime.*

As blob behaviour is strongly dependent upon the structure of the image, this leads one to the conjecture that an *expected image behaviour* may exist. To evaluate this, Lindeberg generates a large number of grey-level blob volumes from white noise data, i.e., images without any structured relations between adjacent pixels. This is because when evaluated through scale, even noise has structure (Figure 3.10). Therefore, if statistics can be accumulated describing how random noise blobs can be expected to behave in such images, then the result will be an estimate of how accidental blob groupings can be expected to occur in scale-space. If a grey-level blob at some scale has a volume smaller than the expected white-noise volume, then the blob cannot be regarded as significant. Conversely, if at some scale, the blob volume is much larger than the expected volume, and in addition, the difference in blob volume is much greater than the expected variation around the average value, then it is reasonable to treat this blob as significant.

Based on these considerations, Lindeberg (1993) suggests that a natural normalization technique is to subtract a measured grey-level blob volume by the mean white-noise grey-level blob volume, and divide by the standard deviation of the white-noise grey-level blob volume. This results in a transformed grey-level blob volume. Unfortunately, this value may consist of negative values, making it unsuitable for integration (a necessary step in computing scale-space blob volume). Therefore, a value of 1 is added to the *transformed volume* to ensure all positive values. This adjusted value is referred to as the *effective grey-level blob volume*.

According to Lindeberg, this implementation empirically produces reasonable results, however, it is only one of several possible approaches. To better understand why white noise normalization is required, I personally corresponded with Dr. Tony Lindeberg on this subject. On August 18 2001, I received the following email response:

Dear Geoffrey,

Thanks for your question. The reason why I chose to normalize with noise images is that I wanted to normalize with respect to the expected behavior of image structures in scale-space, and to estimate the extent to which accidental groupings occur in scale-space. By using noise images for this analysis, the idea was hence to estimate to what extent structures will be detected in images without significant structures. In the original implementation of the scale-space primal sketch, white noise was used for this purpose. In a related more recent work on feature detection with automatic scale selection (Int. J Comp Vision 1998), I used a scale normalization method that has strong relations to normalization over scales based on self-similar noise (1/f^alpha).

One reason for not using the same image for normalization as the image that is being analyzed is because of generality. Imagine that you analyze an image that contains structures primarily at one narrow range of scales. The idea with the scale-space primal sketch is then that the image structures at this scale should stand out relative to other structures. If one in such a case would use the same image for normalization on the other hand, then the presence of a dominance of structures would imply a bias in the reference statistics.

I'm sure however that there should be alternative ways of handling this normalization, e.g. based on fractal noise. If you have geographical images with a self-similar distribution of structures over scales, that could possibly be an alternative, but needs to be carefully examined. Since this normalization is done just once and for all, on an off-line basis, the statistics accumulation may not be as severe as it sounds, if one writes a recursive procedure that only stores the information on disk that is needed.

Best wishes and good luck with your efforts,

Tony

We note that, for the effective grey-level blob volume to be significantly meaningful, the described mean and standard deviation values must represent the results from a large number of stacks (i.e., typically greater than 100) each of which has the same x, y, and t dimensions as the original grey-level stack, and each of which are composed of different white-noise grey-level blob volumes. In several respects, this form of normalization corresponds to the Zen Buddhist reference (see Background section) that suggests 'to obtain the desired information, it is necessary to control the unwanted information'.

- When this normalizing procedure is applied to each layer of raw grey-level blob volumes, it generates normalized scale-space blob volume (v_n) layers, which are assembled together in a stack (S_n) corresponding to their associated scales.
- The corresponding binary blob masks (described in Step I) are also assembled together in a stack (S_b) (Figure 3.11).
- Based on the concepts of blob-events (described in the Methodology: Part I) and *scale-space lifetime* (described below), binary blobs are then topologically evaluated and labeled as 3-D binary scale-space blob objects – or 'hyper-blobs'.

In essence, the 'lifetime' of a scale-space blob is defined by the number of scales between bifurcation events. This concept is central for defining the 4-D topological structure of individual scale-space blobs (Figure 3.12). Computationally, we conduct topological linking in a hierarchical manner, where each binary blob at a single layer (t_n) is compared to the binary blobs in the layer above (t_{n+1}) and below it (t_{n-1}). If the spatial support of a blob at either upper and or lower levels spatially overlaps the support region of the blobs at (t_n) these blobs are linked through scale, and referred to as a 'plain link'. If the spatial support of the upper-blob does not overlap the blob at (t_n), an 'annihilation' event has occurred. If the spatial support of the lower-blob does not overlap, a 'creation' event has occurred at (t_n). If the spatial support of two, or more, upper-blobs overlap then a 'split' event has occurred; and if the spatial support of two, or more, lower-blobs overlap then a 'merge' event has taken place[46]. This form of topological linking is applied to all layers in (S_b)[47].

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[46] This paper outlines the simplest matching relationships between blobs. More sophisticated and computationally complex definitions are provided in Lindeberg, 1994 d.

[47] We note that for topological efficacy, all binary blobs at (t_{max}) define annihilation events, and all binary blobs at (t_{min}) define creation events.

- The result is a stack composed of individual hyper-blobs, each of which exhibit a 3-D topology (x, y, t) that explicitly defines their structure and spatial association through scale.
- The individual hyper-blobs are then used as 3-D masks to extract the normalized scale-space volume (x, y, v_n) from each topologically related layer (t) of the normalized blob volume stack (S_n).
- The extracted (v_n) value of each (t) composing individual hyper-blobs is then integrated to produce a single normalized scale-space blob volume (SS_{bv}). This combination of (SS_{bv}) and corresponding hyper-blob structure represent individual 4-D scale-space blobs.

3.3.3 Steps III and IV:

- *The next two procedures involve sorting the resulting scale-space blobs in descending significance order, i.e., with respect to their normalized scale-space blob volumes. Then for each scale-space blob, determining the scale where it assumes its maximum grey-level blob volume, and extracting the support region of the grey-level blob at this scale.*

In practice, all (SS_{bv}) values are sorted in descending order, resulting in a ranking, where the largest normalized scale-space blob volumes are at the top, the smallest at the bottom. An arbitrary user defined threshold is then applied to define the number of hyper-blobs with the most significant (SS_{bv}) values. From these 'significant' hyper-blobs, the layer (t) representing the maximum normalized grey-level blob volume ($v_{n(max)}$) of each hyper-blob is extracted. From this layer, the 2-D spatial support (i.e., corresponding binary blob) is defined and related back to structures in the original image, at the same location. Thus based on the underlying heuristic, 4-D scale-space blobs (x, y, v_n, t) are simplified to normalized 3-D grey-level blobs (x, y, $v_{n(max)}$), which are further simplified to their 2-D support region (x, y), and then to the corresponding 'significant' objects in the original image.

3.4 Discussion

In this section, we discuss the strengths, limitations, and potential ecological applications of Scale-Space theory. We also note the relationship of linear scale-space to wavelets and non-linear Scale-Space theory.

3.4.1 Strengths

In this paper we have suggested that an important limiting factor of the scale-space community has been its highly mathematical nature; ironically, this is also its principal strength. A number of mathematical proofs (Weickert, 1997) state that within the class of linear transformations, the Gaussian kernel is *the* unique kernel for generating a scale-space representation. It satisfies the solution to the linear diffusion equation. It meets (theoretical) axioms required by an uncommitted vision system, and results from these theoretical considerations are in qualitative agreements with results from biological evolution. In addition, the diffusive quality of the Gaussian kernel results in no new structures being added through the scaling process (as occurs with square kernels during convolution); feature detection techniques based on defining edges, ridges, and corners are well documented; and the elegance and utility of being able to evaluate landscape components within a linear scale-specific spatial representation (i.e., a stack) is truly unique. From an analytical perspective, the spatially explicit nature of the ranked 2-D support regions (i.e., binary blobs that result from blob feature detection) can easily be converted for use in geographic information systems (GIS), spatial models, and or by spatial statistical packages to be evaluated with landscape metrics (Riiters et al. 1995).

From a computational perspective we note that while convolution is efficient with small kernels, processing requirements exponentially increase as kernel sizes (and data set size) increase. To resolve this concern, convolution can be performed in the Fourier domain, where processing is significantly reduced (Jähne, 1999). In addition, the hierarchical nature of a scale-space primal sketch would lend itself well to automation, multiprocessing and distributed-network solutions, and coding within an object-oriented framework.

3.4.2 Limitations

Generating a linear scale-space stack is not exceptionally difficult once the recipe is understood. The theory is sound, and the processing is relatively straight forward, but blob-feature detection is a non-trivial task, and to the best of our knowledge, no commercially available software exists. Ter Haar Romeny and Florack (2000) present a scale-space workbook using the computer algebra package *Mathematica*, where code for edge, ridge, and corner detection are provided but they do not tackle blob-detection. In this paper, all computer programming has been performed using IDL (*Interactive Data Language*), which has the advantage of processing multidimensional array structures (i.e., 2-D images) essentially in parallel.

The remote sensing community is used to discussing *scaling* in terms of pixel resampling techniques (Hay et al. 1997). In Scale-Space theory the pixel size remains constant, yet scaling occurs as the information content of an image is resampled by convolving it with different standard deviations of the Gaussian kernel (i.e., scales) resulting in a stack. While this approach leads to information redundancy, it also allows for the linking of structures through scale. Unfortunately, when applied to a large extent remote sensing data set, significant storage and processing concerns arise. For example, we are currently evaluating scale-space techniques using a high-resolution IKONOS dataset: spatial resolution (grain) is 4.0 x 4.0 m with an extent of 2500 x 2500 pixels x 4 spectral channels. Each channel (i.e., image layer) is approximately 15 MB. If we generate a stack with scales ranging from $t_{0\text{-}100}$, this represents approximately 1500

MB per stack, for each of the four channels. And when one considers that a minimum of 100 equal sized stacks composed of white-noise grey-level blob volumes also need to be evaluated for each channel (1500 MB x 4 x 100 = 600 GB), the sheer task of computation and storage becomes non-trivial. Moreover, this is before any visualization or feature detection occurs. If we strictly obey the axioms of an uncommitted vision system, we need to evaluate a scene at 'all' scales. Consequently, a scale-space cube should be composed of (at least) as many pixels in the x, y dimension, as in t, but as suggested, this represents a significant analytical and data representation challenge. From a computational perspective, we note that there are no set rules for determining the maximum number of scales to define within a stack, the increment between these scales, or the threshold number for significance ranking.

Another limitation of scale-space is that high contrast features will tend to persist in scale, regardless of whether or not such features have ecological meaning. This also includes the persistence of noise through scale. For further treatment of this subject, see Lindeberg (1993) and Starck et al. (1998). In addition, smoothing leads to object shape distortion through scale. We note that while smoothing across 'object boundaries' can affect both the shape and the localization of edges in edge detection, this can be resolved by relating different scales of information together. This is referred to as *feature localization* (Lindeberg, 1999). For example, coarse scale blobs can be identified using coarse scale information, while fine-scale information can be used to further delineate specific structures within the coarse blob boundaries.

3.4.3 Ecological Applications

An impressive characteristic of a scale-space primal sketch is the phenomenological, or implicit multidimensional structures that perceptually populate it. When defined, based on the notion of blob-events, they illustrate where and how individual landscape components interact and evolve through scale. Consequently, we suggest that Scale-Space theory has great potential for improving our understanding of multiscale fragmentation and connectedness in landscapes. In addition, scale-space edge detection has been adapted for tree-crown isolation in forestry (Pinz, 1999; Brandtberg and Walter, 1999), and we suggest that it can be further applied for defining the spatial influence of larger landscape-sized objects, i.e., the grain, extent, and location of significant landscape patches. In particular, we have initiated a research program to evaluate the potential of applying the scale-space concept of an uncommitted vision system as a method for defining unbiased landscape structures within high-resolution imagery to fulfill the non-definitional scaling requirements for hierarchical structures. We are also evaluating how surface interpolation techniques may be applied to bifurcation points – based on their level of appearance – to spatially model critical scale-specific thresholds.

3.4.4 Non-Linear Scale-Space

We note that non-linear Scale-Space theory is another technique for generating a multiscale representation that is gaining increasing interest in computer vision. The classic paper that began this field in computer vision was by Perona and Malik (1987). Interested readers are also referred to Weickert (1997; 1999) for an overview. In addition, scale-space shares similarities with wavelets; consequently, it can be considered as a special case of a continuous wavelet representation. Interested readers are referred to Lindeberg (1994) and Stark et al. (1998) for a more mathematical description.

3.5 Conclusion

We propose that Scale-Space theory, combined with remote sensing imagery and blob-feature detection techniques, satisfy many of the requirements of an idealized multiscale framework for landscape analysis. Namely, they provide sound mathematical theory and methods to generate a multiscale representation of a scene from a single scale of fine resolution remote sensing data. We further note that this technique can be applied to any resolution of data, and that significant image features can be automatically defined and linked through scale, based on their level of appearance and persistence through scales. In this paper, these spatially explicit image features visually correspond to ecologically meaningful structures, such as roads, hedgerows, bare soil patches, agricultural fields, and individual tree crowns.

It is interesting to note that (these) soil patches result from differences in soil moisture, which vary quickly over time. Yet, here the evolution of this time-sensitive component is modeled as an instant through scale (i.e., 3-D space). Through scale, hedgerows, and soil patches that initially appear highly visible at fine scales (illustrated as dark red and orange structures in Figures 3.5 and 3.7) disappear as they coalesce within the coarser scale matrix of larger 'field' objects. At fine scales, individual tree crowns are visible (orange structures under a blue surface in Figures 3.5 and 3.7), while at coarser scales they form structures that visually correspond to different tree stands, and eventually, a large extent forest matrix (upper blue surface in Figures 3.5 and 3.7). When these perceptual structures undergo blob-feature detection, they evolve from 2-D binary blobs (Figure 3.9), to 3-D hyperblobs (Figure 3.11), to 4-D scale-space blobs (Figure

3.12) where they are ranked, and finally simplified to a 2-D support region. The spatial nature of these ranked 2-D blobs allows them to be further evaluated with spatial statistics, and used as inputs in geographic information systems and spatially explicit models. They also provide information for hypothesis testing. For example, from the limited data and analysis provided in this paper it is possible to hypothesis that soil moisture variability in these agricultural fields is spatially dominant only at fine scales, while at coarse scales, the overall spatial homogeneity of the agricultural matrix dominates. Such seemingly contrary results often exist in scale studies. For example, conclusions made from studies of oak seedling mortality reported that at local scales in the western United States, mortality decreased as precipitation increased. While at regional scales, mortality decreased in the drier latitudes (Neilson and Wullstein, 1983)

The primary limitations of this framework are that to produce a scale-space stack, a significant amount of 'redundant' data needs to be generated, thus large datasets may encounter significant processing challenges. In addition, there are no provided methods or theory describing how to upscale between significantly defined 'object' scales[48]. We envision that with increasing access to multiprocessing distributed networks, the first limitation will diminish.

Just as language differences isolated early Japanese and Western scale-space communities, the non-trivial mathematical language used in scale-space formalization also isolates its widespread adoption outside of computer vision by disciplines interested in multiscale theory and methods ranging from biomedical imaging to landscape ecology. The fact that the same body of theory has been developed twice in two very different cultures suggests that it is both natural and noteworthy. Our goal has been to introduce the theory, methods, and utility of scale-space for exploring and quantifying landscapes within a complex-system framework that is explained without mathematical notation. It is our belief that by providing a non-mathematical primer that consolidates the underlying ideas and theory from classical scale-space papers, that the wealth of the scale-space community will be more easily accessible, and that new theoretical construct may evolve, and or be adapted by others. The focus of our immediate research lies in two key areas:

1. Evaluating the potential to link the scale-space concept of an uncommitted vision system as a method for defining unbiased landscape structures within high-resolution imagery to fulfill the non-definitional scaling requirements for hierarchical structures.

[48] However, we note that this requirement was not part of the original intent of this framework.

2. Integrating Complex Systems theory, geostatistics, and 3-D visualization techniques that will allow us to link bifurcation events through space (x, y) and scale (t) so we can evaluate the resulting multiscale surface structures in terms of critical scale-specific landscape thresholds.

We hypothesize that these ideas, in concert with the multiscale Object-Specific framework suggested by Hay et al. (2001), and the Hierarchical Patch Dynamics Paradigm of Wu (1999) will bring us closer to understand the processes that lay encoded within multiscale landscape patterns.

3.6 Acknowledgments

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Linking Chapters 3 and 4

From the preceding chapters, we have determined that Landscape Ecologists require an object-specific multiscale approach that meets three specific criteria in order to successfully monitor, model, and manage the multiscale complexity of landscapes. In Chapter 3, we presented an in-depth investigation into Linear Scale-Space and Blob Feature Detection, which met the second of these three criteria by developing software to conduct analysis, and provided additional insight and understanding into the use of multiscale feature detectors for Landscape Ecology.

Conditions of the third criterion indicate that Landscape Ecologists require topological capabilities to automatically link and evaluate image-object interaction and evolution through multiple scales. To achieve this, Chapter 4 compares the strengths, limitations, ecological applications, and methodologies behind the newly developed Fractal Net Evolution Approach (FNEA), Linear Scale-Space (SS), and Object-Specific Analysis (OSA) and Object-Specific Upscaling (OSU). It also describes how these image-object approaches allow for the hierarchical linking of multiscale pattern components, and introduces *MOST* (multiscale object-specific topology) as a novel combination of concepts from Object-Specific Analysis and Mathematical Morphology. This chapter concludes by outlining how an integration of iterative OSA/OSU (Chapter 2) and MOST (Chapter 4) constitute a unique hierarchical approach capable of multiscale object-specific analysis (MOSA) that meets all three initial criteria.

Chapter 4: A comparison of three image-object methods for the multiscale analysis of landscape structure[⊗]

"… the purposeful destruction of information is the essence of intelligent work."

- Ray, Kurzweil (1999)

[⊗] This paper represents an invited submission to a special issue of the ISPRS *Journal of Photogrammetry and Remote Sensing* (theme: Challenges in Geospatial Analysis, Integration and Visualization). It entered the peer-review process in March 2002, and was accepted for publication in August 2002. It is co-authored by G. J. Hay, T. Blaschke, D. J. Marceau, and A. Bouchard.

4. Abstract

Within the conceptual framework of *Complex Systems*, we discuss the importance and challenges in extracting and linking multiscale objects from high-resolution remote sensing imagery to improve the monitoring, modelling and management of complex landscapes. In particular, we emphasize that remote sensing data are a particular case of the Modifiable Areal Unit Problem, describe how *image-objects* provide a way to reduce this problem, and discuss the importance of recognizing and defining appropriate object hierarchies. We then hypothesize that hierarchical multiscale analysis should be guided by the intrinsic scale of the dominant landscape objects composing a scene, and describe three different multiscale image processing techniques with the potential to achieve this. Each of these techniques (the *Fractal Net Evolution Approach*, *Linear Scale-Space* and *Blob-Feature Detection*, and *Object-Specific Analysis* and *Object Specific Upscaling)* facilitate the multiscale pattern analysis, exploration, and hierarchical linking of image-objects based on methods that derive spatially explicit multiscale contextual information from a single resolution of remote sensing imagery. We then outline the weaknesses and strengths of each technique and provide strategies for their improvement.

Keywords: *Fractal Net Evolution Approach, Scale-Space, Object–Specific Analysis, Object-Specific Upscaling, Scale, Multiscale, Hierarchy theory, Complex Systems theory, Image-Objects.*

4.1 Introduction

Landscapes are complex systems composed of a large number of heterogeneous components that interact in a non-linear way and exhibit adaptive properties through space and time. In addition, complex systems exhibit characteristics of emergent properties, multiscale hierarchical interactions, unexpected behaviours, and self-organization (Wu and Marceau, 2002), all of which produce characteristic patterns that (appear to) change depending on their scale of observation (Allen and Starr, 1982). Thus, the roles of the *observer* and of *scale* are fundamental in recognizing these patterns, which in turn are necessary for understanding the processes that generated them.

In general terms, a hierarchy may be defined as 'a partial ordering of entities' (Simon, 1962); that is, hierarchies are composed of interrelated subsystems, each of which are made of smaller subsystems until a lowest level is reached. Of particular relevance to complex systems is the notion that if something is not hierarchically structured it is beyond our understanding (Simon, 1962), and the fact that scale is *the* principal determinant of both hierarchy and pattern (Levin, 1992). Conceptually, scale corresponds to a 'window of perception'. More practically, scale represents a measuring tool composed of two distinct components: grain and extent. *Grain* refers to the smallest intervals in an observation set, while *extent* refers to the range over which observations at a particular grain are made (O'Neill and King, 1998). From a remote sensing perspective, grain is equivalent to the spatial, spectral, and temporal resolution of the pixels composing an image, while extent represents the total area, combined bandwidths and temporal duration covered within the scene (Hay et al., 2001). In addition, remote sensing platforms are the primary data source from which landscape patterns can be assessed. Therefore, to fully understand, monitor, model, and manage our interaction within landscapes we require remote sensing data with a fine enough grain, and broad enough extent to define multiscale landscape patterns, methods and theory capable of identifying pattern components (i.e., real-world objects) at their respective scales of expression, and the ability to link these objects within appropriate hierarchical structures.

Multiscale analysis is composed of two fundamental components: the generation of a multiscale representation, and information extraction capabilities. In order to achieve the innate pattern recognition abilities of humans, a number of image processing techniques have been developed that incorporate concepts and theory from computer vision and machine learning. These include edge detectors (Marr, 1982), mathematical morphology (Haralick et al. 1987), texture analysis (Jain & Farrokhnia, 1991; Hay and Niemann, 1984; Hay et al. 1996; Hofmann et al., 1998), spectral unmixing (Settle and Drake, 1993), neural nets (Fischer, 1997; Foody, 1999), Bayesian networks (Growe et al., 2000), fuzzy logic (Zadeh, 1965; Wang, 1990) and multiscale techniques such as pyramids (Jähne, 1999), wavelets (Salari and Ling, 1995), and fractals (Chaudhuri and Sarkar, 1995; Niemeyer, 1999). However results from these methods often fall short when compared with those of human vision. This is in part because the majority of these techniques do not generate explicit object topology, or even incorporate the concept of *object* within their analysis. Yet this is innate to humans (Marr, 1982; Julesz and Bergen, 1983; Biederman, 1987). Furthermore, when these techniques are applied to remote sensing data their output are typically used only as additional information channels in per-pixel classification techniques of multi-dimensional feature space (Skidmore, 1999), rather than in object delineation. While many of these techniques provide interesting and useful results over a single scale or narrow range of scales, the ability to apply these methods for the automatic analysis of multiscale landscape patterns and the hierarchical linking of their components through a scale continuum is not well defined (Hay et al., 1997). In particular, remote sensing images are composed of pixels, not objects, there are no explicit scaling laws that define where to scale to and from within an image, the number of scales to assess, or the appropriate upscaling method(s) to use (Hay et al., 2001).

In order to overcome these limitations, we hypothesize that the analysis of multiscale landscape structure should be guided by the intrinsic scale of the varying sized image-objects that compose a scene. To facilitate this, we provide a brief background on the modifiable areal unit problem (MAUP) image-objects, and hierarchy. We then describe three different multiscale techniques: the *Fractal Net Evolution Approach*, *Linear Scale-Space* and *Blob-Feature Detection*, and *Object-Specific Analysis* and *Object Specific Upscaling.* Each of these techniques facilitates the multiscale pattern analysis, exploration, and hierarchical linking of image-objects based on methods that derive spatially explicit multiscale contextual information from a single resolution of remote sensing imagery. We then outline the strengths and weaknesses of each technique and provide strategies for their improvement.

4.2 Background: MAUP, Image-Objects and Hierarchy

4.2.1 Remote sensing and the modifiable areal unit problem

While remote sensing data are often visually impressive, they also correspond to an arbitrary spatial sampling of the landscape, and thus represent a particular case of the MAUP (Marceau, 1992). The MAUP originates from the use of arbitrarily defined spatial units for data acquisition and analysis. The consequence is that data and results achieved from them are dependent upon the spatial units used to collect them (Openshaw, 1981; 1984; Marceau, 1999). Though recognized in the Social and Natural Sciences for several decades (Openshaw and Taylor, 1979; Jelinski and Wu, 1996; Marceau, 1999) we suggest that few understand the challenges this poses, especially when multiscale analysis is applied to remotely sensed data (for an in-depth review of MAUP see Marceau, 1999 and Marceau and Hay, 1999a, b). Fortunately, several solutions to the MAUP have been proposed. In particular, the use of objects represents the clearest way out of MAUP, as an analyst works with spatially discrete entities rather than arbitrarily defined areal units (Fotheringham and Wong, 1991; Hay et al., 2001). However, a remote-sensing image is not composed of spatially discrete real world entities that contain explicit object topology. Instead its fundamental primitive is a square pixel that only exhibits simple topological adjacency.

4.2.2 Image-objects

Despite this topological limitation, almost any person can cognitively group similar toned and spatially arranged pixels into meaningful *image-objects* that correspond to real-world entities within the geographic extent of the scene being assessed. The term *image-objects* (Hay et al., 1994; 1997; 2001*)* refers to individually resolvable entities located within a digital image that are perceptually generated from high-resolution pixel groups. High-resolution (H-res) corresponds to the situation where a single real-world object is visually modeled by many individual pixels; whereas low-resolution (L-res) implies that a single pixel represents the integrated signal of many (smaller) real-world objects (Woodcock and Strahler, 1987). In a remote-sensing image, both H- and L-res situations occur simultaneously. For example, in a 1.0 m-resolution image of a forest canopy, where each tree crown exhibits a 10 m diameter, each crown image-object will be composed of many pixels. In this situation, each 1.0 m pixel is *'part of'* an individual crown, thus it is H-res in relation to the crown-object it models. However, each 1.0 m pixel will also be *'composed of'* the integrated reflectance from many needles/leaves and branches, thus it will be L-res in relation to these individual crown components. As a result, an image-object tends to be composed of spatially clustered pixels that exhibit high spectral autocorrelation because they are all part of the same object; consequently, they have similar digital numbers. These characteristics correspond to Tobler's first law of Geography where 'objects are related to all other objects, but proximal objects are more likely to be related to each other' (Tobler, 1970). In an image-object, this relationship is both spatial and spectral.

4.2.3 Hierarchy

Similar to Tobler's first law, Ecologists have long recognized in nature that many processes produce clusters of entities that are typically generated by a small set of self-organizing principals (Allen and Starr 1982; Waldrop, 1992). These entities emerge at specific scales, and result in visually distinct spatial patterns. Therefore, one way to understand, explain, and forecast the effects of *'natural processes'* is to examine these *'natural patterns'* at their corresponding *'natural scales'* of emergence (Wessman, 1992, Levin, 1999). To assist in this task, the conceptual framework of Hierarchy theory[50] has been developed that builds upon this

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[50] Hierarchy theory was developed in the framework of General System's theory, mathematics and philosophy in the 1960s and 1970s (Wu and Loucks, 1995) and is generally regarded as being introduced into ecology by Allen and Starr (1982).

idea of *natural scales*. Conceptually, a hierarchically organized system can be seen as a nested system in which levels exhibiting progressively slower behaviour are at the top (Level +1), while those reflecting successively faster behaviour are seen as a lower level in the hierarchy (Level -1). The level of interest is referred to as the *focal level* (Level 0) and it rests between the other two. From a landscape ecology perspective, Hierarchy theory states that complex ecological systems, such as landscapes, are composed of loosely coupled levels (*scale domains)*, where each level operates at distinct time and space scales. *Scale thresholds* separate domains, and represent relatively sharp transitions, or critical locations where a shift occurs in the relative importance of variables influencing a process (Meentemeyer, 1989; Wiens, 1989). Thus, interactions tend to be stronger and more frequent *within* a level of the hierarchy than *among* levels (Allen and Star, 1982). This important fact enables the perception and description of complex systems by decomposing them into their fundamental parts and interpreting their interactions (Simon, 1962).

However, to achieve this, *objects* (i.e., fundamental parts) need to be clearly defined and clearly separated from *non-objects* such as *aggregates*. Rowe (1961) distinguishes between objects and aggregates by stating that objects contain structurally organized parts, while aggregates occupy a common area, but have no structural organization. Furthermore, objects have *intrinsic scale*, whereas aggregates do not. Thus according to Rowe, a forest may appear as a solid object when viewed from a distance, but it is not an object itself. Instead it is an aggregate of objects (i.e., vegetation, soils, gaps, etc). This is because a 'forest' is a conceptual human construct; whereas a tree – a necessary forest component - has a characteristic size predicated by specific environmental and biological constraints, and is itself physically composed of structural parts (i.e., bole, bark, and branches). When landscape components are defined as either objects or non-objects, this results in two fundamentally different types of hierarchies. Cousins (1993) states that, 'distinguishing these different types of hierarchies allows for the interpretation of what the hierarchies mean.' In addition, Rowe (1961) warns that different hierarchies should not be mixed, because if you mix them, then their interpretation becomes subject to generalization errors (Gardner, et al., 1982) as you encounter aggregation and scaling problems related to the MAUP.

We suggest that recognizing these different types of hierarchies, and the warning against mixing them has not been fully understood or heeded across a broad range of disciplines. As Rowe

(2001) notes, the biological hierarchy of cell-organ-organism-ecosystem[51] (which is a hierarchy of objects composed of parts within parts within parts) has been imprudently extrapolated to include psychological and social/cultural phenomena; and object and aggregate hierarchies are also routinely mixed[52]. The real problem is that few are aware that any mixing has occurred. As Rowe (2001) states '…the fallacy of mixing different categories, and treating them as isomorphic, traps many otherwise-clever minds.' So where does this leave us? Complex systems are hierarchically structured, and composed of many interacting components. These components are of two fundamental object types: integrated objects, and aggregate objects. From a remote sensing perspective, image-objects are *integrated objects* that exhibit an intrinsic scale and are composed of structurally connected parts (i.e., H-res pixels). To understand how image-objects interact within and across scale domains, we need techniques to automatically define them in remote sensing data and the ability to link them within appropriate (non-mixed) hierarchical structures - thus reducing MAUP (in both cases). The primary unknowns to achieving this are:

- what is the 'optimal' scale to evaluate the varying sized, shaped, and spatially distributed image-objects within a scene, and
- at what scales should hierarchies be established?

We suggest that there is no single 'optimal' scale for analysis; rather there are *many optimal scales* that are specific to the image-objects that exist/emerge within a scene (Hay, et al., 1994; 1997; 2001). Therefore, we hypothesize that multiscale analysis should be guided by the intrinsic scale of the dominant landscape objects (image-objects) composing a scene.

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[51] Cousins (1993) notes that while the concept of 'ecosystem' is a subjectively determined aggregate with boundaries given by an observer, it is possible to define an ecological object which substitutes for ecosystem in a hierarchy of functional objects (pp. 77-78).

[52] For example, Wu, (1999) states that 'levels in the traditional hierarchy of ecological organization (i.e., individual-population-community-ecosystem-landscape-biome-biosphere) are definitional and do not necessarily meet scalar[52] criteria. We note that this 'traditional hierarchy' is a mix of both integrated objects (i.e., individual, ecosystem, biosphere) and conceptual aggregate objects (i.e., population, community, landscape).

4.3 Material and methods

In this section, we introduce the study site and data set used, and then briefly describe three different image-processing approaches, each of which facilitates the multiscale pattern analysis, exploration, and hierarchical linking of image-objects, from a single resolution of remote sensing imagery. They are referred to as the *Fractal Net Evolution Approach (FNEA)*, *Linear Scale-Space* and *Blob-Feature Detection (SS)*, and *Object-Specific Analysis* and *Object Specific Upscaling (OSA/OSU)*.

4.3.1 Study site

The data used throughout this paper represent a 500 x 500 pixel sub-image of an 11-km^2 IKONOS scene that was acquired in August 2001 (Figure 4.1a). Geographically, this area represents a portion of the highly fragmented agro-forested landscape typical of the Haut Saint-Laurent region of southwest Quebec, Canada (Figure 4.1b). We note that IKONOS provides 11 bit multispectral data in the red, green, blue, and near-infrared (NIR) channels at a 4.0 m spatial resolution, and an 11 bit panchromatic (PAN) channel at a 1.0 m resolution. Due to the computational demands required by SS processing (see section 3.3), all data were linearly contrast stretched to an 8-bit equivalent. Since the PAN channel covers a significant portion of the wavelengths represented by the four multispectral channels, a geographically corresponding portion of the 1.0 m PAN image was selected and upscaled to 4.0 m using Object-Specific Upscaling (see section 3.4). During SS analysis, only the single PAN image was assessed; however, during FNEA and OSA/OSU analysis, all five channels were evaluated.

4.3.2 Fractal Net Evolution Approach (FNEA)

The fractal net evolution approach incorporates an object-oriented framework (OO) and image segmentation techniques that are embedded in a commercial software environment[53]. To achieve this, it utilizes fuzzy set theory to extract the objects of interest, at the scale of interest, by segmenting images simultaneously at both fine and coarse scales. The analyst then builds semantics between the specified levels and their constituent image-objects (Figure 4.2). By operating on the relationships between networked (i.e., linked) objects, it is possible to classify

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[53] Developed by Definiens Imaging (www.definiens-imaging.com)

local contextual information, which in addition to the inherent spectral information within an image, can be combined with image-object form and texture features to improve classifications.

From an FNEA perspective, image information is considered fractal in nature. That is, structures typically appear at different scales in a remote sensing image simultaneously. However, to extract meaningful image regions the user has to take into account the scale of the problem that is to be solved and the type of image data available. As a result, users are required to 'aim' for different scale levels by hypothesizing that almost all attributes of image structure – colour, texture, form – are essentially scale-dependent. This is different from many other approaches, which do not require any user-defined parameters (i.e., region growing and watershed algorithms, multi-fractal based segmentation, Markov random fields, etc). In FNEA, defining a specific level of analysis leads to defining objects at a unique scale.

FNEA starts with a single pixel and a pairwise comparison of its neighbours with the aim of minimizing the resulting summed heterogeneity. The common solution for this pairwise cluster problem is described as *global mutual best fitting*. In fact, global mutual best fitting is the strongest constraint for the optimization problem and it reduces heterogeneity primarily over the scene following a pure quantitative criterion. However, there is a significant disadvantage to global mutual best fitting. It does not use the distributed treatment order[54] and – in connection with a heterogeneity definition for colour - builds initial segments in regions with a low spectral variance. This leads to an uneven growth of image-objects over a scene and to an unbalance between regions of high and low spectral variance.

Conversely, *local mutual best fitting* always performs the most homogeneous merge in the local vicinity following the gradient of best fitting. To achieve this, an iterative heuristic optimization procedure aims to get the lowest possible overall heterogeneity across an image. The basis for

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[54] Distributed treatment order of image objects: Except for global mutual best fitting, each decision heuristics needs a given image-object as a starting point for the search of the merging pair. For the maintenance of a similar size/scale of all image objects, it is necessary to let them grow in a simultaneous way. This can be achieved by choosing a sequence of starting points, which fulfills the following two conditions: (1) handle each point respectively for each object, once per cycle, and (2) distribute subsequent merges as far as possible from each other over the whole scene. We note that for each specified object the procedure performs one merge.

this is the degree of difference between two regions. As this difference decreases, the fit of the two regions is said to be closer. 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. According to the original notation provided by Baatz and Schäpe, (2000) for an *n-dimensional feature space* (f_{nd}), the *heterogeneity* (*h*) is described as:

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

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 normalized by the standard deviation of the *feature* in each *dimension* using Equation 2.

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

Equation 3 defines the homogeneity of two adjacent regions by describing the difference of heterogeneity *h* of the two regions before (*h1* and *h2*) and after a virtual merge (*hm*). 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 *hdiff* before and after a virtual merge – but they are beyond the scope of this paper. For more information, see Baatz and Schäpe (2000).

$$hdiff = hm - (h1 + h2)/2 \tag{3}$$

This attribute (*hdiff*) allows us to distinguish between two types of objects with similar mean reflectance values but different 'within-patch heterogeneity'. An application based on this type of heterogeneity was described by Blaschke et al., (2001) where they used the '*mean spectral difference between all sub-objects*' as one example of heterogeneity applied to pastures and conservation changes in a cultural heritage landscape in central Germany. It was found that they could distinguish three levels of delineation appropriate for three different key species, which resulted in the construction of a hierarchical network of image-objects, and semantic rules between these levels.

Since its recent introduction by Baatz and Schäpe (2000), FNEA has been applied to various research projects in Europe (Blaschke et al., 2000, Blaschke and Strobl, 2001, Schiewe et al., 2001), many of which have demonstrated the potential of this multi-scale segmentation approach. In particular, the 'realistic' appearance (Figure 4.3) of the resulting segmented patches of forests, pastures, fields and built-up areas has motivated several European agencies to seriously evaluate the commercial applicability of this approach, and a number of experienced image interpreters have expressed their concern of quickly becoming obsolete.

4.3.3 Scale-Space (SS)

The following overview describes a multiscale approach composed of two principal components: *Linear Scale-Space and Blob-Feature Detection* (Lindeberg, 1994; 1999). For a more detailed non-mathematical description of both, see Hay et al., (2002a). *Linear Scale-space* (SS) is an uncommitted framework[55] for early visual operations that was developed by the computer vision community to automatically analyze real-world structures at multiple scales – specifically, when there is no *a priori* information about these structures, or the appropriate scale(s) for their analysis. When scale information is unknown within a scene, the only reasonable approach for an uncommitted vision system is to represent the input data at (all) multiple scales. Thus, the basic premise underlying SS is that a multiscale representation of a signal (such as a remote sensing image of a landscape) is an ordered set of derived signals showing structures at coarser scales that constitute simplifications of corresponding structures at finer scales. In practice, Gaussian filters are applied to an initial image at a range of kernel sizes resulting in a scale-space cube or 'stack' of progressively 'smoothed' image layers, where each new image layer represents convolution at an increased scale. More explicitly, each 'smoothed' layer is created by convolving the n^{th}-order *derivative*[56] *of a Gaussian* (DOG) function with the original image, where the scale of each derived signal is defined by selecting a different standard deviation for the DOG function (at each new iteration). This results in a 'scale-space cube', or 'stack' of increasingly 'smoothed' images that illustrates the evolution of the original image through scale. Each hierarchical layer in a stack represents convolution at a fixed scale, with the smallest scale at the bottom, and the largest at the top (Figure 4.4).

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[55] The term *uncommitted framework* refers to observations made by a *front-end vision system* (i.e., an initial-stage measuring device) such as the retina or a camera that involves 'no knowledge', and 'no preference' for anything.

[56] In the presented work we have only use the $zero^{th}$ order derivative.

The use of Gaussian filters is essential to linear SS theory as they satisfy necessary conditions or axioms for an uncommitted framework (Weickert et al., 1997). These include (among others) linearity (i.e., no knowledge, no model, no memory), spatial shift invariance (i.e., no preferred location), isotropy (i.e., no preferred orientation), and scale invariance (i.e., no preferred size or scale). In addition, a Gaussian kernel satisfies the linear diffusion equation, thus Gaussian smoothing is considered as the diffusion of grey-level intensity over scale (*t*), instead of time.

The second SS component is referred to as *Scale-Space Blob-Feature Detection*. The primary objective of this non-linear approach is to link structures at different scales in scale-space, to higher-order objects called 'scale-space blobs', and to extract significant features based on their appearance and persistence over scales. The main features that arise at each scale within a stack are smooth regions, which are brighter or darker than the background and which stand out from their surrounding. These regions are referred to as 'grey-level blobs'. When blobs are evaluated as a volumetric structure within a stack, it becomes apparent that some structures visually persist through scale, while others disappear (Figure 4.5). Therefore, an important premise of SS is that blob-like structures which persist in scale-space are likely candidates to correspond to significant structures in the image, and thus in the landscape.

In simple terms, grey-level blobs at each scale in the stack (Figure 4.6a) are treated as objects with extent both in 2D space (x, y) and in grey-level (z-axis) – thus 3D. Grey-level blob delineation may best be defined with a watershed analogy. At each scale in the stack, the image function of all blobs may be considered as a flooded 3D landscape (i.e., a watershed, see Figure 4.6b). As the water level gradually sinks, peaks appear. At some instance, two different peaks become connected. The corresponding 'connected' elevation levels are called the 'base level' of the blob. They are used for delimiting the 2D spatial extent or 'region of support' of each blob, which is defined as a binary blob (Figure 4.6c). 2D binary blobs at all scales are then combined within a new stack to create 3D hyper-blobs (Figure 4.7a).

Within a single hyper-blob there are four primary types of visible structures or 'bifurcation events'[57]: *annihilations* (A), *merges* (M), *splits* (S), and *creations* (C) (Figure 4.7b). The ability to define these SS-events is a critical component of SS, as scales between bifurcations are linked together forming the lifetime (Lt_n) and topological structure of individual SS-blobs. Next, the integrated normalized (4D) volume (x, y, z, t) of each individual SS-blobs is defined. As blob

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[57] In our current SS research (Hay, 2002b) we specifically define eight types of SS-events.

behaviour is strongly dependent upon image structure, it is possible that an *expected* image behaviour may exist[58]. Thus, statistics are extracted from a large number of stacks resulting from random images[59]. These statistics describe how random noise blobs can be expected to behave in scale-space, and are used to generate a normalized 4D SS volume for each SS-blob.

These resulting normalized volumes are then ranked, and an arbitrary number of significant SS-blobs are defined, from which the scale (t) representing the maximum 3D grey-level blob volume (x, y, z) of each hyper-blob is extracted. From these layers the 2D spatial support (i.e., binary blob) is identified and related back to the corresponding structures in the image for further examination (Figure 4.7c). Thus, based on the underlying initial premise, 4D scale-space blobs are simplified to 3D grey-level blobs, which are further simplified to their 2D support region (x, y), and then to their corresponding real-world object in the original image. At fine scales, the evaluated 2-D support regions visually correspond to ecologically meaningful features, such as roads, hedgerows, bare soil patches, agricultural and fallow fields, and individual tree crowns and tree stands. At coarser scales their exact nature is less obvious, though most represent a mixture of larger landscape units i.e., neighbouring and/or adjacent agricultural fields or forest stands that tend to be composed of the same, or similar elements.

[58] Due primarily to image noise, as noise exhibits structure through scale (Hay et al., 2002a)

[59] In our processing, we generated 100 individual stacks resulting from different random images the same size as the original 500 x 500 pixel IKONOS image. Each random SS stack was composed of 200 layers with a scale increment of one – the same as the stack illustrated in Fig 4.

An interesting characteristic of a linear scale-space stack is that when each layer (in a stack) is visualized as part of an animation, it provides a model that illustrates how dominant landscape components (may) become fragmented and or connected through scale. However, it is important to note that each layer in the animation represents a *linear* perspective of the landscape, rather than a non-linear perspective as required by complex systems. Non-linear results are represented by the ranked 2-D support regions that have been extracted from significant scale-space blobs. An important avenue of future research will be to evaluate if these results represent ecologically meaningful patterns, rather than merely visually meaningful patterns. However, this challenge is beyond the scope of this paper.

4.3.4 Object-Specific Analysis (OSA) and Object-Specific Upscaling (OSU)

The final technique we describe is also composed of two primary components: Object-Specific Analysis (OSA) and Object-Specific Upscaling (OSU). OSA is a new multiscale approach (Hay et al., 1997; 2001) that automatically defines unique spatial measures specific to the individual image-objects composing a remote sensing scene. These object-specific measures are then used in a weighting function for automatically upscaling (OSU) an image to a coarser resolution for further analysis. An underlying premise of OSA/OSU is that all pixels within an image are exclusively considered H-res samples of the scene-objects they model (even though as previously discussed, both H- and L-res exist). Thus we use pixels – the fundamental image primitive - to define the spatial extent of the larger image-objects they are a *part of*. To facilitate this, the variance of the DNs located within an iteratively growing window is evaluated over each pixel until a series of object-specific heuristics are met (see Hay et al., 2001 for more detail). These heuristics define a threshold in variance as the kernel reaches the image object's edges. The unique window size (VT_w) and accompanying inflection points defined at this threshold correspond to the objects known size (Hay et al., 1997). Defining this threshold involves appreciating the relationships between the size of each pixel and the object it is a portion of, and the spectral characteristics of these pixels as they change through scale. In practice, the window size one iteration prior to meeting the variance threshold is used to define the maximum area (A_{ij}) at which the central pixel is related to its maximum number of neighbours. Concurrently, the corresponding mean (M_{ij}) and variance (V_{ij}) values are also calculated for the pixel under analysis within VT_w. These procedures are applied to all the pixels within the original image, resulting in corresponding variance (V_I), area (A_I), and mean (M_I) images, which are referred to as the first image-set (IS_1).

4.3.5 Developing an Iterative Multiscale OSA/OSU Framework

Based on promising results from early OSA research, Hay et al. (1997) recognized that the application of object-specific analysis and upscaling rules visually reveal patterns that accurately correspond to the spatial extent of objects at their next coarser scales. This led to the hypothesis (Hay et al., 1998) that by continuously applying object-specific rules to the M_l generated at each OSA iteration, new spatial patterns will emerge that represent dominant landscape objects, and that these multiscale image-object patterns will correspond to real-world objects through a scale continuum.

To test this hypothesis, Hay et al. (2001) developed an iterative multiscale framework that represents a nested hierarchy of image-sets (IS_t) consisting of two iterations of V_l, A_l and M_l, each of which possesses membership in a unique scale domain (SD_n). They also recognized that there is often a range of scales between the end of identifiable image-objects, and the beginning of new image-objects at their next scale of expression. To exploit this information, the initial multiscale framework was modified as follows: at the first OSA iteration, every pixel was assessed within larger windows until a local *maximum* variance threshold was reached (i.e., the 'edge' of an object was detected). When applied over the entire image, this process generated the first image-set (IS_1) – as previously described. From IS_1 the first Mean image (M_1) is extracted and OSA is applied upon this image. During this second iteration, each pixel in M_1 is assessed until a local *minimum* variance threshold is reached. This results in IS_2 (and its associated V_2, M_2, and A_2), which represents the beginning scales of all *newly emergent* image-objects (Figure 4.8). Odd-numbered OSA iterations (where the maximum variance is computed) define scales representing the 'end' of objects, while even-numbered OSA iterations, (where the minimum variance is computed) define the beginning scale of the next emergent objects. Recall that minimum variance indicates that pixels are most alike, thus the corresponding image structure is most 'object-like'.

The result of this iterative approach is a nested hierarchy of image-sets (IS_t) composed of two V_l, A_l and M_l that have membership in a unique scale domain (SD_n). Within a single SD_n, each image shares the same grain and extent, and represents the result of multiscale analysis specific to the image-objects composing it. However, each SD_n has a coarser grain than the previous SD_{n-1} (though it shares the same extent through all image-sets). This is because OSU is applied to ensure that the original image-object heuristics maintain the same conditions for which they were originally designed, and to reduce unnecessary computation and data generation/storage.

Furthermore, each SD_n is a member of a scale-domain super set (SDS) that represents the entire range of OSA and OSU evaluated within the spatial extent of a unique digital landscape (i.e., the image) see Hay et al. (2001) for further details. Thus OSA/OSU is a hierarchal mechanism by which the *spatially dominant* components of an image will automatically emerge at coarser scales, because analysis is specific to the different sized, shaped, and spatially distributed image-objects that compose a scene.

4.4 Discussion

In this section, we outline the principal strengths and limitations of each technique, then suggest strategies for their improvement by integrating appropriate characteristics from each of the other techniques.

4.4.1 Strengths of FNEA, SS, and OSA/OSU

FNEA software was developed to simultaneously identify (and extract) objects of interest at different scales within textured imagery - such as radar and H-res satellite or airborne data - through multi-resolution segmentation. A commercial software product is available that can be integrated within commonly used image processing packages[60], which has helped in the development of a growing user base[61] and novel applications that range from landscape ecology to Proteomics. Additional strengths of FNEA include the following:

- The FNEA region-based approach involves generating hierarchical segments at various scales that yield satisfying results with respect to the desired geometrical accuracy of image-object out-lines/boundaries and their unique class membership within a single region. In addition, several studies illustrate that this type of OO-classification improves land-use classification results - rather than land cover (for an overview see Blaschke and Strobl, 2001; Schiewe et al., 2001).
- Another innovative aspect of FNEA beyond a simple improvement of image classification is the potential to differentiate different 'object-classes' within the same image 'on-demand' for different applications. For example, contrary to the static view of a map, all forest areas in an image could be treated as relatively homogeneous (although in reality

[60] Can be used in PCI remote sensing products (www.pcigeomatics.com/).

[61] http://www.definiens-imaging.com/userforum/

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from raster to a vector topology for use in a GIS, spatial models, and or by spatial statistical packages to evaluate landscape structures and their associated metrics.

- The hierarchical nature and computational processing of a scale-space primal sketch (and its accompanying statistics) would lend itself well to multiprocessing, distributed-network computing solutions, and an OO-programming framework.

Iterative Object-Specific Analysis (OSA) in combination with Object-Specific Upscaling (OSU) represents an automated non-linear framework for generating a multiscale representation of a scene, that allows dominant image-objects to visually emerge at their respective scales. Furthermore:

- OSA/OSU is statistically proven to produce better-upscale results than cubic convolution, bilinear interpolation, nearest neighbour, or non-overlapping averaging (Hay et al., 1997).OSU incorporates object-specific weights, thus minimizing the effects of MAUP. It is based upon concepts related to how humans perceive visual and haptic texture (Hay and Niemann, 1994; Hay et al., 1997), and it incorporates 'generic' point spread function (PSF)[62] model characteristics in relation to object size for determining an appropriate upscale resolution at the next iteration of processing (Hay et al., 2001).
- OSA/OSU allows for upscaling between objects, and within an image hierarchy. The underlying ideas and heuristics are conceptually simple, are based upon strong empirical evidence, and follow many concepts implicit to Complex Systems and Hierarchy theory.
- For iterative OSA/OSU, no *a priori* scene information is required for processing. Essentially, computation proceeds until there is not enough image to upscale. OSU takes into account the relationship between the pixel size and the image-objects from which the original OSA heuristics were developed. The outcome of this is that at fine scales results visually model known image-objects very well, thus a precedent exists upon which to assess OSA/OSU results at coarser unverifiable image-scales.

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[62] The PSF defines the spatial influence or 'spread' of a zero-dimensional point of light resulting from lens aberrations in the sensor.

4.4.2 Limitations of FNEA, SS, and OSA/OSU

Although, FNEA is already embedded in a commercial software environment, its usability is not fully operational as long as a theoretical framework remains undefined, and users have to find useful segmentation levels in a 'trial and error' style. In particular:

- FNEA requires that the user must know the scale of the objects of interest in order to select appropriate segmentation heuristics. We suggest that this is not reasonable when working at scales (and with imagery) beyond common (spatial and or spectral) experience, or when conducting baseline analysis in areas where no *a priori* information exists.
- There is no sound ecological theory presented for linking /defining structures through scale.
- There is no upscaling mechanism in place for scaling between hierarchical levels or image-objects.
- FNEA requires the user to be familiar with an OO-paradigm prior to implementation. As the OO paradigm is more commonly used and taught, this limitation will disappear. However, in many cases, knowledge of OO systems presently requires a retraining of users.

While the mathematical formulation of SS is extremely rigorous, it is also non-trivial for laypersons to understand. Furthermore, to the best of our knowledge, no commercial software exists[63], thus image processing and topological tools must be developed in-house, which limits its widespread utility. In this paper, all SS and OSA/OSU programming has been performed using IDL[64]. Other limitations include the following:

- Pixel size does not change through scale, thus each stack represents large amounts of redundant information, which poses a serious challenge when using large-scale remote sensing data sets. In our work, 100's of gigabytes of statistical (white noise) processing

[63] Ter Haar Romeny and Florack (2000) present a scale-space workbook using the computer algebra package *Mathematica (www.wolfram.com)*, where code for edge, ridge, and corner detection are provided but they do not describe blob-detection.

[64] Interactive Data Language *(www.rsinc.com)*. IDL is a 4GL computer programming language that has the advantage of processing multidimensional array structures (i.e., 2-D images) essentially in parallel.

were required prior to generating normalized 4D volumes, and our image size was only 500 x 500 pixels (by 200 channels). However, once generated, these statistics can be stored in a library and used for any other dataset with the same grain, extent, and number of scales.

- Within a stack, high contrast features tend to persist in scale, regardless of whether or not such features have ecological meaning. This also includes the persistence of noise, as noise has structure through scale. In some cases, these effects will quickly disappear as scale increases. However, no specific noise-reducing technique is defined[65].
- Values for optimal scale generation (i.e., number of scales in a stack), the selected scale increment, and the number of ranked 'significant blobs' to evaluate are all arbitrarily defined. We suggest that these are the most fundamental weaknesses of this framework, because they are critical 'scale' components that represent the observation protocol and filter applied (through scale) from which corresponding entities emerge. However, reasonable assumptions can be made regarding the number of scales to assess, and their scale increment. But determining the number of ranked blobs to define is not trivial. In our evaluation, we allowed for 20% of the blobs to be ranked which resulted in 2537 individual blobs. Many of which appeared to overlay each other (Figure 4.9a), making evaluation difficult.
- SS uses discrete data (i.e., individual pixels at defined scales) to represent what is essentially a continuous process, i.e., an objects' persistence through a range of scale(s). Thus SS events – conceptualized as a point in space – are actually modeled as a single blob. This means that a decision has to be made as to whether this blob (*cum* conceptual point) is a member of the SS-blob below it, above it, or on its own. This in turn affects the 4D-volumetric measure, and ultimately the ranking of significant 2D-blobs. This is not a trivial problem to solve, though 'work-a-rounds' exist (see Hay et al., 2002b).

One of the greatest limitations of the iterative OSA/OSU framework is that it represents relatively new ideas that have not been tested over a large number of different landscapes, or by a significant number of researchers. Though we note that further testing and validation are underway (Hall et al., 2002). In addition, no commercial software is available, and like FNEA, its object heuristics are empirically based. Thus multiscale results require validation against field data, which becomes difficult if not impossible as scales increase. Furthermore, the iterative

[65] We note that generating normalized SS-volumes (see section 3.3) does not compensate for these noise effects.

OSA/OSU framework as described by Hay et al. (2001) depicts only the generation of a multiscale representation. There is no specified feature detector, or information extracting technique, thus no topologically defined image-objects are defined, or the ability to hierarchically link them. Although the variance and area datasets visually illustrate image-objects, these are perceptual only. Therefore, to fulfill the second component of multiscale analysis, an appropriate feature detector is required.

4.4.3 Strategies for Improving Results in FNEA, SS, and OSA/OSU

As discussed in the preceding section, each of the three techniques while novel and powerful, also exhibit limitations that make them less than ideal for the automatic detection, extraction, and hierarchical linking of ecologically meaningful multiscale image-objects within remotely-sensed data. In this section, we describe a number of strategies that draw upon the strengths of each individual method, and discuss how they may be appropriately applied to enhance the capabilities of the other techniques.

FNEA requires that a user possesses *a priori* information regarding the scene. To overcome this limitation, particularly when conducting baseline mapping, where no 'ground-truth data are available, we hypothesize that the scale of expression and location of significant scale-space blobs may be used as early visual operators to automatically define and or refine the aggregation semantics of the FNEA. Unfortunately, based on preliminary results (Blaschke and Hay, 2001), it does not appear possible to incorporate SS-results for the *a-priori* determination of the most relevant FNEA segmentation levels, as SS-blobs cannot be associated to a single level of segmentation. However, it may be possible to combine both approaches during the classification and/or interpretation processes respectively. Since FNEA produces several levels of objects, and the classification process utilizes this multi-level information explicitly, the analyst has to determine how many levels will be incorporated for a certain class definition. In this case, the SS rank-id and the domain/lifetime attributes provide important and potentially useful information.

In a SS-cube a significant amount of redundant data results in large stack sizes, which in our research range from 200 MB to 980 MB each. In order to reduce the memory requirements when defining SS-blob topology, we have integrated a three tier approach from Hierarchy theory with the capability of IDL to 'parallel-process' multidimensional array structures (Hay et al. 2002c). Thus, instead of loading the entire stack into memory, we only need to load three scales of a SS-cube into memory at a time, thus significantly increasing the size of the dataset that can be processed with limited computing power (i.e., a 1 GHz Pentium PC with 512 MB RAM). From a Hierarchy theory perspective, we evaluate the blob locations at the 'focal' scale, and establish links with blobs in the scale above and with those in the scale below. We then shift up an additional scale in the cube, while dropping the bottom scale. Always keeping only three scales in memory at once. We then repeat this procedure until the last scale has been processed.

In order to overcome evaluation problems resulting from the large number of ranked SS blobs that visually obscure each other when overlaid on the study area, we suggest that SS-events represent critical thresholds within a hyper-blob, where fundamentally different geometric structures exists both in scale and the landscape. Thus from an ecological perspective, the lifetime of a SS-blob may be considered as levels within a specific scale-domain. To define this domain, each hyper-blob is topologically registered as a unique entity, and its corresponding SS-events are isolated. That is, the first SS-event of each hyper-blob is geometrically defined regardless of where, and what scale they exist within the stack (i.e., x, y, t). Then the second, third, and n^{th}-events of each hyper-blob are isolated until the last possible event is defined[66]. These event values are then considered as 'scale domain attributes' and are assigned to their corresponding ranked blobs. This domain attribute provides a unique way to query, partition, and evaluate the resulting multiscale 'domain' surface structures, as many blobs can and do exist within a single domain, but no more than one blob can exist within the same 'x, y, z, domain' space. Thus, the overlapping/obscuring problem is resolved and it allows us to evaluate the resulting multiscale surface structures in terms of *critical scale-specific thresholds*. In addition, by integrating these hierarchical concepts with geostatistics, and 3D visualization techniques, domains can be visually modeled as 'scale-domain manifolds' (Hay et al., 2002b), (Figure 4.9b) which we suggest correspond to the 'scaling ladder' as conceptualized by Wu and Loucks (1995) and Wu (1999) in his description of the Hierarchical Patch Dynamics Paradigm (HPDP).

Experience and knowledge gained from SS related to the importance of Gaussian filters, and the axioms they satisfy as an uncommitted vision system have also been applied to OSA/OSU. In particular, to reduce the diagonal bias introduced by the square kernel originally used in

[66] If there were an SS-event at each scale in a stack, this would represent a value equal to the maximum number of scales assessed in the stack.

OSA/OSU, we have incorporated the use of a round filter similar to that used in SS[67]. Though not truly Gaussian, it is a pixilated approximation of a round kernel[68] that results in a more isotropic filter. To implement this change, the variance threshold heuristics have been modified and tested accordingly. The most important result of this implementation is that when analysis is conducted over large window sizes, diagonal artifacts are significantly visually reduced within the image. Furthermore, to increase computational efficiency when using this filter, a 'bank' of varying sized round-filters could be generated once and called as needed, and convolution in the Fourier domain (as done for SS processing) can be used to reduce the need to apply a moving window routine.

An important limitation of the iterative OSA/OSU framework proposed by Hay et al. (2001) is that the resulting multiscale images have no inherent object-topology, thus image-objects can only be visually evaluated at each scale. In SS, we described blob-feature detection using a watershed analogy[69]. From this example came the idea to explore the utility of adapting a watershed algorithm as a feature detector that would automatically define topologically discrete objects within the variance, area, and mean datasets generated by OSA/OSU. Implementation of this has resulted in the development of a *multiscale object-specific topology* (MOST). The MOST (Hall et al., 2002) is based on the *marker-controlled segmentation procedure* (Beucher and Lantuéjoul, 1979; Meyer and Beucher, 1990; Beucher, 1992; Rivest et al., 1993), which is essentially a watershed transformation technique that detects regional similarities as opposed to an edge-based technique that detects local changes. The key characteristic of this technique is the ability to reduce over-segmentation by placing markers or 'seeds' in user specified areas. The elegance of integrating marker-controlled segmentation with OSA is that it requires data inputs that are automatically and explicitly met by V_I, A_I, and M_I generated at each SD_n. In particular, the V_I represents the edges or 'dams' that define watersheds in an image and which isolate the various catchment basins. These basins contain regional minima's, which are naturally represented by the A_I values, due to the low internal variance inherent to image-objects. Once each watershed-object perimeter is automatically defined, it is labelled with a digital number representing the average of the pixels located with the corresponding M_I (Figure

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[67] Early OSA/OSU processing Hay et al. (1997) did evaluate the use of a square-pixel approximation of a round filter, but for computational reasons did not implement it.

[68] The method used is that of Michener's, modified to take into account the fact that IDL plots arrays faster than single points. See Foley and Van Dam (1982) p. 445 for the algorithm.

[69] Though we note that a watershed algorithm is not used.

4.10). From here, the topological tools developed to assess multiscale SS-blob structure can be used to establish hierarchical links with individual (basin) image-objects through all MOST datasets. Consequently, each basin-object and its associated spatial attributes can be explicitly modeled and analyzed within a GIS, and/or used as an additional logic channel for improved land-cover classification results (Hall et al., 2002). Thus the ability exists to create a true OO topology like FNEA, but with a number of the SS advantages inherent to an uncommitted framework. Best of all, no user interaction is required, yet the system and its results are fully decomposable (i.e., tractable) through scale.

4.5 Conclusions

Complex systems are hierarchically structured, scale dependent, and composed of many interacting components. These components are of two fundamental types: integrated objects and aggregate objects. From a remote-sensing perspective, image-objects are integrated objects that exhibit an intrinsic scale and are composed of structurally connected parts (i.e., H-res pixels). In this paper, we hypothesize that multiscale analysis should be guided by the intrinsic scale of the image-objects composing scene. Thus, we suggest that image-objects are a key component in the multiscale analysis, exploration, and hierarchical linking of remote sensing data. To achieve this, we describe and compare the limitations, strengths, and results of three technically and theoretically different multiscale approaches, each with a common theme: their focus on intrinsic pattern, and their multiscale exploration of image-objects within a single image.

FNEA automatically isolates image-objects of different size and shape that are dependent upon scales that are pre-determined by the analyst. The resulting image-objects correspond very strongly to different sized landscape components, as an experienced image interpreter would delineate them. However, human experience tells us that as we move through scale, there is a mixing of geographically 'near' objects that is not captured by FNEA. For example, if you look at a forest located adjacent to an agricultural field from several hundred meters away, the forest and field look like distinct objects. However, the edge between them also represents a mixed object. That is, there is a gradient of microclimatic and vegetated conditions (related to light infiltration, moisture, shade, temperature, wind, etc) from the centre of each forest/field to this edge that are markedly different from conditions in the centre of either the forest or field. In ecology, this is referred to as *depth-of-edge influence* or *edge width* (Chen et al., 1999).

Because linear SS is an uncommitted vision framework, it requires very little user interaction or *a priori* scene information; however, a range of scales and their scale increment must be defined in order to generate a multiscale representation. Unlike FNEA, SS (combined with blob-feature detection) does not provide explicit object delineation, but rather provides a more generalized representation that can support or guide later stage visual processing.

When OSA/OSU is combined within an iterative framework and MOST is applied, the result is an integrated approach for *Multiscale Object-Specific Analysis* (MOSA) that allows dominant landscape objects to emerge that are ecologically meaningful, hierarchically tractable, reduce the effects of MAUP, and require no *a priori* scene information for image-object delineation to occur. It also provides an object-specific mechanism for upscaling[70]. During the early stages of generating a multiscale representation in both SS and OSA/OSU, distinct image-object boundaries are delineated at very fine scales, but as coarser scaled image-objects appear, we see how adjacent image-objects diffusively combine into new structures. We suggest that these new structures correspond to the 'depth-of-edge influence' and to 'emergent structures' as specified in Complex Systems theory.

Because each of the described techniques have evolved beyond individual pixel analysis to analyzing the explicit contextual structure of image-objects, they have significant potential for ecological applications, for example:

- At fine scales, each technique could be used for individual tree crown, forest-object, and landscape patch recognition, though we note that only SS and OSU/OSA offer an 'unsupervised' approach for object delineation. In addition, FNEA output can be used to improve *land-use* classifications and OSA/OSU output can automatically be generated to
- The explicit delineation of image-objects defined by FNEA can be used for baseline mapping and/or for updating existing geo-information; and FNEA has the ability to differentiate different 'object-classes' within the same image 'on-demand' for different applications. This could be especially useful for defining different habitat maps within the same scene based upon different habitat scale requirements.
- Animation of binary blobs within a stack could be used to automatically assess fragmentation and connectedness of dominant forest ecosystem components.

[70] Though we note that this integrated approach is relatively recent and requires further evaluation.

- Blob-events could be used to model critical scale dependent landscape thresholds at multiple scales (Hay et al., 2002b; 2002c). Thus the opportunity exists to link the SS concept of an uncommitted vision system as a method for defining 'unbiased' landscape structures to fulfill the non-definitional scaling requirements for hierarchical structures.
- Within MOSA, ecotones and edge effects become real objects that evolve and are measurable through scale. This could have important implications in reserve and habitat planning, and model development and data type selection could be guided by SS and OSA/OSU scale-domains and landscape threshold patterns.

In this work, we have begun to examine the sensitivity of three multiscale methodologies to landscape structure as modeled in H-res imagery, and provided a comparison of each approach. While the methodological comparison is technically interesting, the overall goal of this study is to contribute to a more coherent understanding of landscape structures, their representation in images, and mechanisms for their linking through scale. The authors independently started from paradigms that most remote sensing and GIS methodologies do not readily support; that is, the representation of geographic entities at a variety of scales and levels of abstraction, within a single image. All three approaches incorporate a *bottom-up* approach designed to convert lower level observational data into higher-level geographic entities. Thus, armed with a visual perspective of the patterns generated at different scales, and methods to decompose them into their constituent multiscale image-objects, we suggest that the ability to understand the processes behind multiscale landscape patterns will be significantly enhanced.

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Chapter 5: Conclusion

"... I believe that the more complete hierarchy theory is one with a metaphysical commitment to individual entities as primary phenomena."

- Stanley N. Salthe (1985)

5. Context

The primary objective of this thesis was to develop an integrated hierarchical approach that improves the ability of Landscape Ecologists to evaluate and understand the relationship between spatial patterns and ecological processes over a range of scales. In particular, this approach requires a judicious integration of ecological theory, remote sensing data, and computer vision capabilities for the automatic multiscale delineation, hierarchical linking, evaluation, and visualization of dominant landscape objects through scale. Consequently, we suggest that when the newly created iterative OSA/OSU framework (Chapter 2) is combined with the topological methods developed for Scale-Space (Chapter 3), and the novel feature detector incorporated in MOST (Chapter 4), the result is an integrated hierarchical approach for non-linear multiscale object-specific analysis (MOSA) that automatically models the emergence of dominant[71] landscape image-objects through scale. Furthermore, the resulting image-objects are ecologically meaningful, hierarchically tractable, able to be topologically linked and queried, and are derived from an approach that minimizes the effects of MAUP.

By implicitly focusing on image-objects, MOSA incorporates all five solutions to the MAUP[72] as described by Fotheringham (1989), which to the best of our knowledge represents a unique characteristic not found with any other landscape approach. Most notably, the analysis, delineation, and hierarchical linking of image-objects results from (1) *the identification of basic entities* within (2) *optimal [object-specific] zoning systems*, which are generated by (3) *abandoning traditional statistics.* That is, unlike traditional scale techniques, which tend to rely on defining either a minimum (i.e., FNEA, pyramids) or a maximum homogeneity criterion (i.e., semivariance), MOSA incorporates both minimum and maximum homogeneity criteria based on the evolution of an image-object through scale. In addition, (4) *sensitivity analysis* was rigorously conducted during the development of object-specific heuristics (Hay et al., 1997); and characteristic spatial 'signatures' - from which these heuristics are based - result from (5) *the search for fluctuations in [image-object] variables and [their] relationship with scale.*

Though seldom recognized, we also stress that the integration of MAUP solutions in future ecological studies are critical when aggregating and scaling spatial data. Specifically as MAUP

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[71] i.e., H-resolution, as described in section 1.2

[72] As described in section 1.2.5

effects indicate that many results from previous ecological studies that are based on spatially aggregated data may be flawed, or seriously biased, and thus in need of re-examination (Wu et al., 2002).

In MOSA we recognize that no single scale is optimal for analyzing a landscape composed of heterogeneous components (Levin, 1992; Hay et al., 1994; 1997). Thus, we have attempted to exploit the unique relationship that exists between the physical dimension of real-world objects, and the size of the operators used to model them. Computationally, this corresponds to quantifying the unique spatial and spectral relationships that exist between the image-objects in a scene, and their constituent pixels, and incorporating their unique spatial influence within upscaled representations. Through empirical evaluation (Hay et al. 1997; 2001), these relationships have been encoded as a series of heuristics that are both specific to an individual image-object at its unique scale of expression (i.e., scale dependent), while also (conceptually) robust enough to be used for any sized, shaped and spatially distributed image-object at any scale[73] (i.e., scale-independent). This unique value-neutral[74] multiscale approach means that any single scale of remote sensing imagery can be used to generate a hierarchy of images representing the interaction of spatially dominant ecosystem components existing at coarser scales within the same landscape extent.

We further envision that OSA will provide new opportunities to visually and statistically analyze how individual image-objects and their resulting landscape patterns will evolve through spatial scales. In particular, we suggest that:

- The opportunity to better understand process from pattern can be achieved by automatically defining dominant image-objects at each scale-domain, and topologically linking their evolution through the scale continuum[75] based on their geographic coordinates. Thus allowing the user to evaluate how different landscape components 'naturally' aggregate to generate new image-objects at different scales.

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[73] Though we note that only a limited number of scales have presently been assessed due to the spatial nature of the imagery examined.

[74] That is, not arbitrarily defined by a user.

[75] SDS – Scale Domain Set: see Chapter 2, section 2.2.3.

- Based on preliminary results (Hay et al, 2001), we note that iterative OSA/OSU have already provided a new and enhanced spatial perception of the influence edges create within their associated patches/matrix through scale. Specifically, edges at each level in the hierarchy (i.e., scale-domain) evolve to form new edge-objects that assume partial characteristics from their contributing image-objects – but which reduce towards the image-objects' center. As a result, we suggest that edges play a more dominant role in multiscale dynamics than had been previously recognized from the single scale perspective. Thus, we recommend that *edges* should be added to the *patch-corridor-matrix model* (Forman, 1995), which (in Landscape Ecology) represents the basic construct from which all landscape components are defined.

From a management perspective, an enhanced understanding of edge effects through scale that result from MOSA may be used as follows:

- To design more appropriate corridors between patch remnants scattered within the matrix.
- To provide a perspective of the landscape (i.e., habitat, vegetation maps) at scales specific to the spatial requirements of wildlife and plant populations that exist there.
- To develop more ecologically representative buffers around sensitive areas i.e., riparian zones.
- To recognize that fragmentation and connectedness in the landscape have very different physical appearances at different spatial scales, and that these differences should (and can) be quantified, recognized, and incorporated within environmental assessments, habitat mapping, and land-use management.

A fundamental goal of Landscape Ecologists is to better understand how the Ecosphere[76] functions so we can more appropriately manage our interaction within it. This planet and the landscapes that compose it are complex systems. Complex systems are inherently multiscale. Thus to fully monitor, model, and manage our interaction within the landscape, we require appropriate approaches to assess the multiscale dynamics of such systems, and the ability to link these dynamics at multiple scales. In answer to this need, the principal contribution of this thesis has been to propose and develop an integrated hierarchical approach for the *multiscale object-specific analysis* (MOSA) of landscapes that automatically defines the dominant multiscale landscape objects within a single scale of remote sensing imagery. In particular, MOSA meets the requirements for generating an object-specific multiscale representation of landscape components that employs concepts from Complex Systems theory, solutions to MAUP, appropriate scaling theory, object-specific feature detectors, and techniques that allow for the hierarchical linking and analysis of topologically explicit image-objects. We suggest that the multiscale results generated from this approach are a precursor to defining and linking appropriate ecological models at the defined scales, which can then be used to further improve management strategies. In addition, we have formally introduced Scale-Space theory into Landscape Ecology (Chapter 3), and we have integrated concepts from Hierarchy theory within our own scale-space code. This allows topological constructs to be defined and queried within mainstream geographical information systems (Chapter 4), and processing to be accomplished on inexpensive computing platforms. Thus improving the utility of Scale-Space applications for Landscape Ecologists (Blaschke and Hay, 2001; Hay et al., 2002b; 2002c).

[76] '...*Ecosphere*: literally the *Home-sphere*. This word for the planetary ecosystem has the double advantage of reminding humanity where it is domiciled, while expressing no prejudice in favour of organisms, hence no denigration of earth, water and air as less than organisms, as merely their environment. It implies equal importance among all components, while also implying that everything existing within the Ecosphere, including the human race, is a product of it, a subdivision of it, a part of it, and therefore less important than it. The Whole Home is the prime reality; all else within is fragmentary, disarticulated, lost and meaningless until conceived and experienced in the context of the Ecosphere...' (Rowe, 1989).

It is the intent of the author that the contribution of this thesis will foster new multiscale understanding from which the landscape can be more appropriately evaluated and managed. We note that there is no obvious validated connection between the methods described and the processes occurring in the landscape. However, we are confident that the use of the described approaches will provide researchers with new opportunities to explore object-specific spatial patterns and link them through scale. By comparing such multiscale patterns with their corresponding real world components, new process related hypothesis could be formulated and tested. For example, prior to developing iterative OSA/OSU, the author had no *a piori* knowledge regarding 'depth-of-edge influence' (Chapter 2). However, by evaluating the multiscale results generated from iterative OSA/OSU, new understanding was gained by the author, as were recommendations for including this understanding to improve landscape management.

5.1 Future work

Future work will focus on two main areas:

- The first involves determining whether MOSA can/should be integrated within the recent theoretical framework of the Hierarchical Patch Dynamics Paradigm (HPDP - Wu and Loucks, 1995) to improve multiscale analysis, modeling, management, and linking of complex landscapes. The HPDP provides an established theoretical and organizational framework that explicitly integrates Hierarchy Theory (a vertical perspective) with Patch Dynamics Theory[77] (a horizontal perspective) to enhance understanding pattern-process-scale relationships in complex landscapes. Within this theoretical framework, Wu (1999) proposed the conceptually elegant idea of a 'scaling ladder' (i.e., discrete spatial and temporal domains of scale that can be linked) yet it assumes nested patch hierarchies (which may not meet scalar criteria, or actually exist); it does not provide clear methods for defining patches; nor does it provide clear methods for selecting the grain and extent in remote sensing data where such hierarchies may be evaluated at, or scaled to and from. To overcome these limitations, we suggest that concepts from HPDP coupled with MOSA, and applied to a high-resolution remote sensing dataset represent the appropriate theory, methods, and data to define and test the hierarchical patch structure

[77] Since the 1970's, patch dynamics has become one of the most central perspectives in ecology.

of complex landscapes, the ability to define scale domains within these landscapes, and the capacity to upscale across these domains.

- The second area of research will be to further explore the utility of Scale-Space in Landscape Ecology (Hay et al, 2002b; 2002c), particularly as it relates to evaluating multiscale landscape fragmentation and connectedness.

I shall be telling this with a sigh
Somewhere ages and ages hence:
Two roads diverged in a wood, and I -
I took the one less traveled by
And that has made all the difference.

- Robert Frost

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Table captions

Table 2.1. Image information and object-specific procedures for generating Figure 2.7.

Table 2.2. List of general terms and abbreviations

Table 2.3. List of Object-Specific terms and abbreviations

Table 2.1 **Image information and object-specific procedures for generating Figure 2.7**

SD_n	IS_t Components	OSA_t	OSU_n	M_l Dimensions	Grain (m^2)	# Pixels
SD_0	O_l		0	400 x 400	1.5	160000
	$IS_1 = V_1, A_1, M_1$	1		400 x 400	1.5	160000
	$IS_2 = V_2, A_2, M_2$	2		400 x 400	1.5	160000
SD_1	U_1		1	250 x 250	2.4	62500
	$IS_3 = V_3, A_3, M_3$	3		250 x 250	2.4	62500
	$IS_4 = V_4, A_4, M_4$	4		250 x 250	2.4	62500
SD_2	U_2		2	156 x 156	3.84	24336
	$IS_5 = V_5, A_5, M_5$	5		156 x 156	3.84	24336
	$IS_6 = V_6, A_6, M_6$	6		156 x 156	3.84	24336
SD_3	U_3		3	98 x 98	6.14	9604
	$IS_7 = V_7, A_7, M_7$	7		98 x 98	6.14	9604
	$IS_8 = V_8, A_8, M_8$	8		98 x 98	6.14	9604
SD_4	U_4		4	61 x 61	9.83	3721
	$IS_9 = V_9, A_9, M_9$	9		61 x 61	9.83	3721
	$IS_{10} = V_{10}, A_{10}, M_{10}$	10		61 x 61	9.83	3721

Table 2.2 List of general terms and abbreviations

AVHRR	Advanced very high resolution radiometer
AVIRIS	Airborne Visible Infra-Red Imaging Spectrometer
C.Cut	Clear-cut
CASI	Compact Airborne Spectrographic Imager
CCD	Charged-couple device
DNs	Digital numbers or gray-scale values
FPAR	Fraction of photosynthetically active radiation
HPDP	Hierarchical Patch Dynamics Paradigm
H-res	High resolution
IFOV	Instantaneous field of view
LAI	Leaf area index
L-res	Low resolution
MAUP	Modifiable areal unit problem
MODIS	Moderate-resolution Imaging Spectroradiometer
PSF	Point-spread function
RMSE	Root mean square error
SPOT	Satellite pour l'Observation de la Terre
TM	Landsat Thematic Mapper

Table 2.3 List of Object-Specific terms and abbreviations

$\forall$	For each…
$\in$	Has membership in…
A_I, A_{ij}, A_2	Area-image, Area value defined at (i, j), Area-image generated at OSA_2
EOs	Edge-objects
IOs	Image-objects
IS_t	Image-set generated at OSA iteration (t)
K, S_K	Upscaling kernel of (k*k) user-defined dimensions, Sum of all A_{ij} within K
LTD_v	The Landscape-threshold-domain, where (v) represents the number of landscape thresholds defined by TSV within the SDS
M_I, M_{ij}, M_2	Mean-image, Mean value defined at (i, j), Mean-image generated at OSA_2
O_I	Original CASI image
OSA_t	Object-specific analysis at iteration (t)
OSU_n	Object-specific upscaling at the (n^{th}) upscaling iteration
P_{ij}	Pixel located at row (i), column (j) in a 2D image
R_h	Resampling heuristic
SD_n	Scale-domain, resulting from the (n^{th}) OSU iteration
SDS	Scale-domain-set
TSV	Total scene variance
U_I, U_2	Upscale-image, Upscale-image generated at OSA_2
UP_{LM}	An upscaled pixel located at row L, column M, in the U_I
V_I, V_{ij}, V_2	Variance-image, Variance value defined at (i, j), Variance-image generated at OSA_2
$VT_{w\,(max)}$	Local *maximum* variance defined with the variance threshold window
$VT_{w\,(min)}$	Local *minimum* variance defined with the variance threshold window
VT_w, VT_{ij}	Variance threshold window, Pixel location (i, j) defined at the variance threshold
W_{ijK}	Object-specific weight defined at row (i), column (j) within K

Figure Captions: Chapter 1

Figure 1.1 This figure Illustrates the conceptual framework of Hierarchy theory based on various diagrams and concepts described by Simon, 1962, 1973; Allen and Starr, 1982; O'Neill et al., 1986 (Adapted from Wu, 1999).

Figure 1.2 This figure represents the Object-Oriented *'aggregation relationship'*. When moving down through the hierarchy the focal object class (e.g., tree) '*is composed of' the* object class(es) beneath it (e.g., branches). When moving upwards through the hierarchy, each class is '*a part of*' the class above it.

Figure 1.3 This figure represents the Object-Oriented '*generalization/specialization relationship'*. When moving down the hierarchy, the focal object class (e.g., tree) '*can be'* a member of the object class beneath it (e.g., Pine). When moving upwards through the hierarchy, each class is '*a kind of*' the class above it. Class *generalization* results when moving up through the hierarchy, and *specialization* when moving down.

Figure 1.1 The conceptual framework of Hierarchy theory

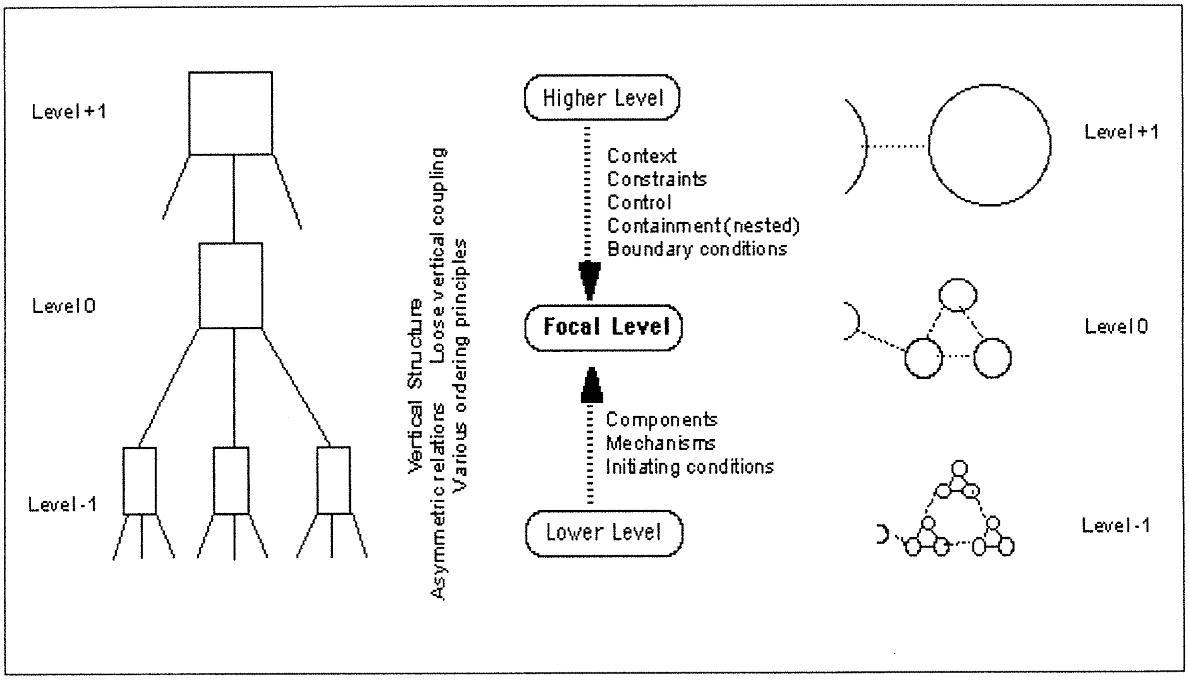


Figure 1.2 The Object-Oriented 'aggregation relationship'

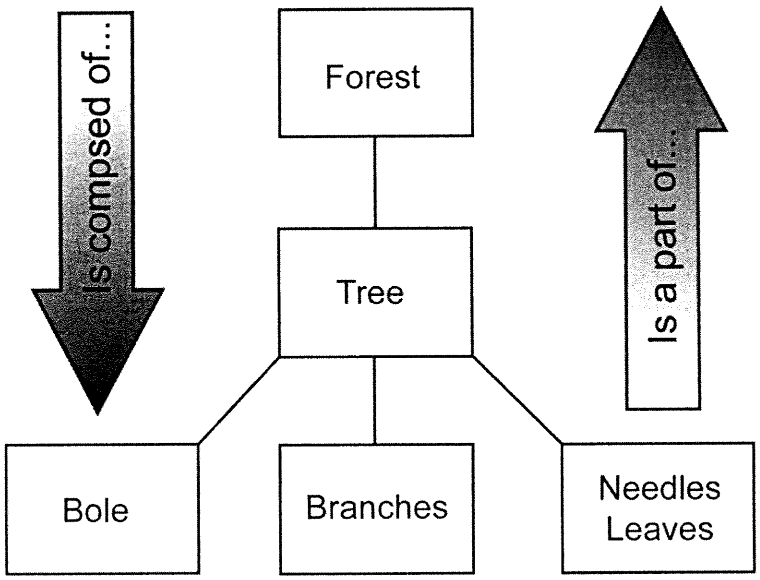


Figure 1.3 The Object-Oriented 'generalization/specialization relationship'

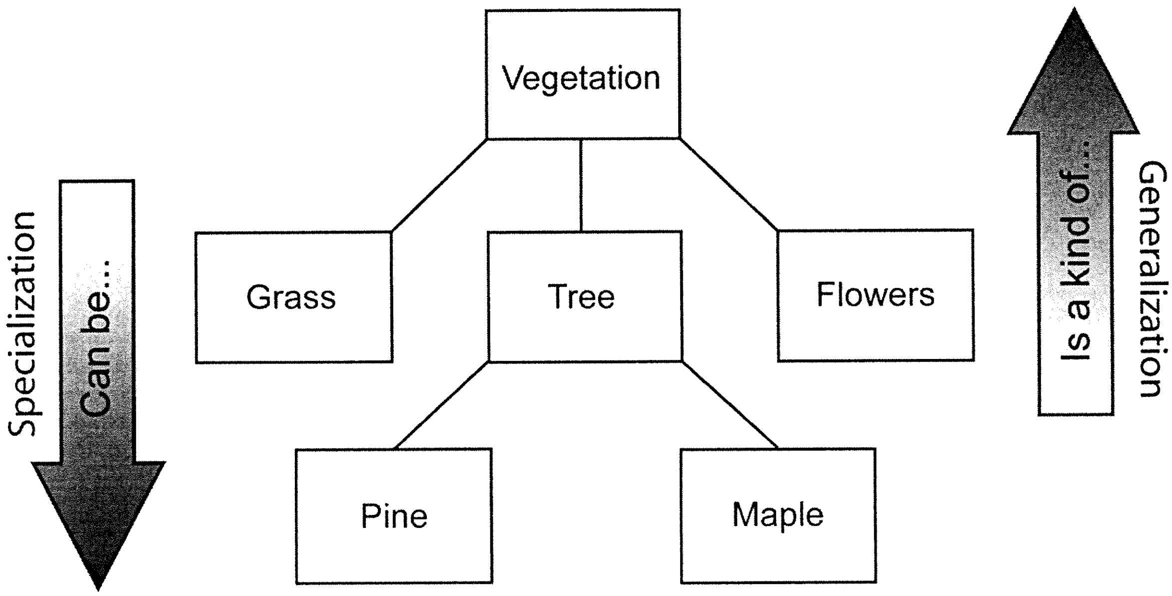


Figure Captions: Chapter 2

Figure 2.1 The relationship between grain and extent in remote sensing imagery.

Figure 2.2 Tree-crown image-objects.
This CASI sub-image has been magnified to illustrate the relationship between individual pixels (gray-tone squares) and the tree-crown image-objects they perceptually represent. Individual crown centers are defined by a single black pixel. The spatial resolution of each pixel is 1.5 m^2.

Figure 2.3 Rithet Creek study site map.

Figure 2.4a CASI image illustrating the study area (36 ha^2) at a spatial resolution of 1.5 m^2.
Figure 2.4b Thematic site map and legend (same scale).

Figure 2.5 Variance characteristics of a single tree-crown pixel defined through multiple scales. The curve of this graph results from plotting the variance of the digital values of all pixels located within increasing sized square windows. In this illustration, varying sized windows are centered over an individual tree-crown (circular image-object) that is located within the white bars of the inset image. The crown center is defined by a single white pixel that represents the apex of the tree. As the window size increases, the resulting variance value is plotted. In practice this form of multiscale analysis is applied to all pixels composing a scene. The maximum window size specified for each pixel is defined when variance measures meet unique object-specific heuristics that correspond to the spatial extent of the real-world objects they model.

Figure 2.6 Hierarchically nested components of iterative object-specific analysis (OSA) and object-specific upscaling (OSU).

Figure 2.7 Scale domain sets (SDS_{0-3}) consisting of variance (V_l), area (A_l), and mean (M_l) images.

Figure 2.8 This upscale image (U_{1-4}) composite illustrates the different image extents resulting from four iterations of object-specific upscaling (OSU).

Figure 2.9 Total Scene Variance (TSV) defined at odd-numbered object-specific analysis (OSA) iterations. Poly.(TSV) represents TSV values modeled by a high order polynomial curve ($R^2 = 0.999$) that is similar to the curve illustrated in Figure 2.5.

Figure 2.1 The relationship between grain and extent in remote sensing imagery

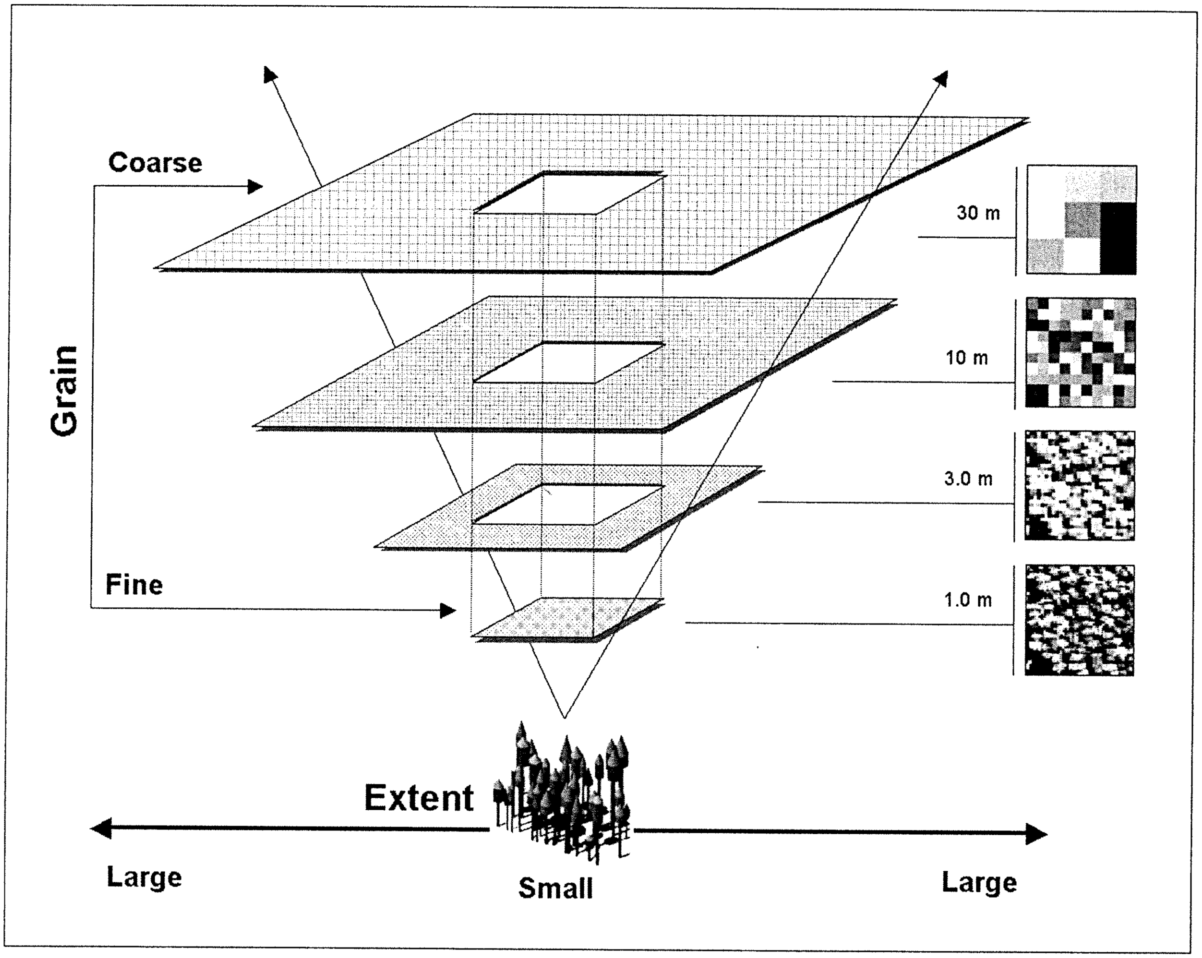


Figure 2.2 Tree-crown image-objects

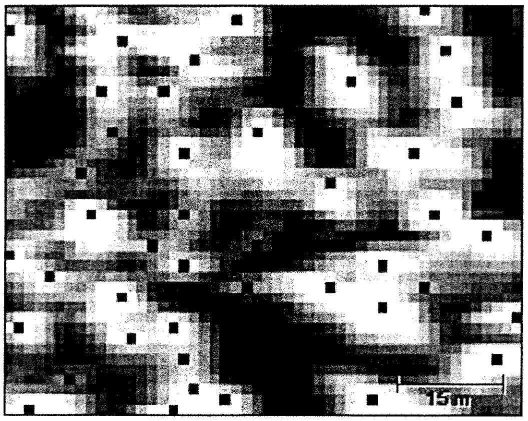


Figure 2.3 Study-Site Map

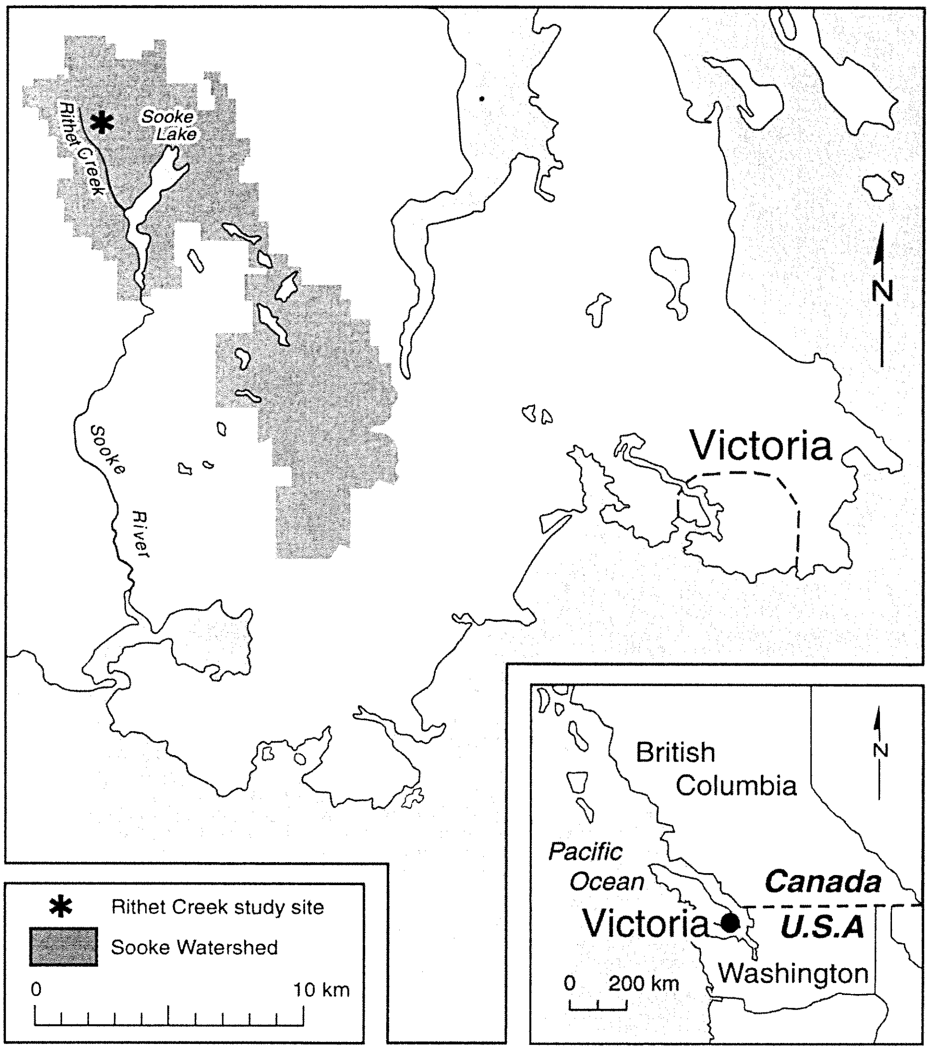


Figure 2.4a, b Study Site and Thematic Site Map

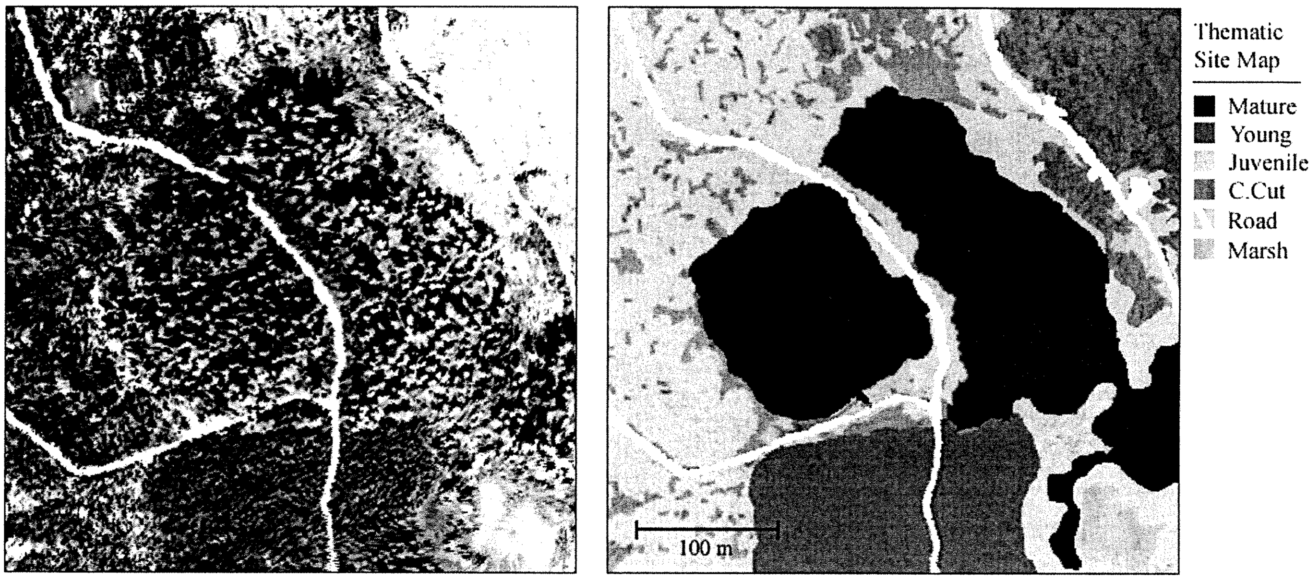


Figure 2.5 Variance characteristics of a single tree-crown pixel through multiple window sizes (i.e., scales)

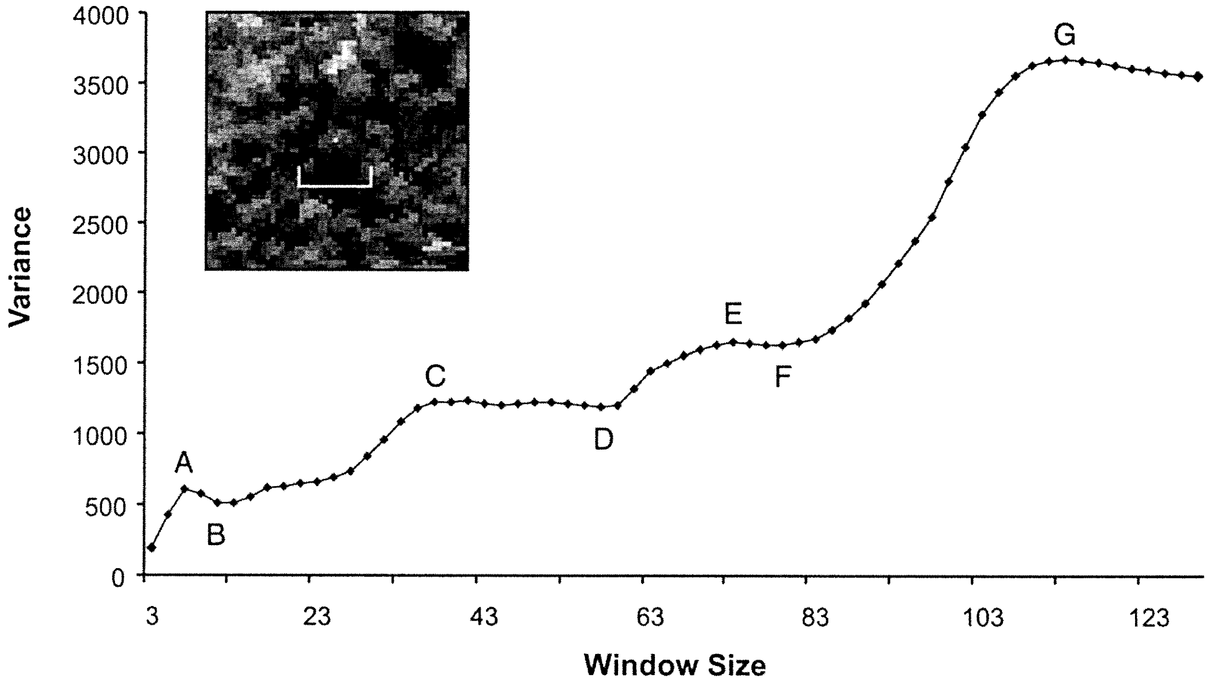


Figure 2.6 Hierarchically nested components of iterative OSA and OSU

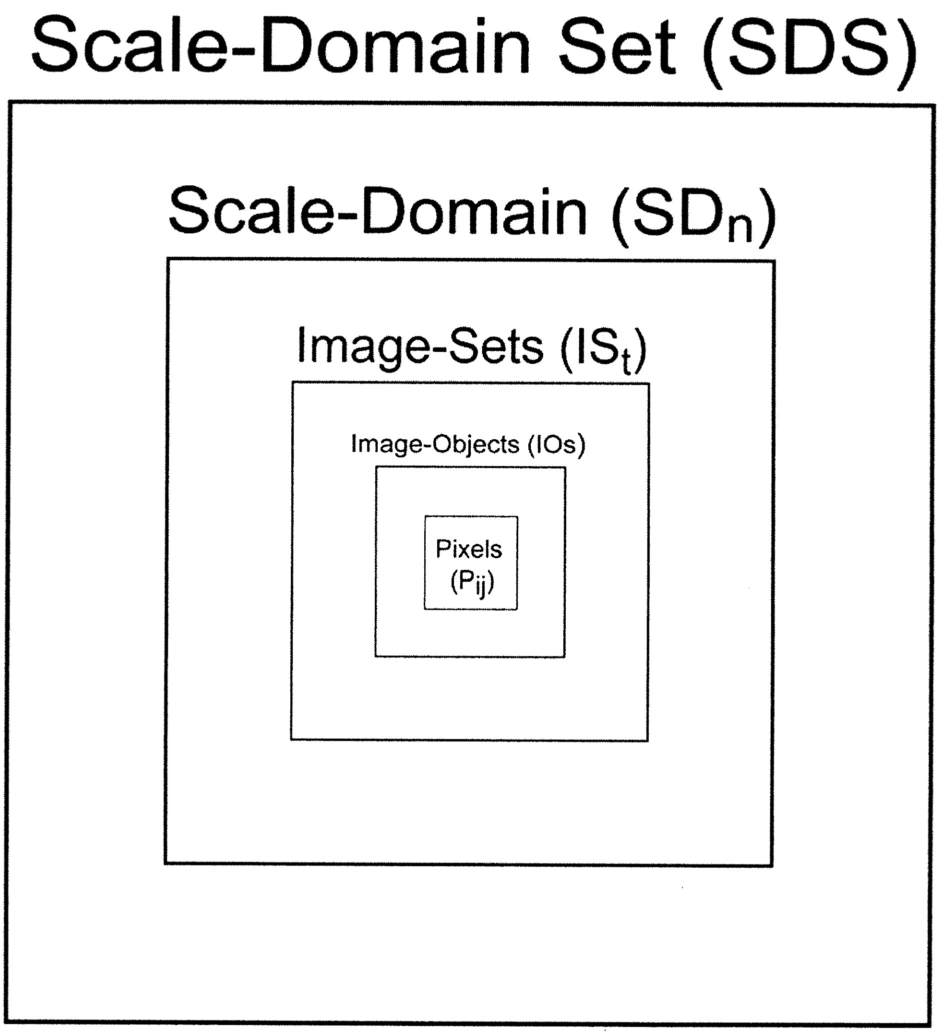


Figure 2.7 Scale domain sets ($SDS_{0\text{-}3}$) consisting of variance (V_l), area (A_l), and mean (M_l) images

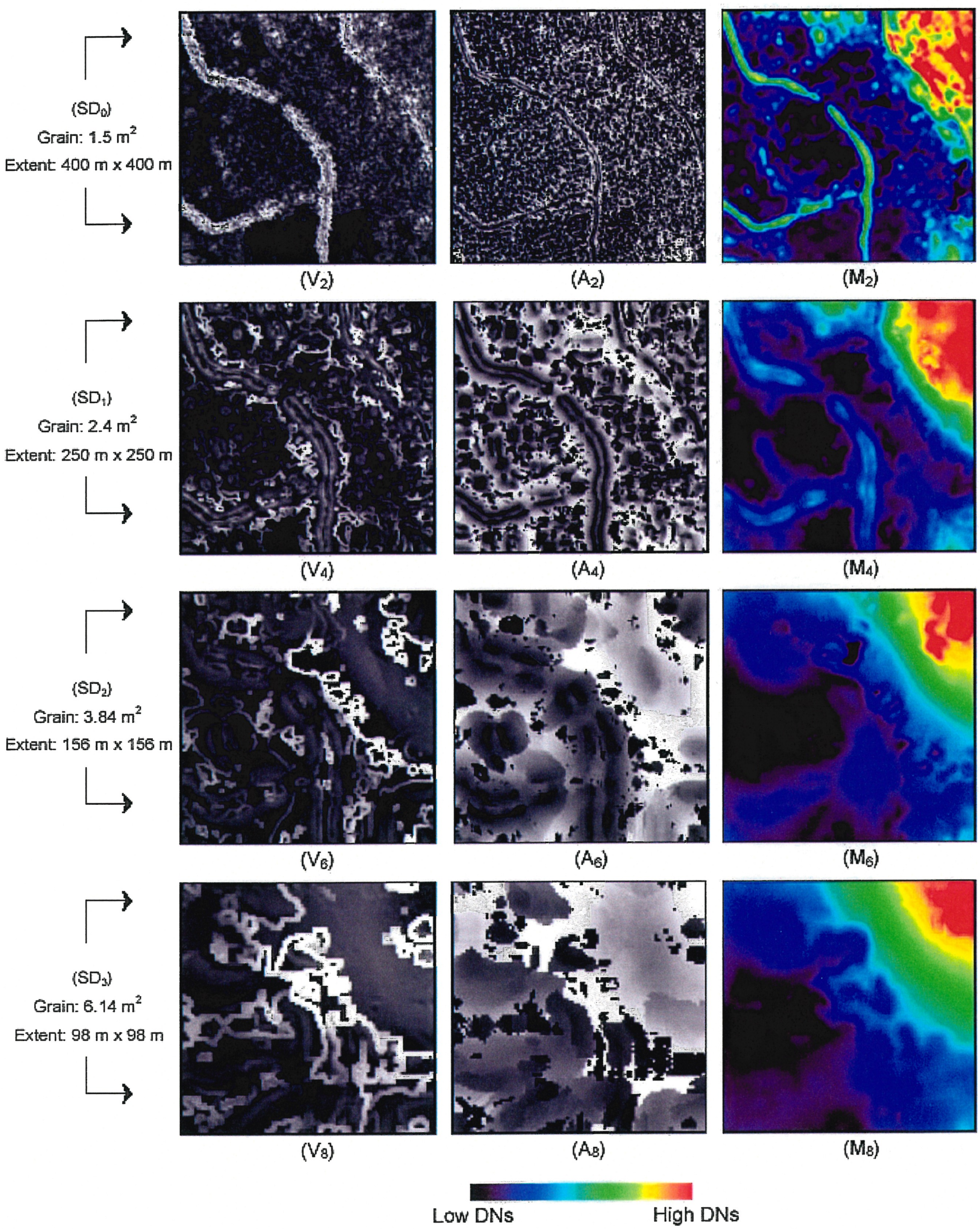


Figure 2.7a A Flowchart summary of iterative OSA/OSU processing

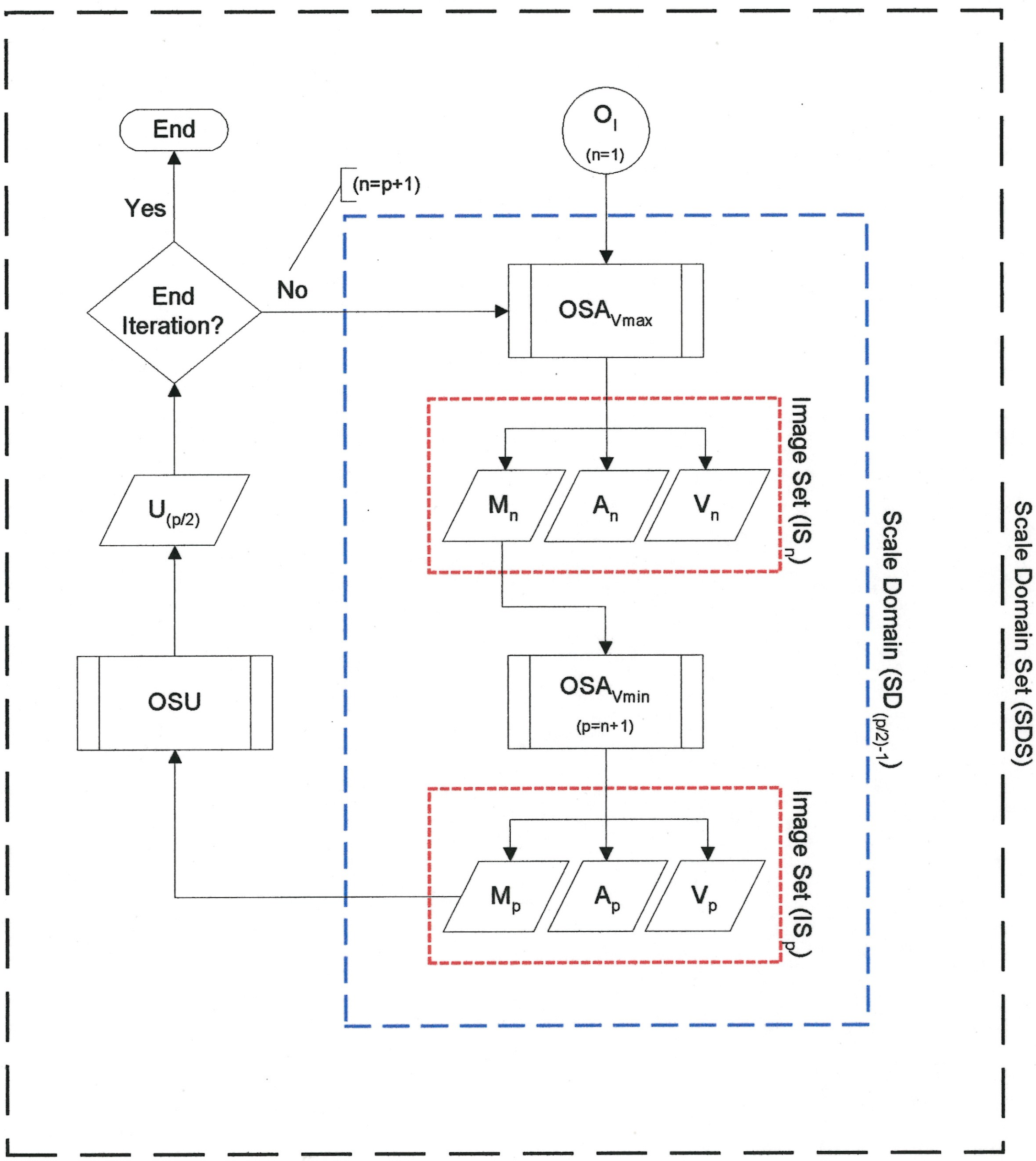


Figure 2.8 Upscale image ($U_{1\text{-}4}$) composite

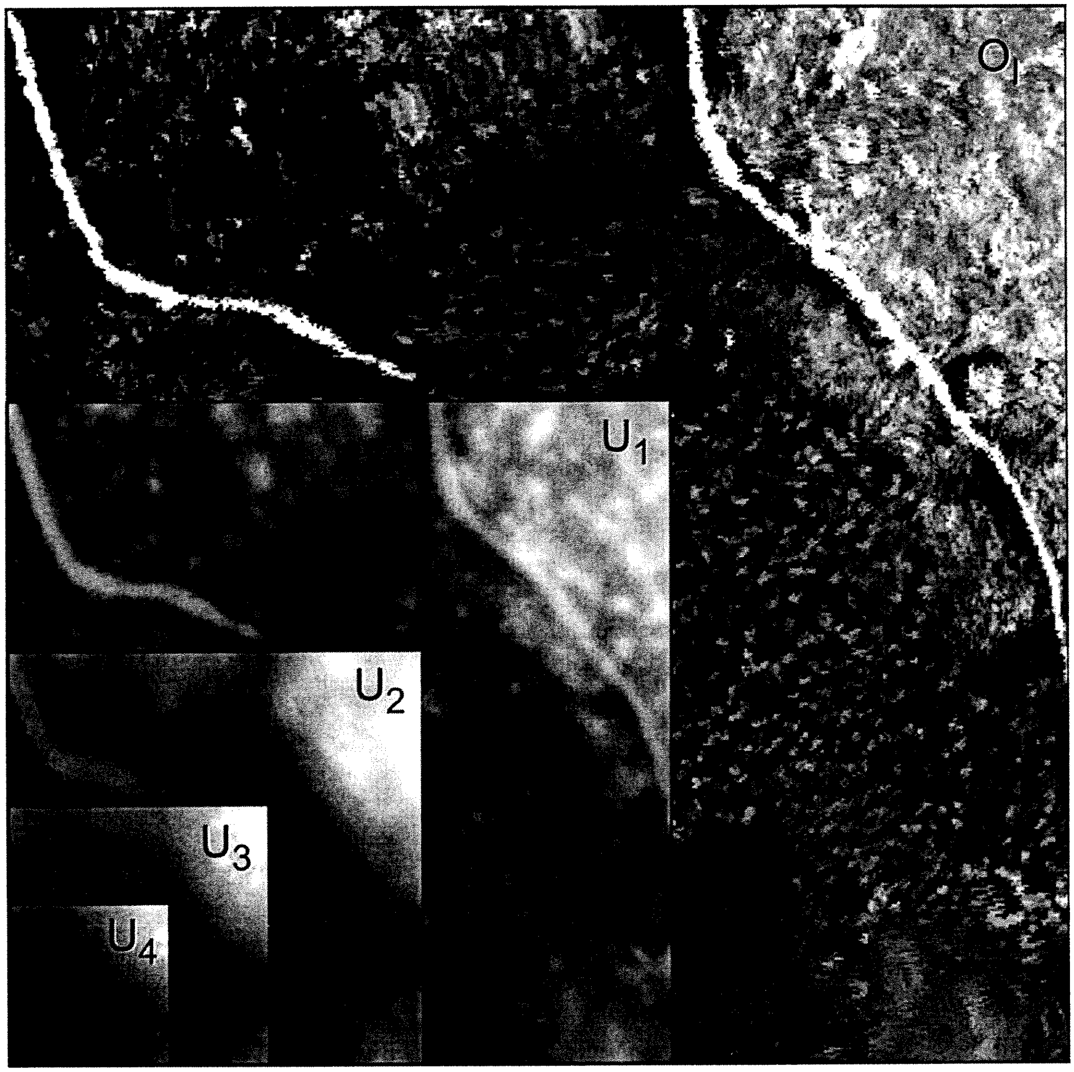


Figure 2.9 **Total Scene Variance (TSV) defined at odd-numbered OSA iterations**

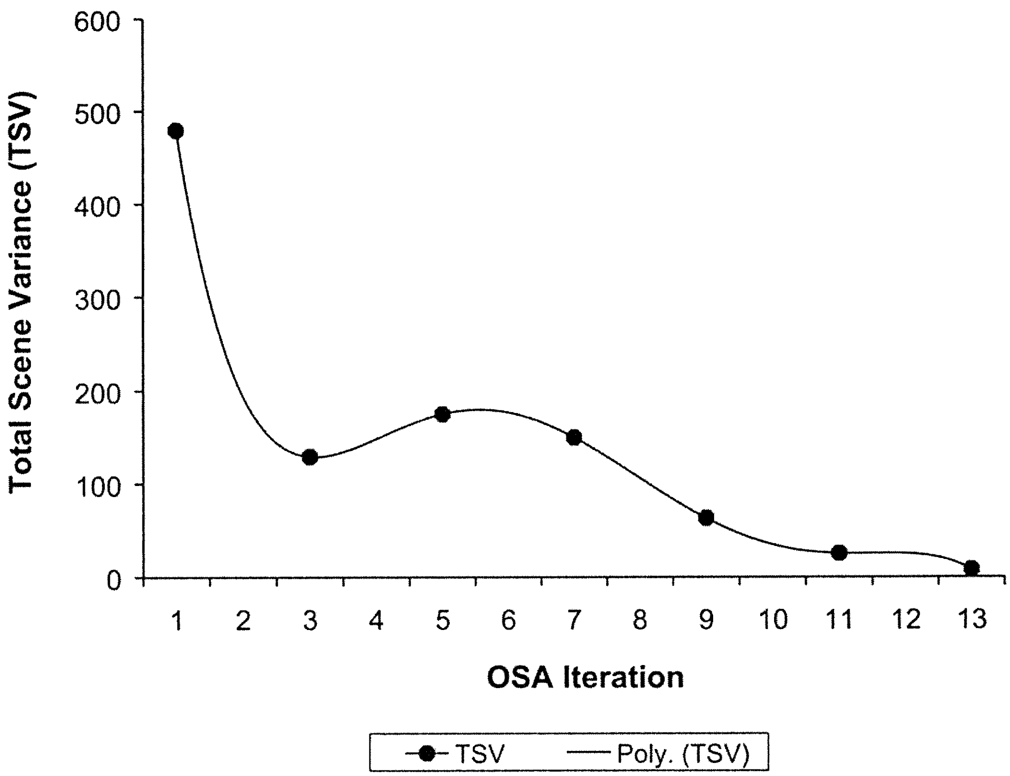


Figure Captions: Chapter 3

Figure 3.1 Figure 3.1(A) illustrates the distribution of a 1-D Gaussian kernel at four standard deviations, (B) illustrates the zero-th order Gaussian derivative of this kernel as a 2-D grey level image, and (C) as a 3-D wire frame representation.

Figure 3.2 This figure provides a visual comparison of two Gaussian derivative kernels and their biological equivalents. The top row illustrates how well a first-order Gaussian derivative kernel – shown as a 2-D grey level image (A) and a 3-D wire frame representation (B) - spatially models the measured receptive field sensitivity profile of a cortical simple cell (C)*.

The bottom row illustrates how well the Laplacian of a Gaussian derivative kernel - shown as a 2-D grey level (D) and 3-D wire-frame representation (E) - models the spatial characteristics of a Lateral Geniculate Nucleus (LGN) center-surround cell in the visual cortex (F)*. It is believed that these (2) cells are responsible for vision characteristics related to orientation, position, motion, contrast, color and texture.

*As measured by DeAngelis et al. 1995; [http://totoro.berkeley.edu/]).

Figure 3.3 In this figure, the left diagram illustrates the concept of a *scale-space cube*, or *scale-space stack*, where individual images have been successively smoothed by convolution with a Gaussian kernel of increasing scale (t) and grouped together. During processing, the spatial resolution and extent of each image remain constant. The smallest t resides on the bottom of the stack; the largest is on the top. In this example, the scale of convolution arbitrarily ranges from t_0 (original image) to t_{100}. The right graphic represents the resulting scale-space stack generated by applying linear Scale-Space theory to an image, through scales ranging from $t_{0\text{-}100}$.

Figure 3.4 Grey-Level blobs generated from the HSL airphoto (top left). The scale (*t*) of each image beginning from the top left, to the bottom right is $t_{0,\ 10,\ 20,\ 30,\ 40,}$ respectively. The large inset image is t_{50}.

Figure 3.5 These images have been generated to illustrate the perceptually implicit multiscale structure contained within a linear scale-space representation. They represent a feature enhanced image-set of the HSL-stack at two scale ranges. The top scene ranges from $t_{0\text{-}100}$, the bottom scene from $t_{0\text{-}50.}$ The same orientation, colour-table, and opacity level have been applied to each stack. The colour palette was developed for visual exploration only.

Figure 3.5a This figure depicts the colour palette used in Figures 3.5 and 3.8. The grey-tone values correspond to the colours directly above them in the illustrated colour table.

Figure 3.6 This figure illustrates four generic blob events and the location of their individual bifurcation events. Circular objects represent binary blobs, while the exterior boundary represents their perceptual structure through scale. Adapted from Lindeberg, 1994.

Figure 3.7 This enhanced image-set has been generated to provide further visual exploration of the HSL-stack. Each image-set illustrates a rotated perspective of Figure 3.5. The left column represents the range: $t_{0\text{-}100}$, the right column represents the range: $t_{0\text{-}50.}$ Colour-tables and opacity have been held constant for each image-set. In $A_{1,\,2,}$ the right side is illustrated facing forward; in $B_{1,\,2}$ the rear view faces forward, and in $C_{1,\,2}$ the left side faces forward.

Figure 3.8 This figure illustrates a single scale (t_{50}) 2-D HSL grey-level blob, represented as a 3-D surface, where z (height) equals the intensity value of each grey-level pixel (vertical exaggeration x 20)

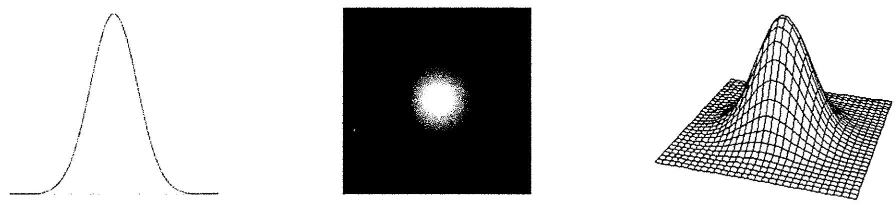
Figure 3.9 This figure illustrates defined grey-level blob *base levels* (white), which have been converted to binary blobs. The scale (t) of each image, beginning from the top left to the bottom right is $t_{1,\ 10,20,30,40}$, respectively. The large inset image is t_{50}. The (black) linear features separating each binary blob represent the saddle line, or demarcation zone segmenting two or more different blob (watershed) regions. Mathematically, these lines are composed of zero dimension points; computationally they are composed of single pixels as illustrated.

Figure 3.10 Grey-Level blobs generated from a random white-noise image (top left) illustrate that even random noise has structure at different scales. The scale (t) of each image beginning from the top left, to the bottom right is $t_{0,\ 10,20,30,40,}$ respectively. The large inset image is t_{50}.

Figure 3.11 This figure illustrates a stack composed of binary blobs. For illustrative purposes, each scale of binary blobs has a grey-value associated to it based on its scale of expression. Consequently, the tones grade from dark values at the bottom (t_1), to lighter values at the top (t_{100}). The textured base image (t_0) is the original airphoto.

Figure 3.12 The graphic on the left represents an imaginary scale-space object (as may be perceived in Figures 3.5 and 3.7) that has been defined by binary blobs in x, y, and t dimensions (shown as stacked grey-level disks). However, this scale-space object exhibits no defined topological relationship with the blobs that perceptually compose it. Conversely, the graphic on the right illustrates how the binary-blobs that compose this perceptual object can be linked (by curved black lines) between bifurcations points (black dots) to define the topological structure of individual Scale-Space blobs. This linking is based on the concepts of scale-space events (see 3.2 Methodology: Part I) and scale-space lifetimes (Lt_n). (A) Represents the bifurcation location of an annihilation event, (M) is the location of a merge event, (S) is a split, and (C) is a creation event. In this graphic, five unique lifetime events are defined (in a bottom up approach). For illustrative purposes, the binary-blobs that compose each lifetime are defined with five different shades of grey.

Figure 3.1 Illustration of Gaussian kernel in 1D, 2D, and 3D



A B C

Figure 3.2 A visual comparison of two Gaussian derivative kernels and their biological equivalents

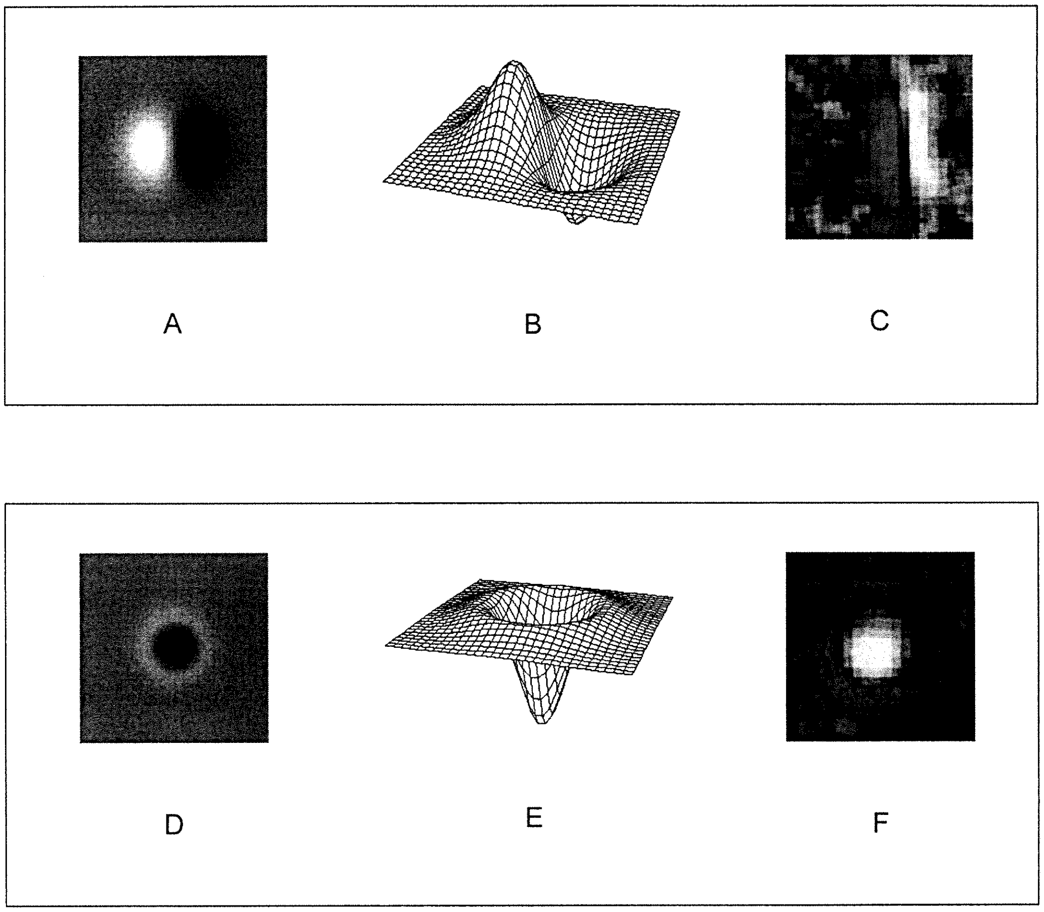


Figure 3.3 The structural components of a scale-space cube

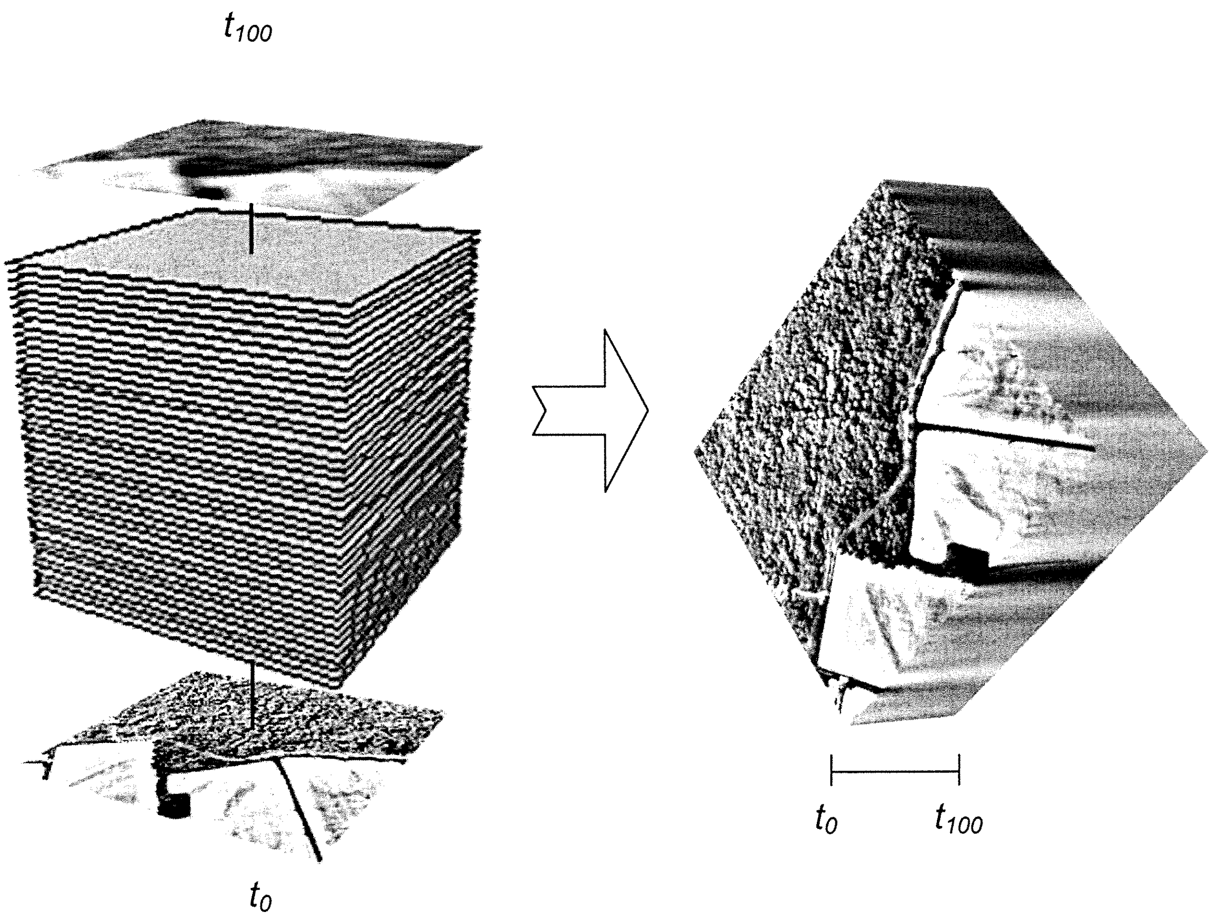


Figure 3.4 Multiscale grey-level blobs

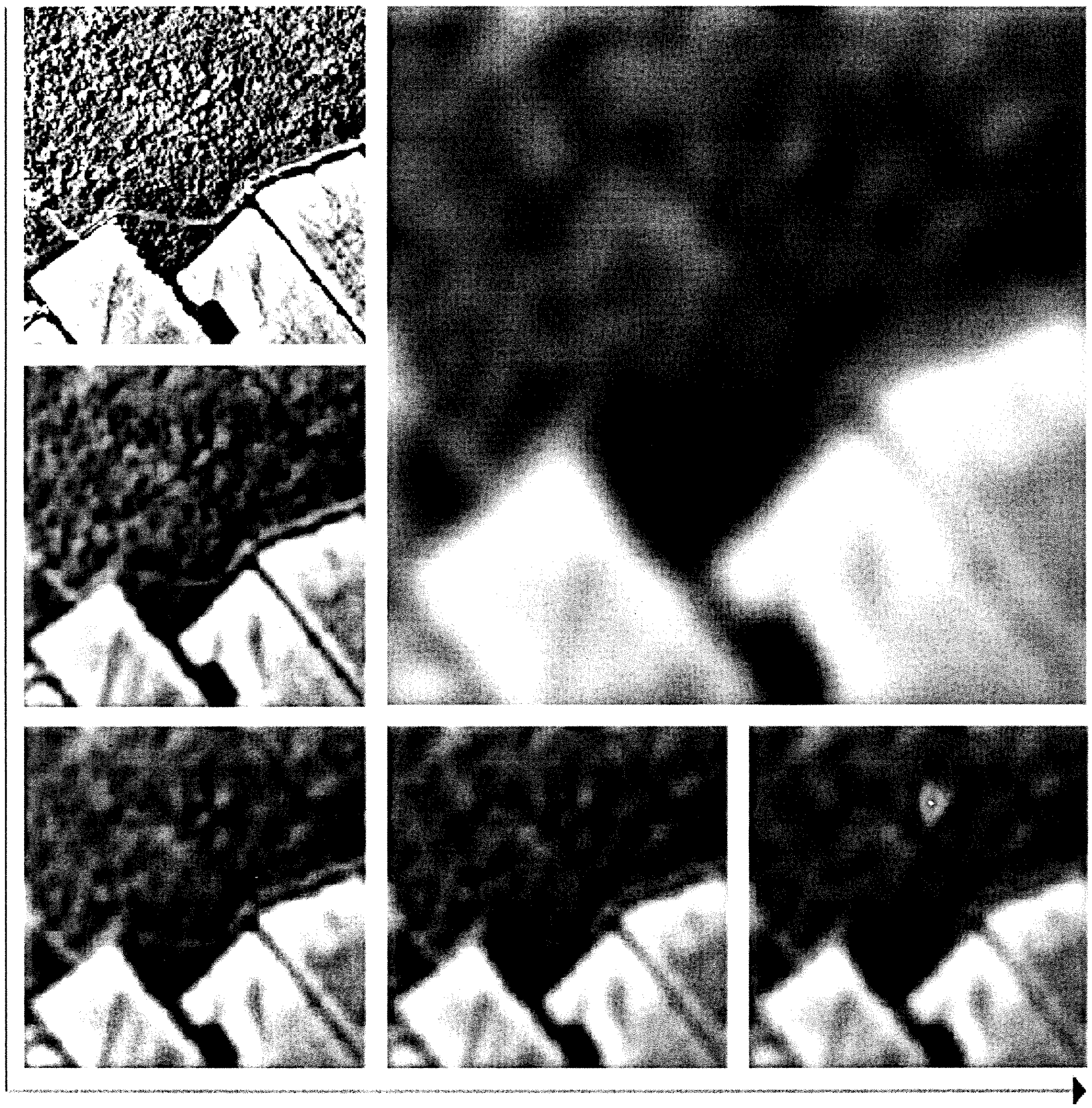


Figure 3.5 Colorized grey level stacks at $t_{0\text{-}100}$ (top) and $t_{0\text{-}50}$ (bottom)

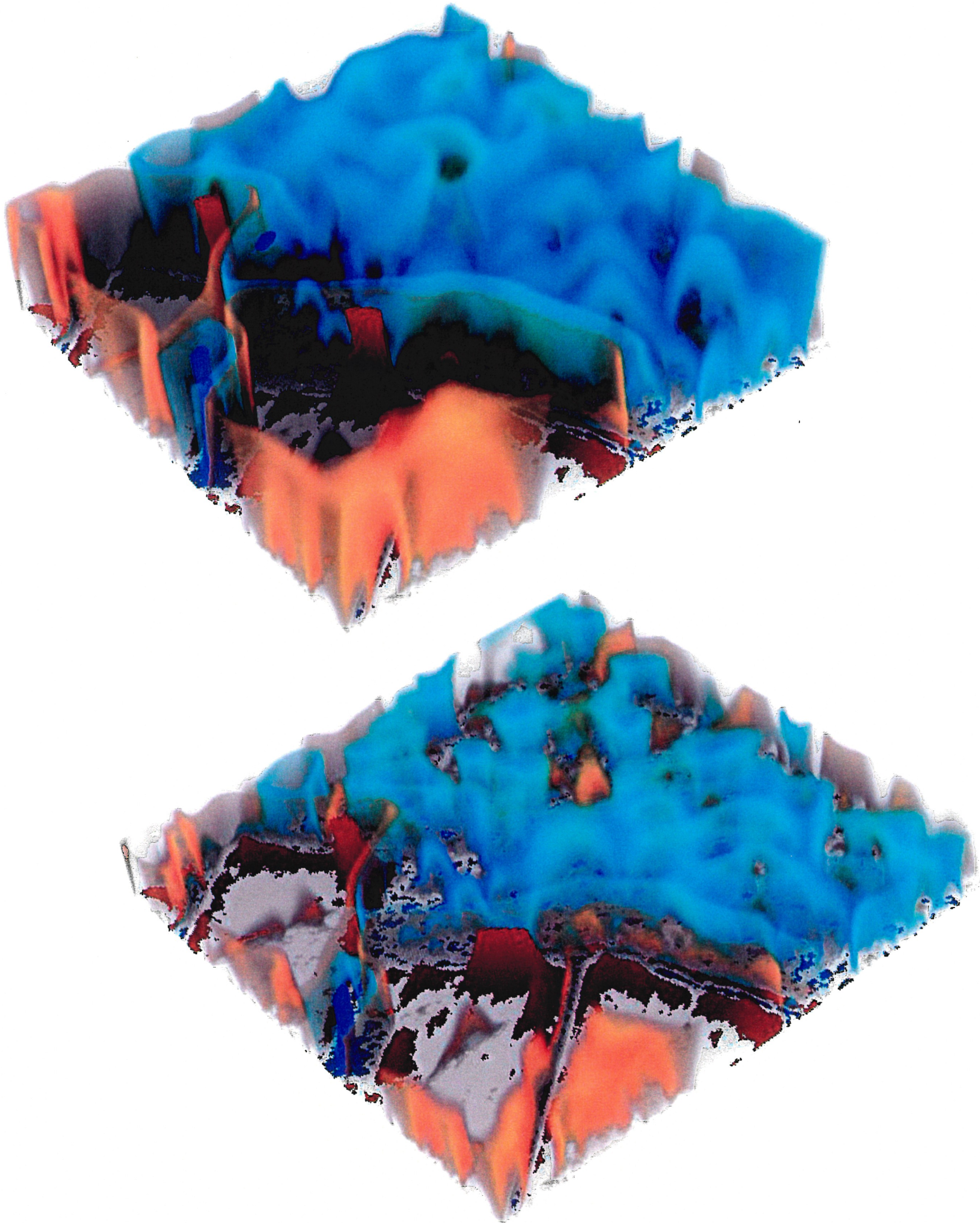


Figure 3.5a Detail of the colour palette used in figures 3.5 and 3.8.

Figure 3.6 **Four generic blob events and the location of their individual bifurcation events (Adapted from Lindeberg, 1994)**

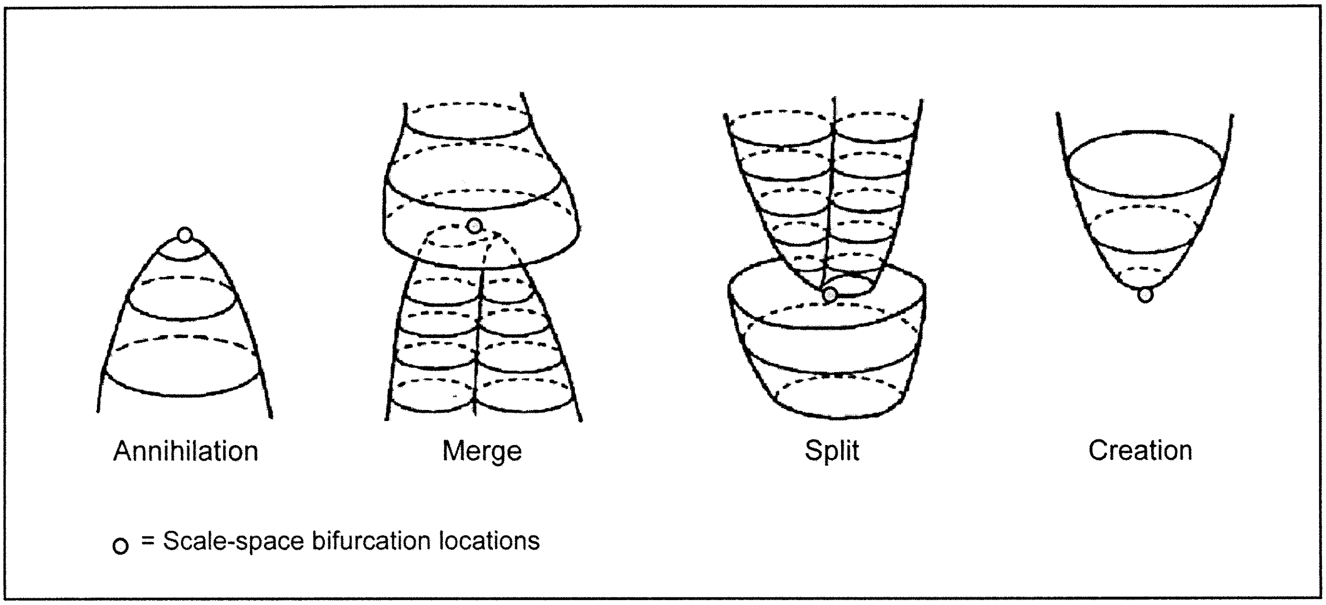
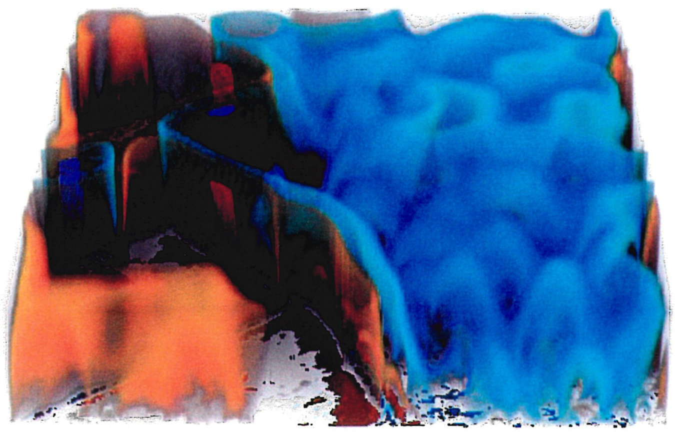
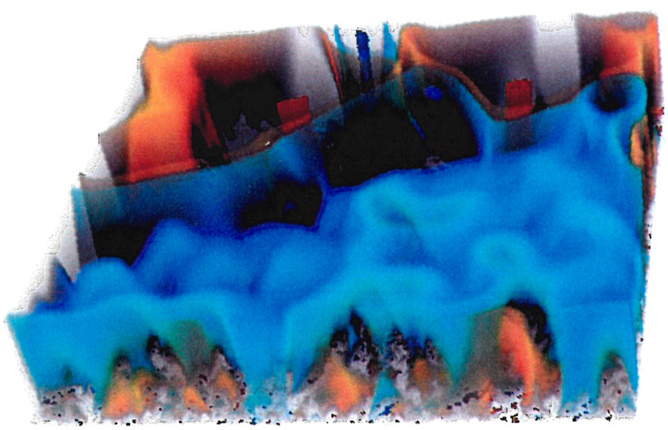


Figure 3.7 **Two sets of enhanced and rotated colorized grey-scale stacks at $t_{0\text{-}100}$ (right) and $t_{0\text{-}50}$ (left)**

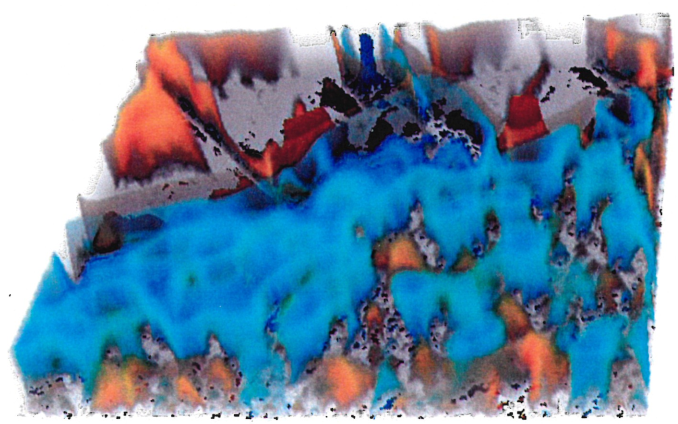


A_1

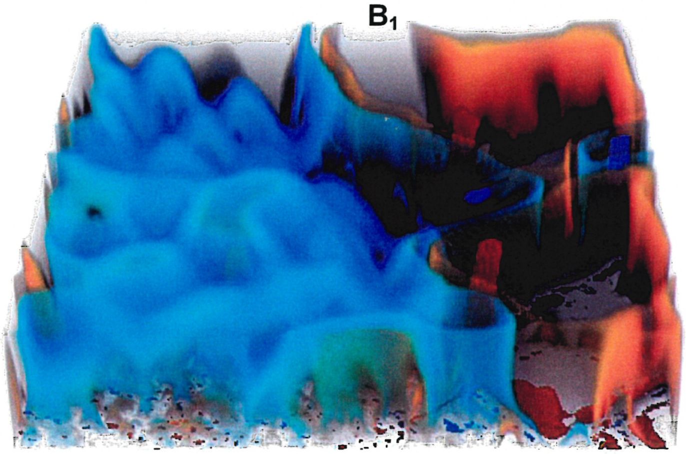
A_2



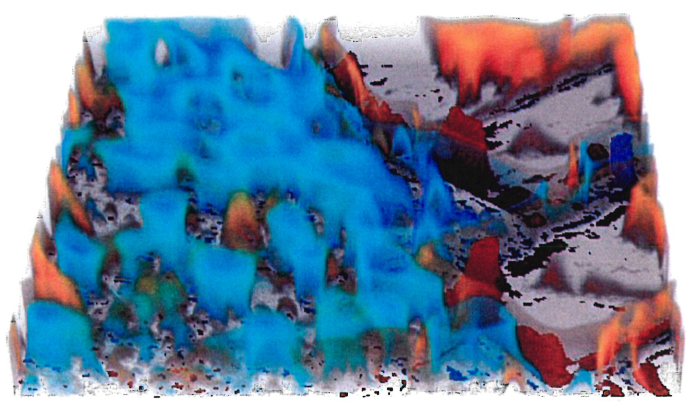
B_1



B_2



C_1



C_2

Figure 3.8 A single scale (t_{50}) 2-D HSL grey-level blob, represented as a 3-D surface

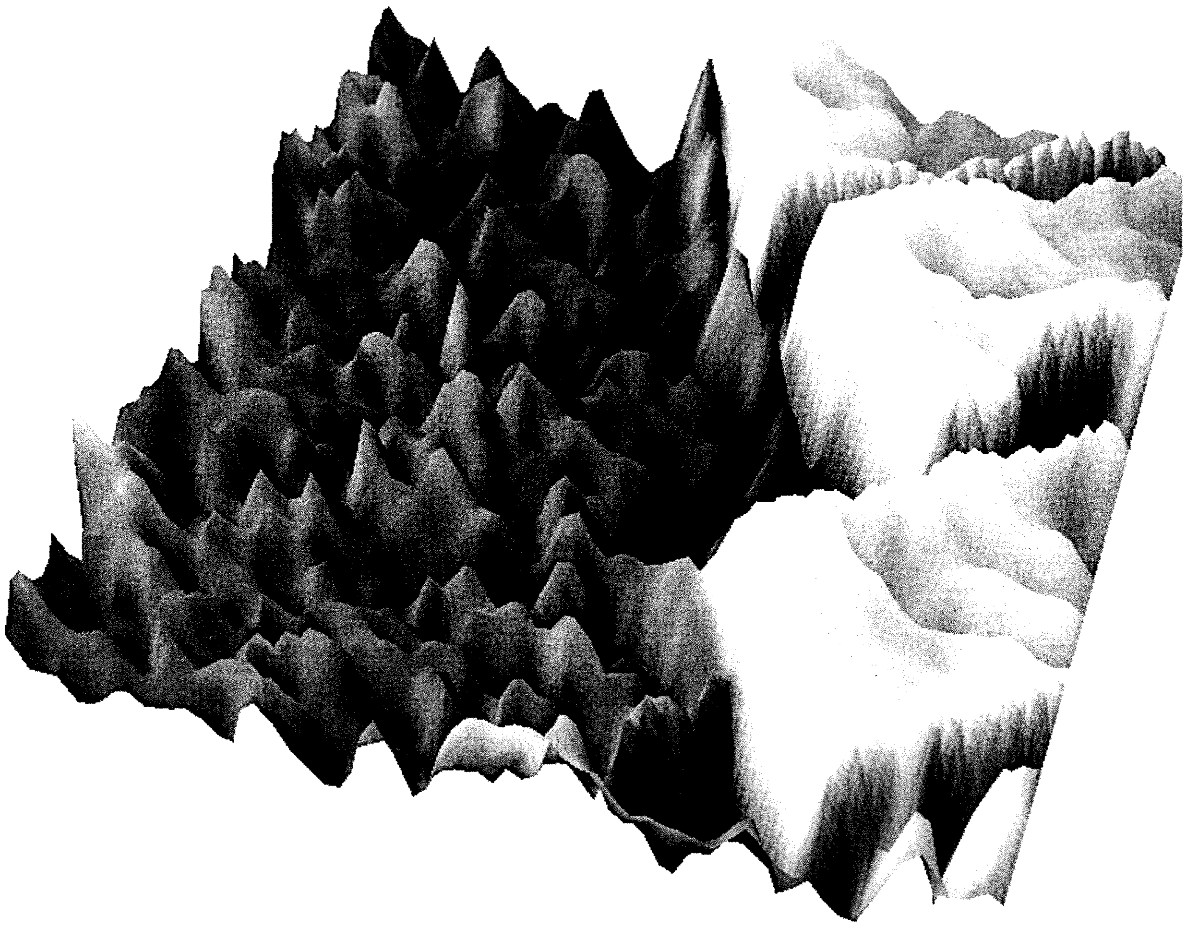


Figure 3.9 Multiscale grey-level blob base levels (white), which have been converted to binary blobs.

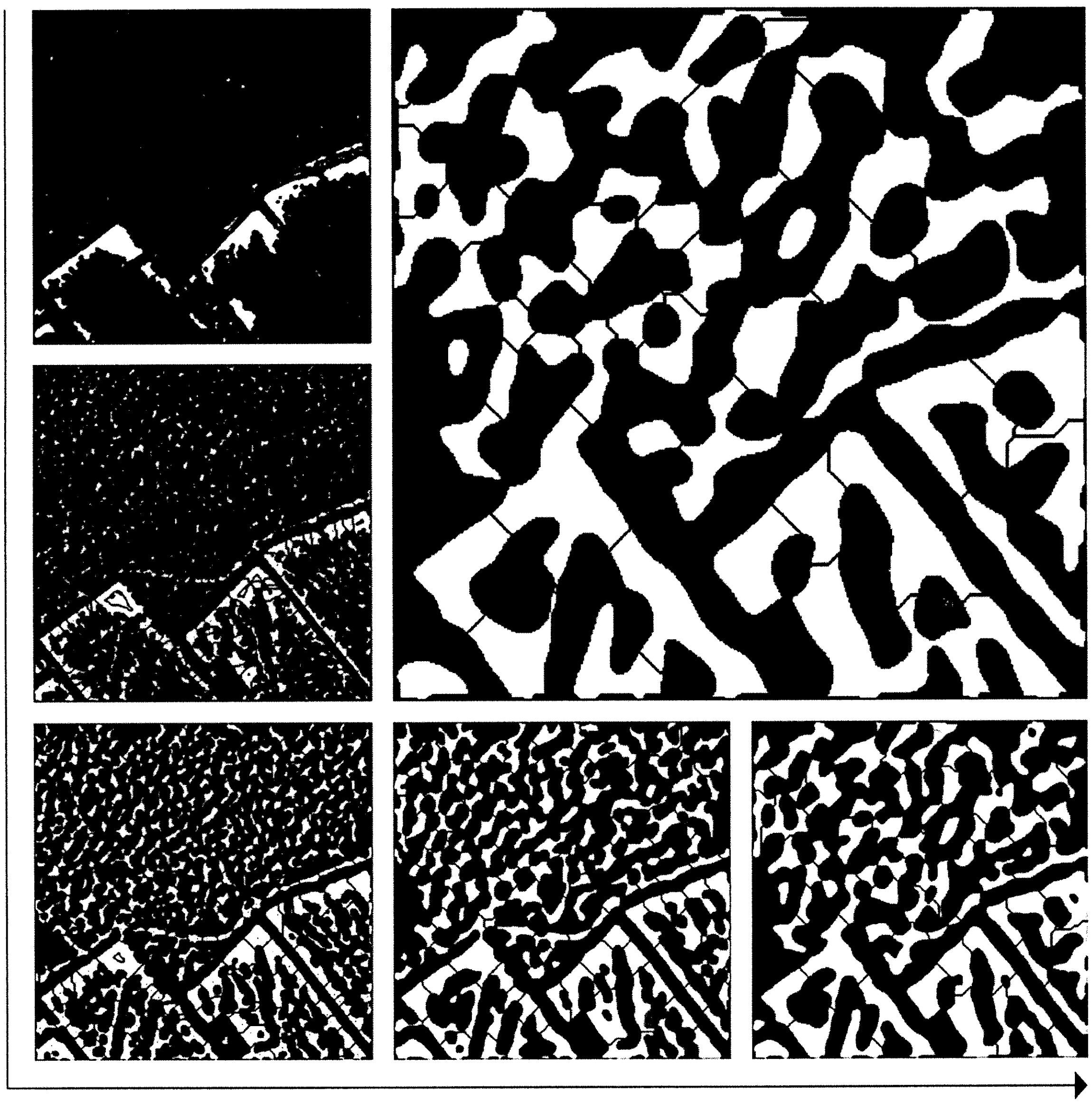


Figure 3.10 Grey-Level blobs generated from a random white-noise image

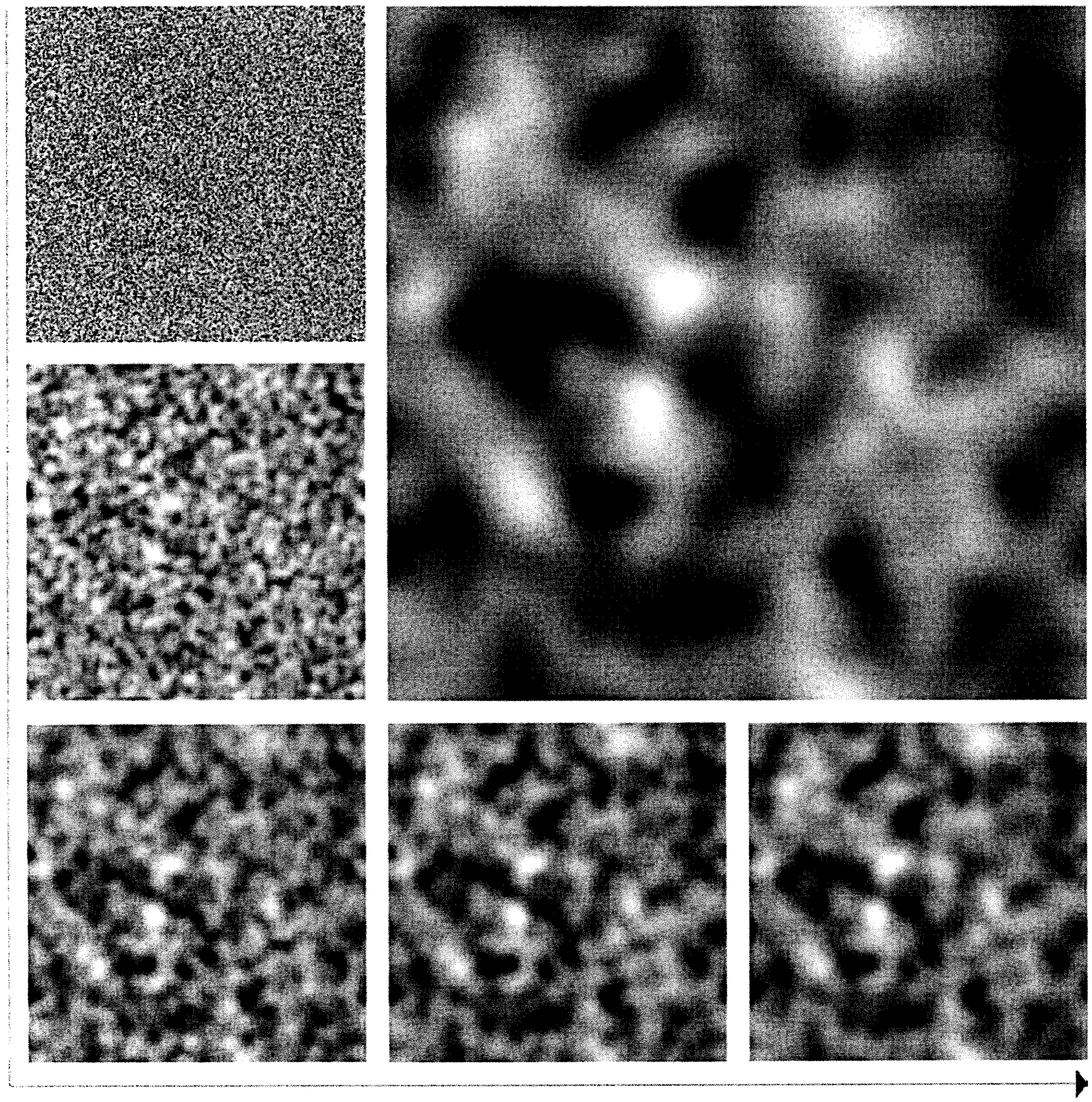


Figure 3.11 A hyperblob stack composed of binary blobs

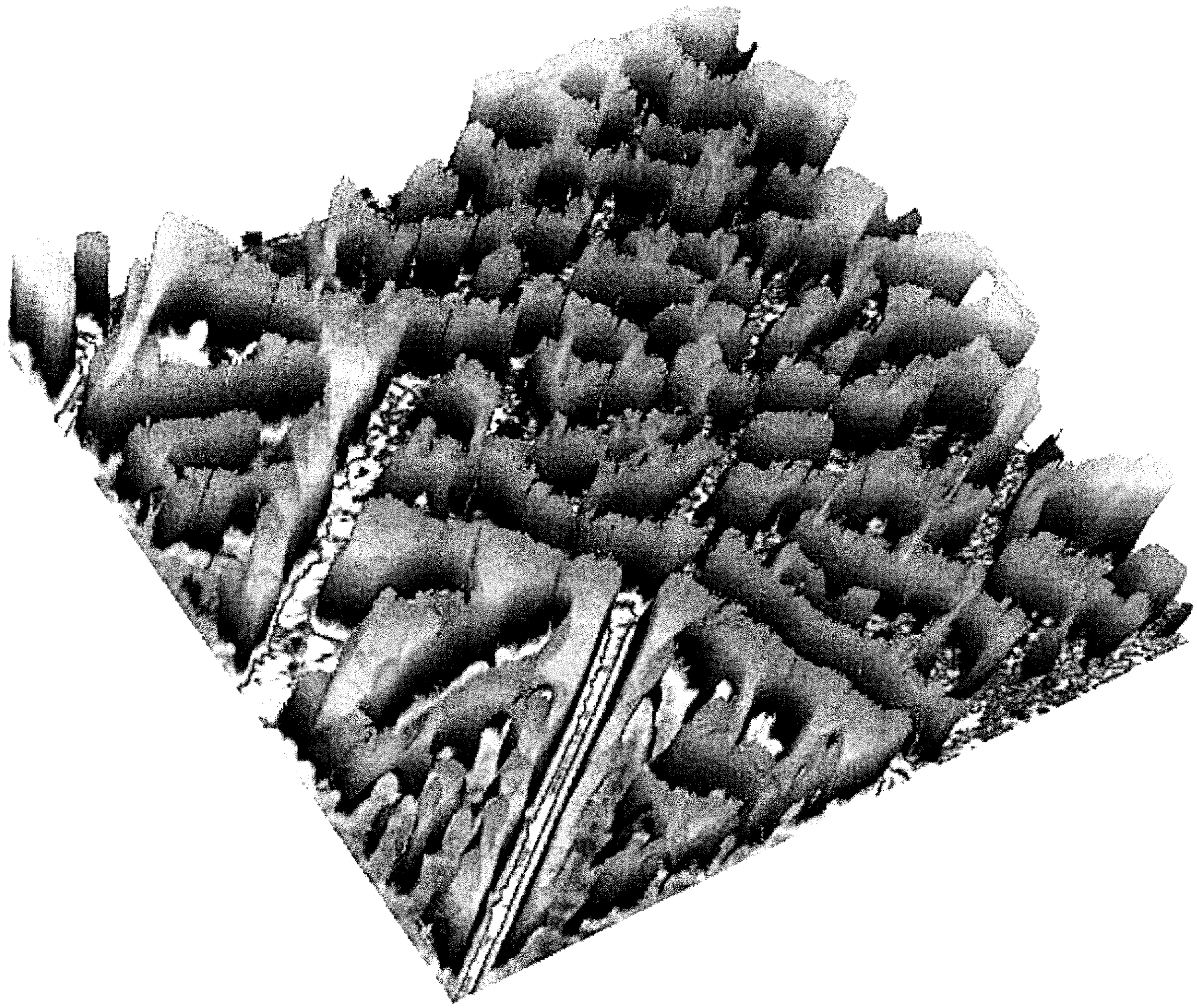


Figure 3.12 Defining scale-space blob topology

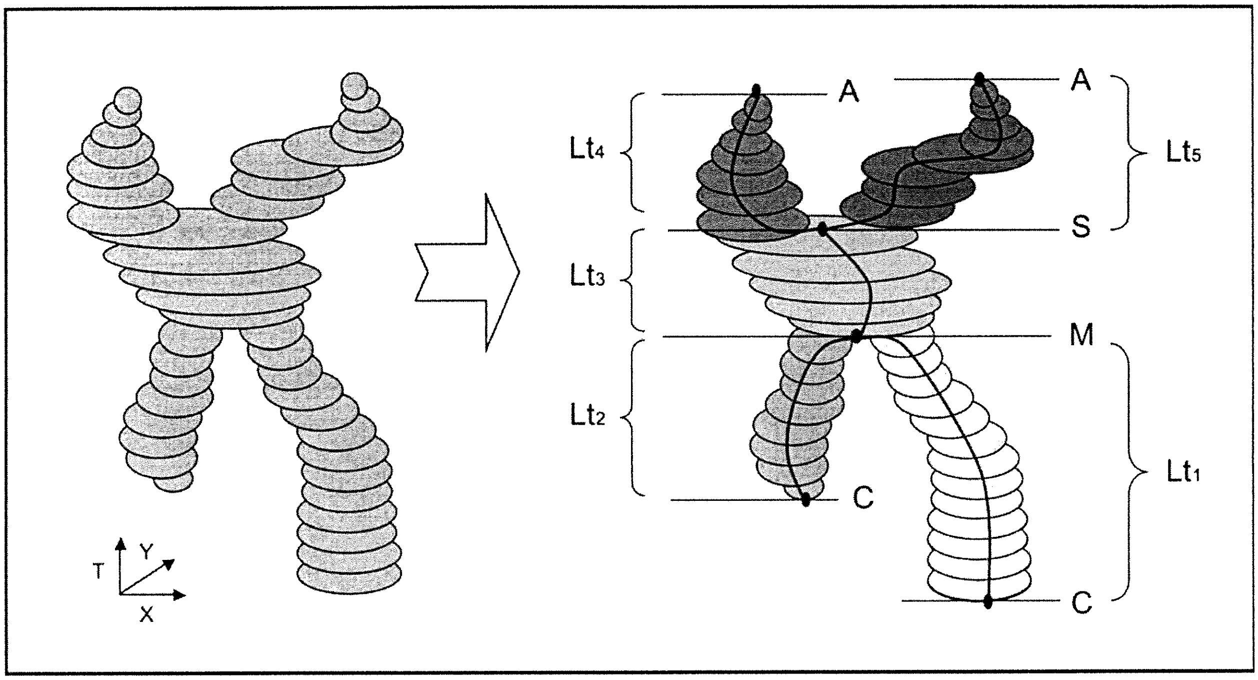


Figure Captions: Chapter 4

Figure 4.1 Ikonos sub-image and Study site map.

4.1a A 500 x 500 pixel IKONOS of the study site (4.0 m panchromatic image).

4.1b Map location of the image.

Figure 4.2 This figure illustrates an example of object semantics (i.e., linked lines). The bold lines illustrate the relationship of an image-object (the dark center polygon) with its super-object (a), its neighbouring objects (b) and its sub-objects (c). The lowest level (d) represents the individual pixels in the image.

Figure 4.3 Three different levels of FNEA segmentation.

4.3a A panchromatic Ikonos sub-image (245 x 210 pixels) extracted from the top right corner of Fig 1a.

4.3b A close up of typical FNEA results using three different segmentation levels. These levels roughly correspond to the smallest units of interest (e.g. single groups of trees or bushes) indicated with bright grey lines. Medium sized black outlines show a medium level, which corresponds best with 'forest' stands". Bold black lines indicate the coarsest level of segmentation used in the image where some semantically different landscape objects are growing together but can still be exploited as 'super-objects'.

Figure 4.4 This illustrates a linear scale-space 'stack' or scale-space 'cube'. The smallest scale is on the bottom, and the largest scale (thus most smoothed) is on the top. If you look carefully at the sides of the right-hand graphic you will be able to see the diffusive pattern of scale-space objects through scale.

Figure 4.5 Colorized Grey-level stack, illustrating the persistence of blob structures through scale.

Figure 4.6 2D and 3D grey-level and binary blob representations

4.6a 2D Grey-level blob at scale 20 (t_{20})

4.6b 3D Grey-level blobs (t_{20}) illustrated as a topological surface from which a blob-delineation watershed analogy is described.

4.6c Binary blob (t_{20})

Figure 4.7 3D hyperblob stacks, scale-space topology, and ranked blobs overlaid on the study site

4.7a A hyper-blob stack composed of 2D binary blobs. For illustrated purposes only, each binary layer has been assigned a value equal to its scale. Thus dark values are on the bottom, while bright values are near the top.

4.7b Idealized hyper-blob illustrating four different SS-events or 'bifurcations': annihilations (A), creations (C), merges (M) and splits (S). The number of scales between SS-events represents the lifetime (Lt_n) of a SS-blob. Five different Lt_n are illustrated.

4.7c Ranked blobs overlaid study site.

Figure 4.8 Examples of Variance (V), Area (A) and Mean (M) images from the first three scale domains ($SD_{1\text{-}3}$). These data corresponds to the sub-image illustrated in Figure 4.3a. The variance images represent a 'segmentation' or 'edge-detection' image. Essentially each pixel in $V_{2,\,4,\,6}$ represents the edge of the image-object under analysis. Dark tones represent low variance, (i.e., pixel groups that are more 'object-like'), while bright tones represent high variance, (i.e., edges between two or more image-objects). $A_{2,\,4,\,6}$ define the spatial extent of individual objects that are revealed at their particular scale of measurement. Thus dark tones represent small spatial extents because closer pixels are more 'object-like', while bright values represent large spatial extents, as they are less 'object-like'. $M_{2,\ 4\ 6}$ represent an average of the H-res pixels that constitute part of individual objects assessed within each object-specific threshold window.

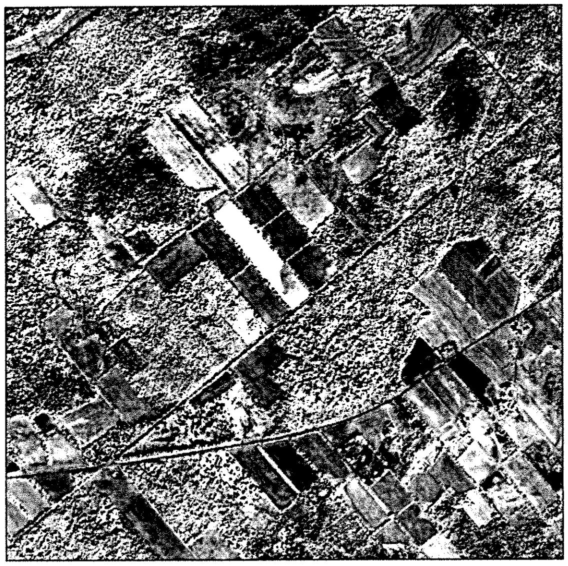
Figure 4.9 Ranked blobs converted to individual queriable vectors, and threshold domain surfaces.

4.9a Ranked blobs converted to individual queriable vectors. Note how polygons overlay each other making analysis non-trivial. Compare with Fig 4.1a.

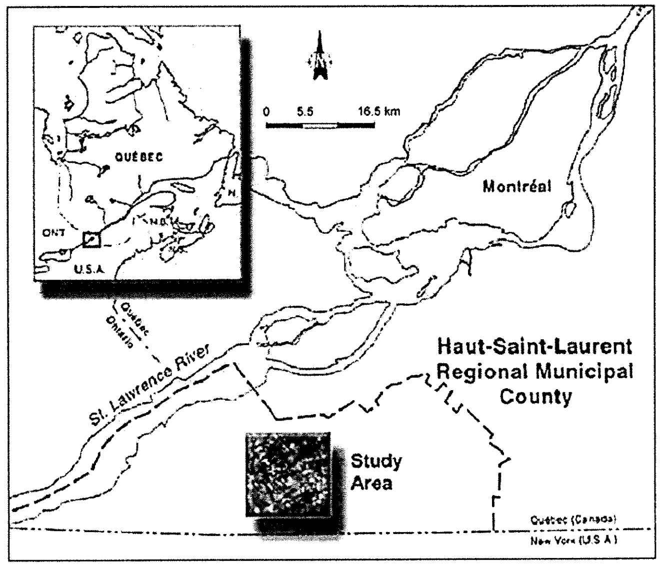
4.9b This is an example of 8 threshold-domain surfaces visually modeled from a stack of 100 layers (thus the value 800 in the scale axis), and an x, y dimension of 200 x 200 pixels. Each domain layer is modeled one above the other for visual interpretation only. Conceptually, each domain surface stacks exactly upon the surface underneath it, with no peak protruding into the upper or lower surface. Peak locations represent the bifurcation point of each scale-space blob defined within a single hyper-blob.

Figure 4.10 MOST results from the first three scale domains ($SD_{1\text{-}3}$) illustrated in Figure 4.8. It its important to note that each grey-tone represents a topologically distinct watershed image-object.

Figure 4.1 Ikonos sub-image (left) and Study site map (right)



4.1a



4.1b

Figure 4.2 An example of multiscale object semantics

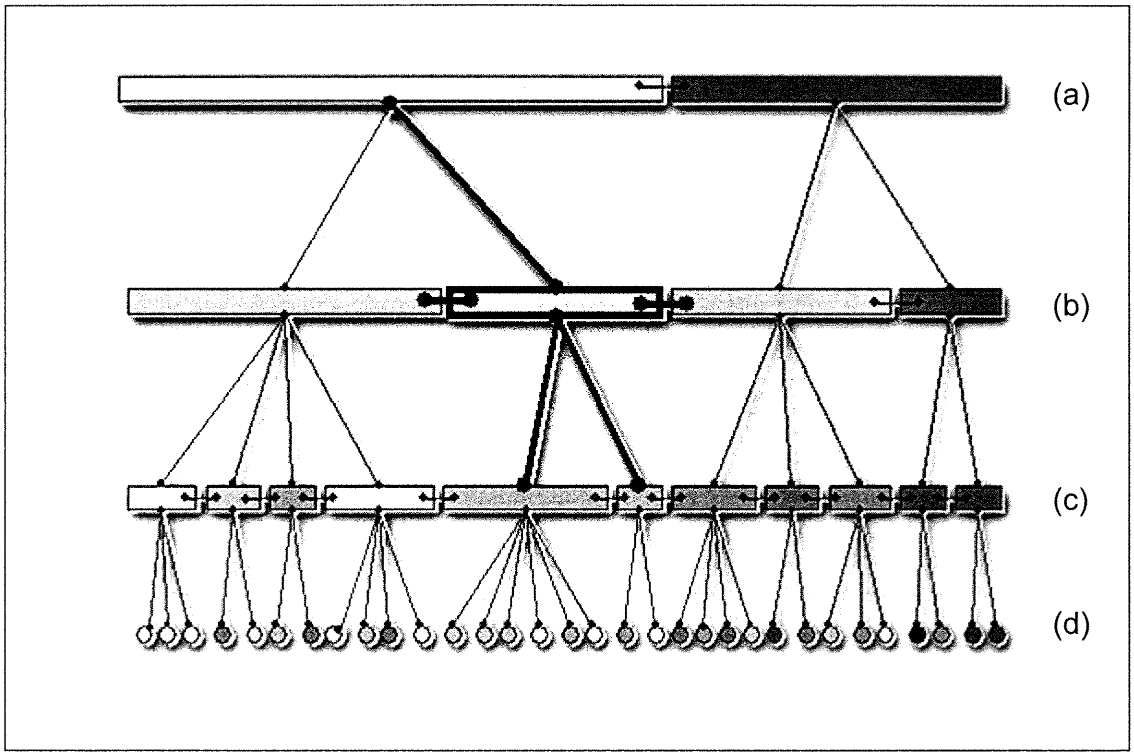
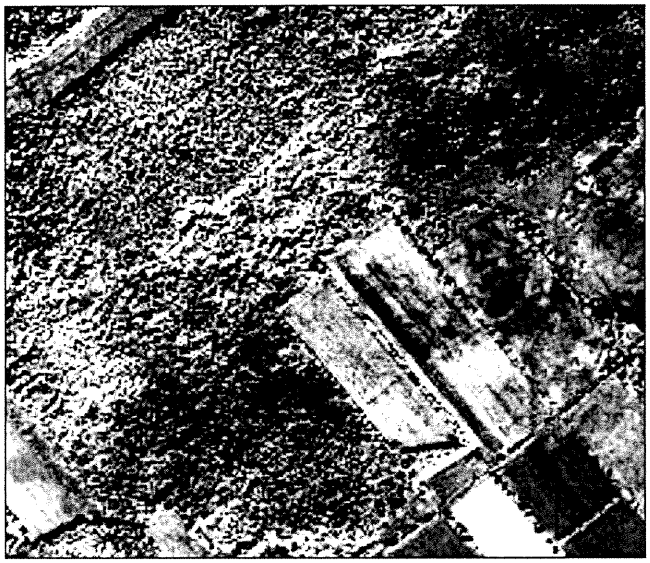
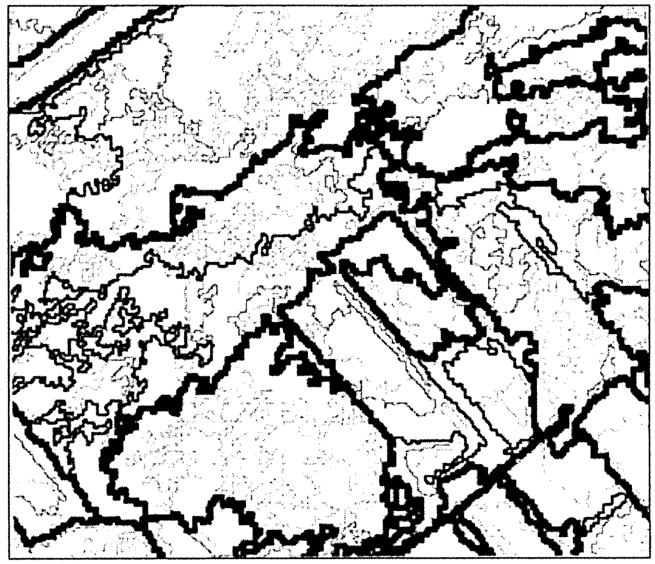


Figure 4.3 Three different levels of FNEA segmentation



4.3a



4.3b

Figure 4.4 This illustrates a linear scale-space 'stack' or scale-space 'cube'

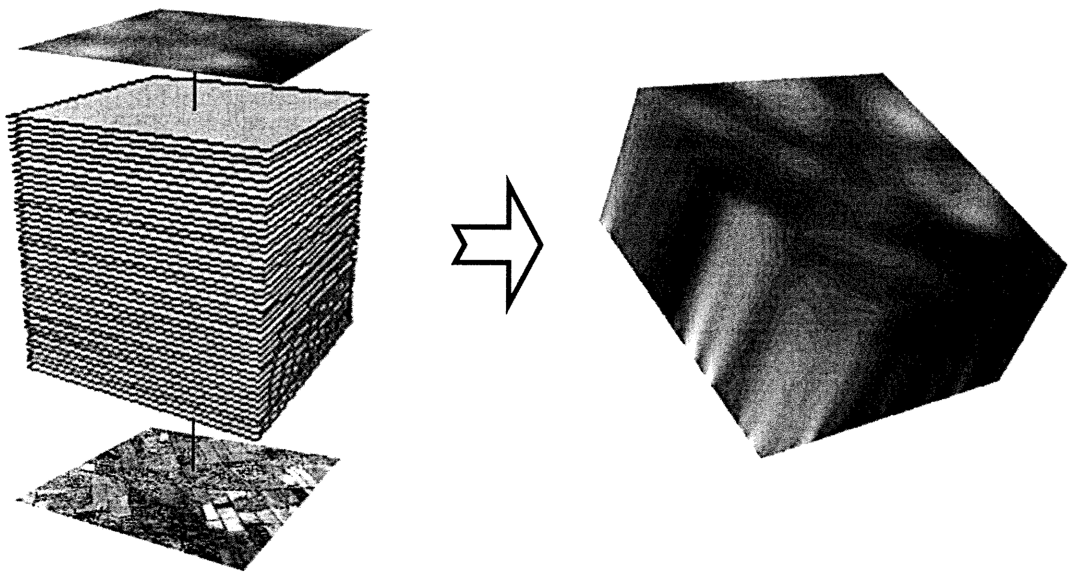


Figure 4.5 **Colorized Grey-level stack, illustrating the persistence of blob structures through scale**

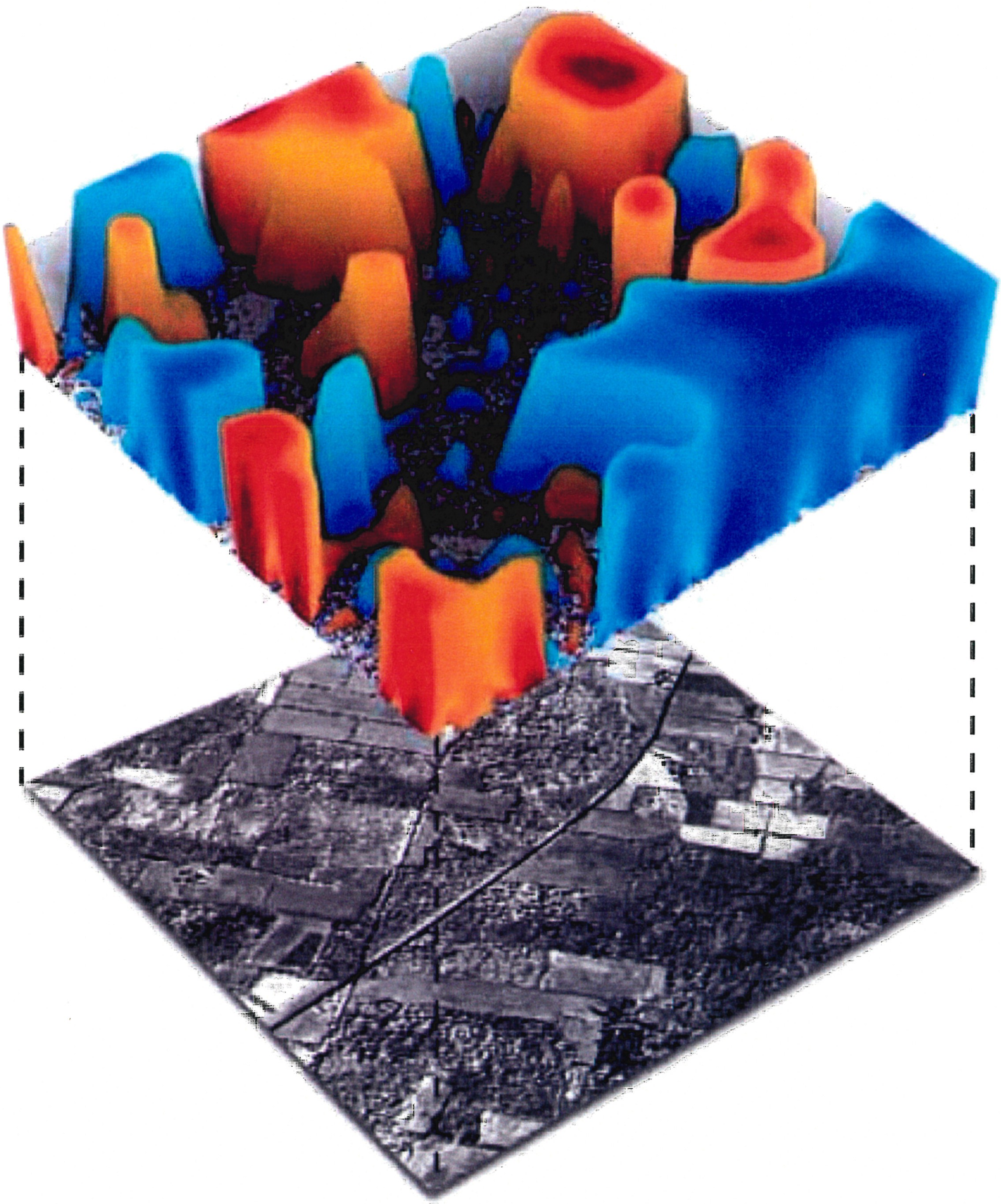
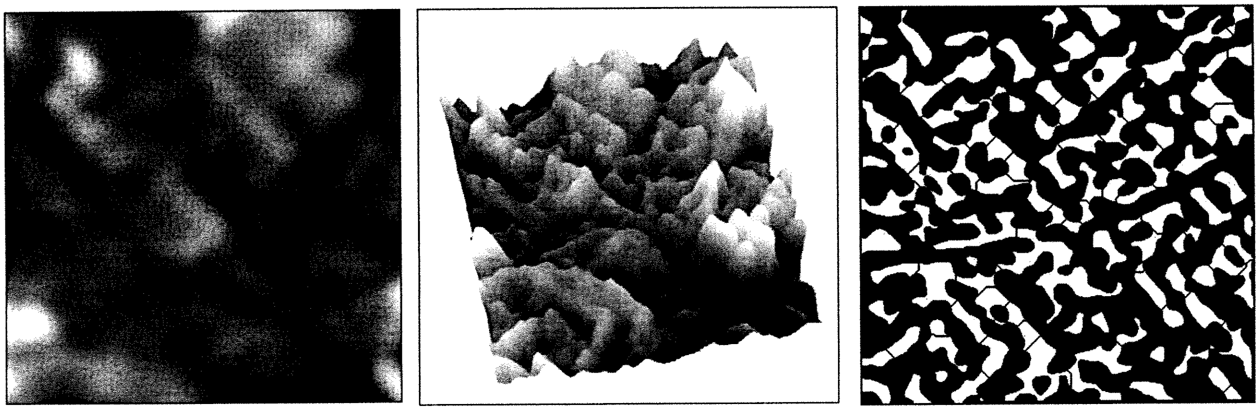
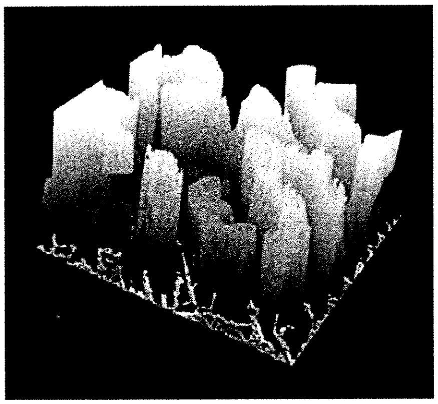


Figure 4.6 2D and 3D grey-level and binary blob representations

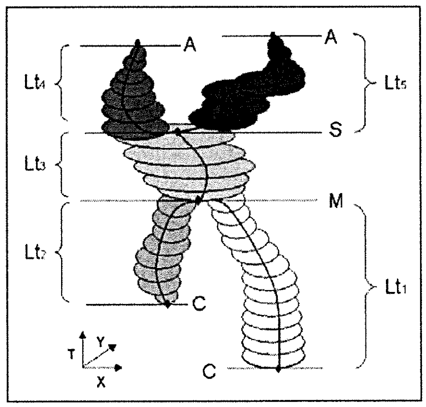


4.6a 4.6b 4.6c

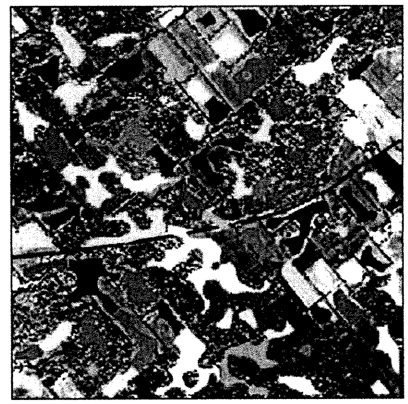
Figure 4.7 3D hyperblob stacks, scale-space topology, and ranked blobs overlaid on the study site



4.7a



4.7b



4.7c

Figure 4.8 **Examples of Variance (V), Area (A) and Mean (M) images from the first three scale domains (SD_{1-3}) defined by objects-specific analysis (OSA) and object-specific upscaling (OSU)**

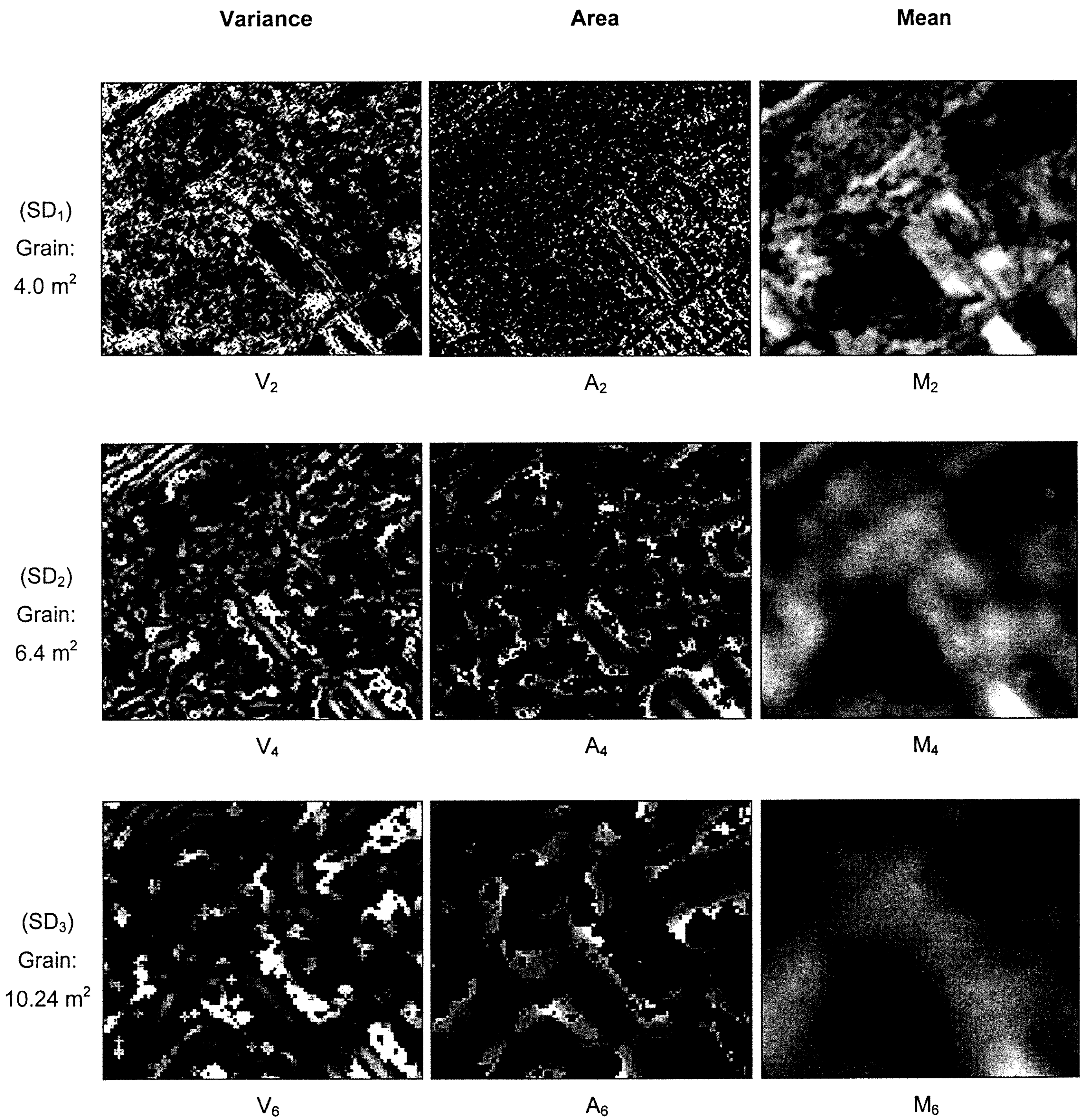
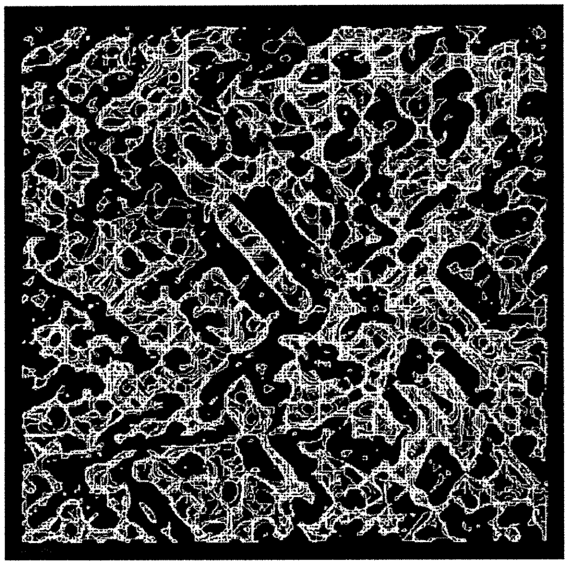
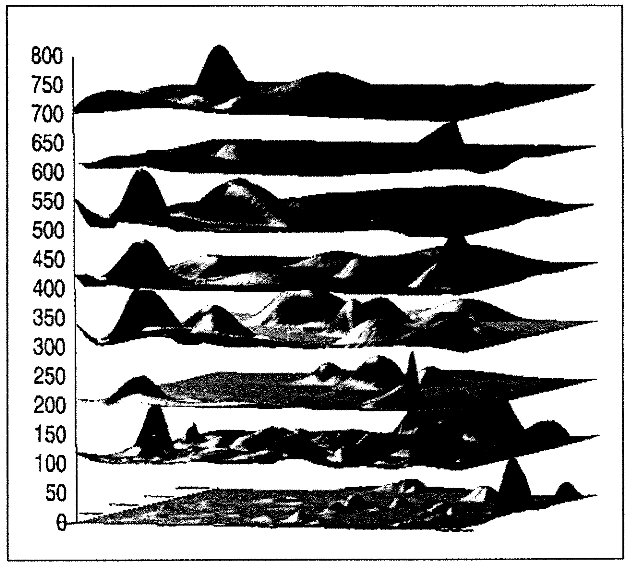


Figure 4.9 Ranked blobs converted to individual queriable vectors, and threshold domain surfaces

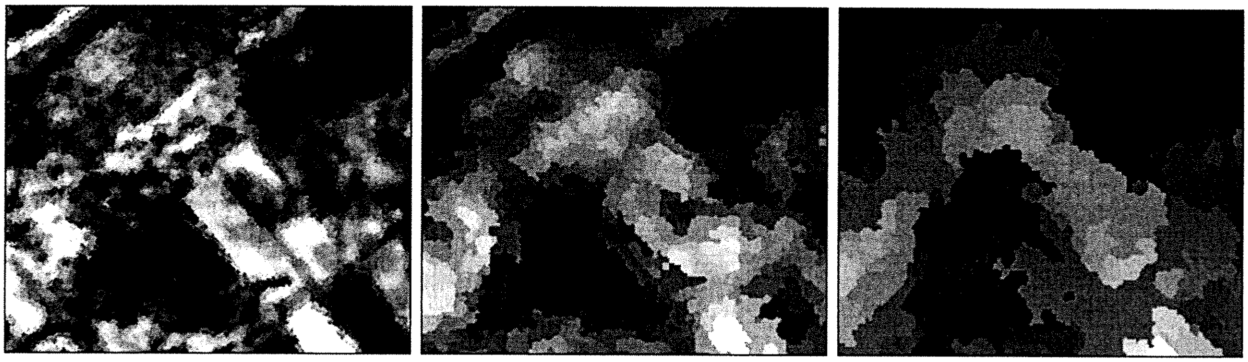


4.9a



4.9b

Figure 4.10 MOST results from the first three scale domains (SD_{1-3}) illustrated in Figure 4.8



MOST at SD_1 | MOST at SD_2 | MOST at SD_3