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Title: Multi-spatial Scale Representation of Landscape Transitions Using Landsat Thematic Mapper Data and Scale-space Filters.

Abstract approved
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This thesis considered current approaches to describing landscape pattern, identified scale issues associated with defining objects, and explored techniques to reliably group elements based on land cover as represented by satellite imagery. It was recognized that there is an important need to develop tools that can be applied using remotely sensed data to objectively identify landscape features at multiple spatial scales. The thesis focused on the potential for the use of specific digital image processing techniques to objectively generate multi-scale landscape heterogeneity models from Landsat Thematic Mapper (TM) satellite imagery. An approach using Difference-of-Gaussian (DoG) scale-space filters was used to process TM satellite data, transformed into the Normalized Difference Vegetation Index (NDVI), to define discrete landscape units across a range of scales.

A series of Difference-of-Gaussian filters, with standard deviation (σ) pairs of 0.9 and 1.1, 0.8 and 1.2, and 0.7 and 1.3, was applied to TM data. Results were compared against published ecoregion classifications and aerial orthophotography. These comparisons showed that the applied filters failed to accurately define landscape elements at a range of spatial scales. Filter size was found to be highly sensitive to the resolution of the image and object boundaries were maldelineated when complex boundary combinations were encountered.

A modified approach using Gaussian/Difference-of-Gaussian or Gaussian/Laplacian filter combinations and an alternate approach of watershed segmentation were recommended as potential techniques to test in further study. Future study should also include statistical approaches to aggregate zones and relate delineated zones to an actual, on-the-ground physiognomic classification scheme.

Multi-spatial Scale Representation of Landscape Transitions Using Landsat Thematic Mapper Data and Scale-space Filters

by
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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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Dale R. Lindeman, Author

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INTRODUCTION

OVERVIEW

Patterns, from both natural and human influence, are observed on landscapes at many levels; as an abrupt boundary between native grass pasture and oak woodland, as groupings of pasture, agricultural fields, farmstead and woodlots, or in the broad distribution of rural, urban, and forest areas. At each of these levels the pattern at the same geographic location can be described differently. It may be described very specifically as native grass pasture because the observer is close enough to discern what species of grass is present. Or it may be described simply as pasture, because grass species cannot be discerned because the observer has moved further away in order to include other nearby areas in the observation. In moving away yet further, the observer cannot differentiate pasture from other agricultural fields with any certainty and must therefore apply a general description of "rural". In addition to recognizing and describing patterns, we can associate particular processes with each distinct area and draw relationships between the areas identified.

Landscape patterns are not necessarily obvious and distinct areas cannot always be identified as in the examples above, particularly under predominantly natural conditions. In a forest stand of trees of various species and age classes, there may not be a definitive way to divide the area into groups. Additionally, direct observations cannot be made over very broad geographic extents. Other sources such as aerial photography or satellite image may be required. In such cases, the resolution of the imagery may be coarse and elements, such as trees for example,

cannot be identified. The observer must identify the object based upon the interpretation of tones, colors, and relationships between areas on the image, and what is known to actually exist on the ground. Reliability in interpretation, as determined through either the interpreters own ability or clarity of the data, influences the accuracy with which elements are grouped and areas identified.

In landscape studies, investigations into relationships between pattern and process can be undertaken at any level (scale of observation) and the quality of the data reflects directly on the study results. This thesis considers current approaches to describing landscape pattern, identifies scale issues associated with defining objects, and explores techniques to reliably group elements based on land cover as represented by satellite imagery.

BACKGROUND

Vegetation distribution is a primary landscape characteristic used to describe landscape pattern and is typically represented as a mosaic of differentiated landscape units (i.e., patches). Landscape units are defined as rule-based aggregations of landscape elements into predetermined categories. For example, in a forested landscape, trees are landscape elements that may be categorized into discrete landscape units as stands using rules based upon species composition, canopy characteristics, and age class. Collectively, the discrete landscape units form the landscape mosaic. Depending upon what criteria were used in defining landscape units, each discrete unit can be described as a product of natural disturbance, anthropogenic influence, actions of biotic agents, distribution of climatic and edaphic factors, and temporal fluctuation (Forman and Godron 1981, Pickett and White 1985). Spatial pattern in a mosaic, therefore, is an expression of a variety of scale-dependent processes with resultant patterns emerging from a complex of interactions (Turner 1989).

Specific processes and associated patterns can be assigned to spatial and temporal domains (Schumm and Lichty 1965, Allen and Hoekstra 1992, Delcourt and Delcourt 1992). Though such domains do not have definite bounds, Delcourt and Delcourt (1988) provide a framework for definition. The mesoscale space-time domain is described as spanning 500 years to 10,000 years and ranging 1 km^2 to 10,000 km^2 in geographical extent. In this space-time domain, dynamics can be explained by disturbance regimes which shape the landscape mosaic. The mesoscale domain is bounded by the microscale (1 year to 500 years and 1 m^2 to 1 km^2) and the macroscale (10,000 years to 1,000,000 years and 10,000 km^2 to 1,000,000 km^2) domains. Dynamics at the microscale involve individual plants or dynamics within plant patches. Dynamics at the macroscale are driven by regional or global environmental changes. In practice, no distinct boundary can be drawn, only approximated over a range of temporal and spatial scales. Identifying discrete transitions between domains is further complicated when patterns attributable to processes at one scale superimpose on patterns within other domains. Natural disturbance such as wildland fire can largely obliterate pattern that may have developed over time and historical condition or legacy can influence or drive subsequent process and pattern. Additionally, landscape pattern (particularly from climate driven processes) is often mitigated by abiotic variables and vegetation life histories and responses (Walter 1984, Neilson 1987, Neilson et al. 1992).

Describing landscape pattern by means of a landscape mosaic requires that heterogeneous elements at a fine-scale be organized into relatively homogenous areal units to describe heterogeneity at coarser scales. Two important properties of landscape heterogeneity are therefore the landscape element itself and the transition between landscape units within and across scales in space and time. These transitions can be termed intra- and inter-scale transitions. Intra-scale transitions between landscape units relate to what has been described as ecotones; scale is held constant and distinction between landscape units is defined as either abrupt

boundaries or as a zone of change between the landscape units. Inter-scale transitions emerge as units are described differently when scale changes, even though geographic location may remain constant. The inter-scale transition is, in part, a function of resolution or scale of observation, which can determine how the individual elements are described and organizational units defined (Allen and Hoekstra 1992). For example, the boundary between biomes could be described as an abrupt division based on the identity of two different and separate regions (Crumley 1993), a patch mosaic of microhabitats in areas of complex topography (Neilson et al. 1992), or simply the density of a single species (Milne et al. 1996). These examples provide three separate representations of an intra-scale transition (i.e., a biome boundary), illustrating how a specific geographic location can be described at specific resolutions based upon the scale dependent definition of elements and units. At the finest scale in these examples, individual trees are elements that are aggregated into canopy density units and compared against a background of grasslands. At a coarser scale, a variety of species constitute elements aggregated into habitat units. And finally at the coarsest scale, vegetation groups (or habitat patches) are the elements that are aggregated to define regional units. Although the same geographic location is represented, the geographic extent (study area) and grain (the minimum resolvable element) increase with a consequent decrease in resolution. This relationship between grain and extent dictates that element and unit definitions are scale-dependent. The evolution of elements and units with change in scale represents inter-scale transitions. The above three examples chart inter-scale transitions from species, through habitat patches, to expansive regions, with other potential permutations in-between, as grain and extent change.

An alternate description of the ecotone (intra-scale transition) is the ecocline. This landscape model recognizes the difficulties in delimiting distinct boundaries to define individual landscape units or even zones of transition. The ecocline is a

gradient of continuous change within which no homogenous landscape unit can be defined without subjectively setting threshold values for membership in a specific unit (Curtis and McIntosh 1951, Whittaker 1956). Therefore, attempts to organize spatial heterogeneity into homogeneous units within an ecocline can be of unlimited permutations. The primary models for representing ecotones assume thresholds across a range of variability to facilitate differentiation of elements and assignment to categorical groups (landscape units). Apart from applying rules to differentiate the co-occurrence of elements into distinguishable groups, what differentiates ecotones from ecoclines is how these two models are described across spatial scale. Ecoclines are described primarily by gradient analysis. The elements measured in gradient analysis are individual plants, cataloged by species within quadrats of variable size and sampled along transects which, in turn, vary by length and inter-sampling distance (Whittaker 1967). While the entity being measured in gradient analysis remains constant, the extent of transects can vary to exceed hundreds of kilometers (Ohmann and Spies 1998). As such, the ecocline appears invariant across scales (i.e., resolution, or relationship between grain and extent, does not change) and does not fit neatly into categorizations of intra- and inter-scale transitions. The scale of observation does not change and observations are not spatially explicit but rather relate to a generalized complex of environmental gradients (Billings 1952, Whittaker 1956).

In contrast to the gradient model, the patch model is scale-dependent with the identification of landscape elements and aggregation into units highly dependent on the changing relationship between the grain and extent of the data. An image from remotely sensed data can reveal distinguishable regions at broad spatial extent, suggesting measurable differences or thresholds can be quantified objectively (Figure 1a). Visually we realize this through the ability of human vision to organize patterns of tone, texture, and context to differentiate the scene into separable, relatively homogeneous units.

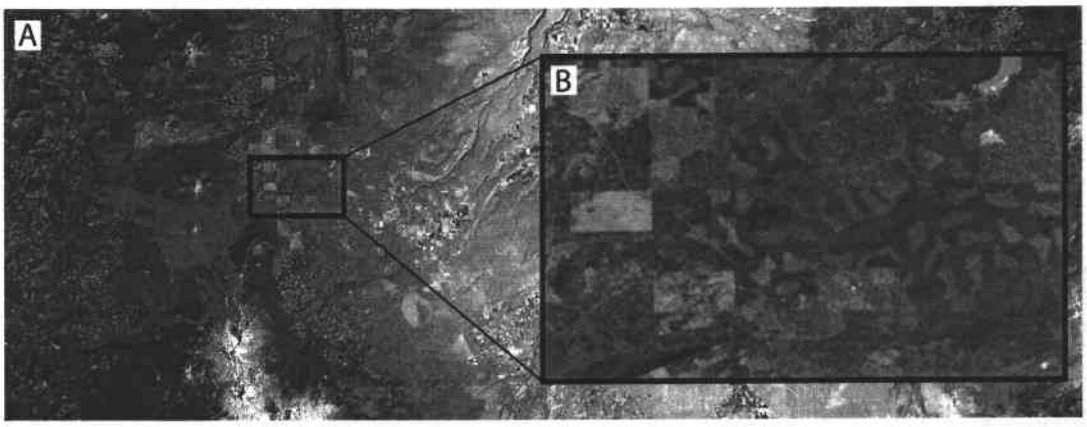

Figure 1: Example image. Visual perception of picture elements changes at varying scales.

Homogeneous regions can be assembled while still recognizing the heterogeneity within regions. Yet organization of picture elements (pixels) is very much scale dependent and the combination of increased resolution and decreased context (i.e., change in grain and extent) changes perception. What appears as a region or distinguishable boundary at one scale may become less distinguishable at another and other patterns emerge (Figure 1b). Therefore, in the context of describing landscape units, inter-scale gradients or transitions may be represented by organizing pixels at varying resolutions.

Remotely sensed data, in the form of aerial photos and satellite imagery, are important information sources for landscape ecology studies at many different scales. However, landscape metrics or statistics require that these forms of data be translated (classified) into a thematic format, either categorical or binary. Classification of aerial photographs relies on the interpreter's ability to visualize pattern and segregate the image into landscape units based on a predetermined classification scheme (Lillesand and Kiefer 1994). This process can be highly subjective. Distinct groups may be defined, however, there can be wide differences between where interpreters delineate boundaries and the amount of detail they

apply to the boundary shape (degree of crenulation). Aerial photographs can be of very high spatial resolution and result in extremely detailed delineations. Satellite imagery is classified by processing the data using algorithms and statistics (Jensen 1996, Lillesand and Kiefer 1994). Computer processing makes classification more replicable and consistent than aerial photo interpretation, however, pre-processing decisions determine the number of classes and the statistics applied in combining pixels into classes. These pre-processing decisions can arbitrarily affect the outcome and make image processing almost as subjective as aerial photo interpretation.

The landscape elements defined in both aerial photo interpretation and digital image classification represent only one possible outcome of combining data into a class. The classifications are made for one single spatial scale and lack inter-scale dimensionality. Additionally, the classifications tend to subjectively de-emphasize heterogeneity in the image or scene and thereby introduce bias with the use of the final product for statistics or deriving landscape metrics.

OBJECTIVES

Apart from reviewing definitions of the structure and nature of landscape transitions, the above discussion suggests the need for objective methods that allow for multi-scale analysis of digital image data in investigations of landscape transitions. Ecotones can emerge at all scales, and the nature of transitions between scales can provide useful information to identify and characterize landscape boundaries. The primary purpose of this thesis is to explore the potential for the use of specific digital image processing techniques that can objectively generate multi-scale landscape heterogeneity models from Landsat Thematic Mapper (TM) satellite imagery. A Difference-of-Gaussian (DoG) scale-space filter will be used

to process TM satellite data, transformed into the Normalized Difference Vegetation Index (NDVI), to define discrete landscape units across a range of scales. The DoG filter, applied in a moving-window analysis, will evaluate each individual pixel (element) based on a summary of its surrounding neighborhood and the processed image will be segmented into units through edge detection. This technique will be applied iteratively to generate landscape units at increasingly generalized (i.e., coarser) resolutions.

The focus of this thesis is describing vegetation pattern, on the basis of NDVI, across the macro- and meso-scale space-time domains. Temporal scale is not addressed in this investigation; only spatial scale is considered. Elements, 30 meter^2 in size, will be aggregated into units or zones representing vegetation patches and then organized into larger geographic regions. This study is not an investigation of landscape dynamics per se; vegetation is only one component used in the study of landscape pattern and dynamics. Other components such as climate, topography, soils, and disturbance regimes are not included in this study but all have important influence on the distribution and pattern of vegetation. Findings from this study could contribute to providing objective vegetation datasets for investigating relationships among these various components.

The processed results will be compared against established, regional delineations of biome boundaries and medium-scale (1-meter pixel size) aerial orthophotography. For a multi-scale technique to be useful, the technique must be able to successively aggregate pixels into meaningful landscape units at a range of scales. The effectiveness of the technique will be assessed by: 1] ability to define landscape elements at a range of geographic extents; 2] ability to describe or characterize specific transitions; and 3] sensitivity in differentiating scale-related pattern in relation to broad-scale boundaries.

LITERATURE REVIEW

SCOPE

An investigation into modeling landscape features should consider current concepts and models along with appropriate and available technologies. At least a century of documented studies have been devoted to conceptualizing and describing the dynamics and distribution of vegetation on the surface of the earth (Wallace 1892, Merriam 1894, Adams 1905, Gleason 1926, Clements 1936, Billings 1952, Curtis 1959, Whittaker 1967, Forman and Godron 1981, Gosz and Sharpe 1989, Delcourt and Delcourt 1992, Neilson et al. 1992, Ohmann and Spies 1998, Urban et al. 2000). Scientists have successively refined conceptual models by incorporating environmental interaction, both biotic and abiotic, at multiple temporal and spatial scales (Cowles 1901, Transeau 1905, Billings 1952, O'Neil et al. 1986, Neilson 1991, Allen and Hoekstra 1992). Physical models were developed for landscape description, resource management, and research applications (Forman and Godron 1981, Neilson 1991, Gosz 1993). These developments evolved along with a wide variety of methods and metrics to study landscapes in an objective and rigorous manner. The introduction of computers, geographical information systems (GIS), and remote sensing technologies has brought landscape study to where it is today. This literature review outlines the evolution of landscape concepts and models, describes a variety of methods and metrics that are applied in landscape studies, provides a survey of remote sensing techniques used in processing satellite imagery, and presents what previous investigators have envisioned as future research goals.

LANDSCAPE CONCEPTS AND MODELS

Complexity in nature and science is easier to study and comprehend when organized or categorized based upon perceived similarities or hierarchies. As such, the diverse distribution of species on the surface of the earth has long been described in terms of relatively homogeneous regions. Over the last century scientists have developed theories and models to represent landscape features at multiple scales. These models became more detailed as technology advanced and measurement of environmental variables became more sophisticated and precise.

Environmental Constraints and Dynamics

Historically, distribution patterns of broad geographic extent were formalized as Zoological Regions (Wallace 1892) or Life Zones (Merriam 1894) with a particularly acute interest in why discontinuities, or the boundaries to these zones or regions, occurred where they did. The distribution patterns were related to climate in general; temperature and precipitation served as one basis for demarcating the major zones. However, in observing that isotherms did not exactly coincide with vegetation belts in the northern hemisphere, Merriam (1894) recognized that temperature in itself was an inadequate descriptor for boundary location and postulated that temperature during the periods of the reproduction and development of a species was a more accurate descriptor to more precisely locate the exact latitudinal extents. Nevertheless, a highly deterministic climatic climax concept was the predominant model for vegetation distribution for many decades (Clements 1905, 1936). Yet, it was recognized by many that boundaries were not static. Boundary dynamics were primarily described as fronts of plant migration and dispersal following broad scale climate change or periods of glaciations, though others observed that the boundaries did not necessarily represent climatic

constraints. Several scientists hypothesized that plant migrations had not yet adjusted to the change in more recent climatic conditions (Adams 1902, 1905, Griggs 1934a, 1934b). With respect to landscape boundary dynamics, Cowles (1901) in particular describes "vertical zonation" as a historical legacy where one plant association is superimposed upon the preceding one and introduces the term "zones of tension", inferring dynamic transitions where regions overlap as a function of boundary migration. In addition to climatic constraints, mechanical factors such as grazing (Cowles 1901), fire (Bessey 1905), wind or slope instability (Griggs 1938, Cairns 1998), and geomorphic processes (Swanson et al. 1992) add to the complexity in regional boundary definition and location. Walter (1984) suggests there are basically five factors that determine growth and development of plants: heat or temperature conditions, water or hydrature conditions, light intensity and length of day, various chemical factors (nutrient or poisons), and mechanical factors (fire, grazing, trampling, and wind).

Broad-scale climate-biotic relationships at biome boundaries have been the primary focus of a majority of landscape boundary studies due to interest in climate change and its potential consequences (Holland et al. 1991, Hansen and di Castri 1992). Several recent papers focusing on the potential responses of biomes to climatic change relate climate to changes in vegetation over time, suggest patterns that could hypothetically emerge, and propose how boundaries might be located on the ground and change predictively detected through space (Gosz and Sharpe 1989, Neilson 1991, Turner et al. 1991, Neilson et al. 1992, Neilson 1993). Potential outcomes modeled under several climate change scenarios suggested that a relatively slow climate change could induce a visually-evident shift in ecotone location, in which direction of shift could be discerned, whereas rapid or drastic changes in climate could result in catastrophic disturbance causing the ecotone to disappear for a period before re-establishing in another location (Neilson 1993). These scenarios address both expectations for change within ecotonal zones and

large-scale events affecting the entire region. This is otherwise described as 'ecotones in space' where species sort out in response to climatic-biotic interaction on a local scale as opposed to 'ecotones in time' in which climate change places entire regions outside the physiological limits of the resident vegetation (Neilson 1991). This suggests that, with respect to the effects of climate change, an emphasis on studying and monitoring currently perceived boundaries might lead to an important dynamic being overlooked.

Scale in Space and Time

Though similarities, or relative homogeneity, can be defined over broad geographic expanse, elements comprising or influencing the regions are not distributed evenly (either within time or space) across a region and patterns of heterogeneity emerge at finer scales and narrower geographic extent. Changes in scale usually involve redefinitions of homogeneity and heterogeneity (Meentenmeyer and Box 1987). No single finite scale can be identified for any one particular phenomenon; transitions occur over a range of spatial and temporal and scales and depend on how the entity is defined (O'Neill et al. 1986, Allen and Hoekstra 1992). Additionally, relevance depends on perception of the landscape at scales appropriate to the reference organism (Allen and Hoekstra 1992, McIntyre and Hobbs 1999).

Early in the twentieth century the "physiographic" approach recognized scales or hierarchies of influence in which climatic factors such as temperature and precipitation were the primary determinants of plant distributions over large geographical extents and local differences were driven by site factors including soil characteristics, slope, and light (Cowles 1901). The most important of the site factors was topography in terms of drainage and conditions under which soils were

formed. During this same period the "geographic" approach emphasized gradients and the comparison of climatic factors. Comparisons were drawn between the center of a species' distribution where conditions were most favorable for a species' development, and the margins of the species' distribution where conditions were postulated to be less favorable (Transeau 1905). The schools of physiography and geography were, in part, bridged by what has been referred to as 'Blytt's concept' (see Griggs 1914):

> "In general, a species grows in the largest numbers at its center of distribution, since the climatic conditions favor it most highly. Near its areal limits, it can grow only in those areas that resemble most closely in an edaphic way the climatic features at the distribution center."

Allen and Starr (1982) generalize boundaries as natural surfaces, relative to the structure or function of interest, and place the surface at the portion of gradient so steep as to be considered a step. This expresses boundaries in terms of system dynamics, as locations where the rate of ecological transfers change abruptly in relation to those within the relatively homogeneous units (Wiens et al. 1985, Gosz and Sharpe 1989). Landscape models typically translate the increase in spatial variation across an ecotone as a physical pattern of increased numbers of small patches relative to patterns more distant from the ecotone (Neilson 1991, Gosz 1993). These patterns arise from threshold response to variations in soil, micro-topography, and geology with pattern size reflecting areas (geomorphic facets) that fall within the physiological limits of species (Neilson 1993). The net result of pattern within an ecotone is increased heterogeneity as compared to the core of the region (Neilson 1991) and can be described quantitatively with measures of gamma- and beta-diversity (Whittaker 1967, Delcourt and Delcourt 1992, Neilson 1993). Walter (1984) describes the environment of plants as an ecotope that is defined by habitat factors, and biotope that is defined as the place on which they grow. Therefore, as the ecotope changes, the biotope can compensate for the

change so the habitat conditions remain relatively constant. Walter (1984) also draws the distinction between ecological and physiological optimum; conditions under which a species occurs most abundantly in nature and the conditions under which it thrives that are controlled.

Hierarchies of environmental constraints are hypothesized to exert dominant influence at specific spatial and temporal scales. These scales can be associated to landscape features, across a hierarchy of ecotones characterized as biome, landscape, patch, population, and plant ecotones (Gosz 1993). With this consideration, an ecotone is defined as:

> "a zone of transition between ecological systems, having a set of characteristics uniquely defined by space and time scales, and by the strength of the interactions between adjacent ecological systems" (di Castri et al. 1988).

Ecotones can be described for any hierarchical level, and in this definition attention is given to the interactions and connectivity within or across systems. Landscape models, therefore, reflect the theory that patterns and their cause and effect depend on the spatial and temporal scale over which the process is examined (Schumm and Lichty 1965). Large-scale patterns are related to large-scale processes and constraints are arrayed hierarchically on the basis of spatial and temporal extent of influence. Delcourt and Delcourt (1988) define time-scale domains linking temporal and spatial scales with associated environmental disturbance regimes, biotic responses, and vegetation patterns. Though the domain definitions provide a general framework within which to study landscape dynamics, there can be no distinct boundary between domains. Edaphic conditions can be considered as biotic-geomorphic interactions that have occurred over a broad range of time scales encompassing geologic time, as in landform and soils formation. However, edaphic conditions are equally influenced through relatively frequent disturbance

regimes such as flood, slope failure, or frost heaving (Swanson 1980). And though hierarchies dictate that past states affect current states, relationships between an entity and place can be interactive. Vegetation and disturbance regimes influence landform and soil development, while landform and soils influence plant distribution and disturbance regime (Melton 1957, Swanson 1980). These biotic interactions with geomorphic and fluvial processes are particularly evident in mountainous areas of complex terrain as revealed by orientation of patches and ecotones with respect to slope, fire scars across slope, and landslides along slope (Swanson et al. 1992). Stream networks also play important roles in the development and distribution of vegetation and plant communities (Swanson 1980). Overlap between space-time domains also occurs where processes at several spatial and temporal scales influence the character of a single landscape feature. It has been demonstrated that both long-term climatic patterns and topography influence the characteristics of the biome (Neilson 1991, Neilson et al. 1992). The transitions between biomes are driven by seasonal oscillations in large scale air mass dynamics while characteristics of the ecotone, within the larger-scale transition, are often associated with variability in weather patterns and local variation in topography (Neilson 1987, Neilson et al. 1992). Diverse patterns arise from these multi-scale interactions based on how the range of temporal patterns coincides with the life cycles of the plants (i.e., the period over which a species reproduces, establishes, and thrives) and the spatial scale at which the pattern is observed. This model is described as a mix of wavelengths of low- and high-frequency in both the biotic and abiotic realms that can be in or out of phase (i.e., association or non-association of pattern and process).

The complexities between various scales, processes, and emerging patterns are difficult to categorize into discrete realms of spatial and temporal scale. Gosz (1991) found it to be particularly challenging to sort fine-scale process (local factors) from pattern evolving from more broad-scale constraint and dynamics.

Though it is generally accepted that levels of organization in nested hierarchies can be linked by changes in grain and extent of the observation, the problem with scale becomes a decision of how to correctly aggregate elements from fine-scale. Statistical or mathematical aggregation of fine-scale processes to describe large-scale processes is not a simple matter. Processes exhibit non-linear relationships, making rigorous statistics, correction, and calibration a necessity (Rastetter et al. 1992). In ecological terms, the problem is one of understanding how fundamental entities evolve from the combination of numerous complex, fine-scale entities into a minimal structure with attributes or properties and interactions that define systems (Pickett et al. 1989, King 1990).

Physical Models and Feature Representation

In the early 1990's, the prevailing concepts of vegetation and the distribution of species postulated that plant species were deterministically sorted into specific species-site/species-species associations (Clements 1905, 1936). In contrast, recognizing the multitude of factors that could potentially influence the dispersal and distribution of plants, other scientists argued that communities intergrade and the factors that drive or constrain the dynamics are complex and not easily interpreted (Gleason 1926, Whittaker 1951). As vegetation surveys became more rigorous and quantitative, applied studies using gradient analysis within "tension zones" suggested that species distributions could not be definitively assembled into higher levels of organization as discrete units (Curtis and McIntosh 1951, Whittaker 1956, Curtis 1959).

In gradient analysis, the frequency distribution of a species shows population centers along an environmental gradient that could indicate optimal conditions for growth and development; however, the gradual overlap of species provides no

objective means to identify ecotones (Whittaker 1967). The environmental gradient is defined as the total range of environmental factors, including effects of other species, considered to be representative of the total environment and its cycles (Billings 1952, Whittaker 1956). Factors within the gradient such as temperature, growing season, precipitation, humidity, wind velocity, atmospheric pressure, and evaporation are interrelated. Therefore, though a strong correlation may exist between vegetation patterns and a particular factor, the relationships are more typically due to many influences. Spatial patterns in vegetation distribution are revealed, but a correlational approach cannot explain why or how the observed patterns develop (Neilson 1993). Gradient analysis at least shifted research emphasis from classification to the analysis of relationships between vegetation and environment. However, an areal representation of landscapes as being composed of discrete units or elements prevailed as the dominant model.

The landscape has been depicted as patches, dynamically related to each other within a "space-time mosaic" as constituents of a community (Watt 1947). The concept of the space-time mosaic held that though orderly change could occur at a given time or place (patch), the mosaic would remain essentially the same (i.e., a state of equilibrium). Subsequent representations of the patch model in landscape and ecological study minimized the concept of a steady state. Disturbances external to the community, including human influence, were considered to have equal importance with internal processes as agents of change (Forman and Godron 1981, 1986, Pickett and White 1985). The patch model can carry definitions that are very generalized relative to the system being studied or described and attach no particular metric (Pickett and White 1985). Forman and Godron (1981, 1986) define the structural components, or landscape elements, as patches of several origins, corridors of four types, and a matrix. Patches are defined as originating from transient or short-lived fluctuations (ephemeral patch), localized disturbance (spot disturbance patch), small areas left undisturbed surrounded by large-scale

disturbance (remnant patch), planted or cultivated areas (introduced patch), and relatively permanent resources (environmental resource patch). Corridors are differentiated into four types as line or strip corridors, networks (line or strip corridors that loop), and stream corridors. The matrix is the dominant, encompassing landscape element within which patches and corridors reside. Landscape dynamics and fluxes therefore involve patch-matrix, patch-patch, patch-corridor, and corridor-matrix interactions (Forman 1981). This complex landscape model is often reduced to a binary model of patch-patch interactions in which patches represent habitat within an inhospitable environment, as represented by the matrix (MacArthur and Wilson 1967, Harris 1984).

The complexity of landscape form and structure can also be described through equally complex classification schemes for boundary or edge types (e.g., curvilinear, tiny-patch, and linear), edge anatomy (saum, mantel, and veil), patch perimeter or surface (e.g., shape, crenulations), and patch-corridor-matrix configuration (Forman and Moore 1992, Forman 1997). Such descriptions and characterizations relate to observations of biotic diversity along edge habitats (Leopold 1933), suggest interaction among adjacent ecosystems, but appear to assume that edge structure and function are the same across all spatial scales (Forman 1997). As such, edge is a structural element that can influence the characteristics of the patch with "edge effects" of sunlight or wind penetration into the patch changing habitat conditions, creating "edge" and "interior" habitat (Harris 1988). A "Peninsula effect" is also described for interdigitated patch-corridor-matrix configurations (Forman 1997).

Other investigators provide more generalized, or otherwise less rigid system- and scale-dependent boundary models (Pickett and White 1985, Brunt and Conley 1990, Gosz 1992, Neilson 1991, 1993), applying the concept of ecological neighborhood (Addicott et al. 1987). Landscape features that are described in

terms more relative to scale and the specific entity, function, or process under study are more meaningfully referenced to the species perception of the landscape (Turner 1989, Milne, 1990, McIntyre and Hobbs 1999).

LANDSCAPE METRICS AND GEOGRAPHIC INFORMATION SYSTEMS

General Types and Descriptions of Landscape Metrics

There are various landscape metrics to quantify heterogeneity within landscapes, each with particular capabilities suited for specific applications or data types (Gustafson 1998). Patch-based metrics can be organized into three broad categories: landscape composition, spatial structure and configuration, and fractals. Methods using point data are categorized as geostatistics or spatial statistics (Turner et al. 2001). Examples of landscape composition metrics include frequency, proportion, and measures of richness, diversity, and dominance. Composition metrics typically are not spatially explicit but are generally applied as summary statistics. However, composition metrics can be stratified within a landscape to facilitate spatially explicit analyses (Moser et al. 2000). Spatial structure and configuration metrics that include indices such as size, shape, connectivity, and fractal dimension can likewise be applied as general descriptive statistics for an entire region or in a spatially explicit manner as metrics relative to other landscape elements or features. Though most structure metrics are generally derived from patch models, transect data can be used in calculating patch size (Greig-Smith 1983) and fractals (Burrough 1983). However, the resulting statistics summarize the transect data and are not spatially explicit. Methods within the category of spatial statistics do not assume patch structure, using sample data (point data) to calculate landscape metrics to detect pattern.

Ritters et al. (1995) evaluated 55 metrics and found 29 to be highly correlated. Through principal component analysis, they found that six factors explained 87% of the variation in the 36 landscape metrics. The axes were termed average patch compaction, image texture or edge-type frequencies, average patch size, contagions, perimeter-area fractal, number of attribute classes, and large-patch density-area scaling. Other reviews of landscape metrics describe how each method addresses different statistical questions, might have different sensitivities across scales, or may be appropriate only for particular applications, thus making it necessary to use a combination of methods for complete landscape analyses (Turner et al. 1990, Cullinan 1992). Turner et al. (1990) suggest that semivariogram, spectral analysis, and time series analysis are appropriate for detecting scale of landscape for regular patterns whereas moving window analysis is appropriate for use with irregular patterns.

Despite the burgeoning toolbox of landscape methods and redundancy of metrics, several scientists have expressed a need for the development of indices that measure spatial pattern (Gustafson 1998), particularly techniques for ecotones (Turner et al. 2001), and image processing for edge detection (Fortin et al. 2000). There is a general perception that most landscape metrics deal with patch models and that point-data acquisition and analysis should be designed so as to be more compatible with ecological theory (Gustafson 1998). Point data analysis, using field-gathered data, appears to be widely used in describing pattern. The application of categorical and binary data in landscape analysis has been more problematic and addressed in part using fuzzy set theory (Zadeh 1965).

Applied Methodologies in Landscape Boundary Studies

Gradient analysis is applied to study vegetation patterns based on how species are distributed relative to environmental gradients and one another (Whittaker 1956), and is invariably conducted using field-gathered data. The field sampling effort can be as intense as hundreds of meters or less (Phillips 1985, Dale 1988), more typically across transects of thousands of meters (Whittaker 1956, 1960, Whittaker and Niering 1965a, 1965b, Urban et al. 2000), or area plots across an entire state (Ohmann and Spies 1998). The more recent applications of gradient analysis study multi-scale aspects of vegetation and environmental gradients. Ohmann and Spies (1998) compared regional distributions of vegetation based upon broad-scale climate variables against local topographic factors and fine-scale precipitation surfaces (see Daly et al. 1994). Urban et al. (2000) similarly used a physical template of 'slope facets' at varying geographic extents for scale comparisons. Both studies found scale-dependent relationships between environmental gradients and biotic response.

Other approaches to analyzing transect data for edge detection include variations of moving window analysis. The dimension of the window is defined as segments of a linear transect, or a grid of regular- irregularly-spaced area plots. The simplest form of moving window compares and summarizes values within the window. Using transect data and a simple moving window analysis, vegetation patterns could be differentiated as primary edges, overlap, primary patches, and secondary and tertiary patches (Brunt and Conley 1990). Effectiveness of pattern detection in such analyses depend on the ability to detect large-scale variation (patch edge) from fine-scale noise, and are facilitated by varying the window size. Split-window analysis divides the window in half and compares adjoining values for boundary detection (Webster and Wong 1969, Ludwig and Cornelius 1987). The technique called lattice wombling measures within-neighborhood differences for 3-by-3 pixel

windows and is applied to regularly spaced plot data (Fortin 1994). A variation on calculating neighborhood values is provided by triangulated wombling for irregularly spaced data (Fortin 1994). Lattice and triangulated wombling were applied to species presence/absence data to detect ecotones. Moving window techniques can also be applied to aerial photography or satellite imagery and categorical or binary data (Johnston et al. 1992).

The semivariogram measures rate of change over a succession of lags and has primarily been used to determine "ecological scale" or sample size, a range over which spatially independent data can be collected (Curran 1988, Carlile et al. 1989). The rate of change can also be used to characterize shapes within an area (Woodcock et al. 1988a). The sill, where rate of change levels, was found to relate to the density of objects and range, and distance of the sill from the origin was associated with the size of the feature when applied to a binary image of theoretical objects. When applied to scanned aerial photographs, interpretation of the semivariogram is more problematic, due to issues of image resolution and periodicity or anisotropy in the data (Woodcock et al. 1988b).

REMOTELY SENSED DATA

Remote sensing has become a valuable tool in landscape ecology studies because it provides extensive and exhaustive coverage of landscapes and biogeographic regions in a multi-dimensional format. A wide range of techniques takes advantage of this multi-dimensionality in resolution, temporal scale, and spectral values to characterize landscapes and measure biophysical characteristics.

Digital Image Processing Techniques

Common techniques applied in landscape studies include image classification and spectral or spatial transforms. Image classification is the process of extracting information from remotely sensed images by converting the spectral data into descriptive labels that categorize distinguishable features in the image. This process is 'image-centered' in that the primary interest is to create a map of earth surface features. Spectral transformation of digital images is the process of redefining spectral data through band ratioing, principal components analysis, and contrast stretching. The purpose of spectral transforms is generally to enhance the interpretability of the image without adding any new information. Spatial transformation alters the image space in modulating spatial frequency to either emphasize or de-emphasize features within the image.

Image Classification

As related to landscape ecology, the image classification procedure requires that every location on the ground is given a unique label to categorize that landscape on thematic maps using the techniques of supervised or unsupervised classification. Supervised classification involves three basic steps: training, classification, and output (Lillesand and Kiefer 1994). In the training stage, representative areas for each land cover type are selected to identify the defining range of spectral values for sampled pixel groups. A feature cannot be characterized by a single spectral value, but rather requires a group of data values that most accurately portray the feature. The training area should be a homogenous sample of the respective class but, at the same time, include the range of variability for that class by using more than one training site per class. There is no guarantee that classes will actually be distinguishable from one another based on spectral separability, requiring that some

classes be either dropped or combined. The data group becomes the 'class signature' and is applied in the classification stage through discriminant functions to assign each pixel a corresponding class label value. The output stage is the actual production of the map. Unsupervised classification does not use a training stage to determine class signatures but rather uses spectral classes as determined by their spectral separability (Lillesand and Kiefer 1994). Spectral classes are determined through clustering algorithms and, once applied to the image, are then visually interpreted to assign descriptive class labels.

In some respects, clustering routines are highly subjective and can be considered data mining (Townshend 1981a, Allen and Hoekstra 1992). Unsupervised classification is based on the values of the pixels more than spatial organization. The resulting spectral classes may not represent classes in ways that are intended, in which case the clustering algorithm is modified to decrease or increase (i.e., combine or subdivide) the number of resulting classes. Supervised classification is similarly limited in that classes are determined by specific spectral combination in feature space. In either classification technique, class data signatures do not always correspond well to feature characteristics on the ground. Contextual information, such as location and time of image acquisition, can add extra image contrast to enhance classification (Townshend 1981a). Oetter et al. (2000) used multi-date imagery to refine their classification scheme by distinguishing land cover classes based on known phenological characteristics of natural and agricultural systems. Another contextual enhancement is the physiographic approach of exploiting interrelationships between surface landform, geology, climate, soils, water, and vegetation (Townshend 1981b).

An alternative to unique or thematic labels is to assign likelihood of membership to a class through fuzzy classification (Jensen 1996). Fuzzy set theory represents imprecise objects in qualitative terms (Zadeh 1965) as grades of membership in a

set. Applied to image classification, likelihood values represent the relative proportions of each category within the pixel.

Spectral Transformation

Band ratioing and principal components analysis in digital image processing are used to reduce data dimensionality, produce vegetation indexes, and generally provide unique information that was not available in any one single band (Jensen 1996). Ratio transforms have the added benefit of reducing the effects of topographic shading (Schowengerdt 1997). One particularly common ratio transform, the normalized difference vegetation index (NDVI), has been used for many years to monitor vegetation cover from multispectral satellite data as an indicator of relative biomass and greenness. The NDVI for TM data is calculated as a normalized ratio between the visible red and near-infrared regions of the electromagnetic spectrum with the following formula:

$$NDVI = (Band\ 4 - Band\ 3) / (Band\ 4 + Band\ 3)$$

Chlorophyll strongly absorbs visible light in the red wavelength and reflects near-infrared light. Therefore, vigorously growing, healthy vegetation will have a high NDVI value.

The "tasseled-cap" is another frequently used ratio transform, derived from principal components analysis. The three primary "tasseled-cap" components represent wetness, soil reflectance (unvegetated areas), and greenness (amount of vegetation present) (Kauth and Thomas 1976, Crist and Cicone 1984). The "tasseled-cap" transformation is normalized and therefore can be compared across separate databases or analyses to monitor developmental cycles in vegetation across

broad areas. Contrast enhancement is a form of spectral transformation that redistributes the brightness values using global functions (Schowengerdt 1997). The products from contrast enhancement are not used in analytical applications, but are purely for display purposes.

Spatial Transformations

Spatial transformations alter the image space by modulating spatial frequencies to either emphasize or de-emphasize features within the image. This is accomplished using convolution filters, Fourier transforms, or scale-space transforms. The basis for all these techniques is the decomposition of an image at different scales (Schowengerdt 1997). The convolution filter is a moving window passed over the image with an operation performed at each pixel location. The calculated value is assigned to the same coordinate as the coordinate for the center pixel of the window in a second image as output. Low-pass filters reduce spatial frequency and have the effect of smoothing the image. Low-pass filters are the simplest of the convolution filters and use such operators as mean, median, maximum, or minimum values of the neighborhood (Jensen 1996). The neighborhood is defined by the size and shape of the window and contains all pixels within the window. High-pass filters emphasize spatial detail and exaggerate local contrast. This family of spatial transforms includes edge and gradient filters. Edge enhancement filters emphasize the spatial detail, exaggerating local contrast to sharpen edges (Lillesand and Kiefer 1994), and are referred to as directional, gradient, or edge filters. The filters can operate directionally as emboss or compass direction or can be insensitive to direction as is the Laplacian operator (Jensen 1996). Non-linear edge enhancement operators include the Sobel edge detector and Robert's cross. Sobel's operator detects horizontal, vertical, and diagonal edges, enhances the center cell, and is typically used to create edge maps. Robert's cross operator is the

simplest gradient operator, using two masks and only 4 elements of the 3x3 window.

Fourier analysis, or synthesis, is a continuous function applied to the image. Fourier synthesis decomposes many scales, mathematically separating an image into its spatial frequencies (Jensen 1996, Schowengerdt 1997). Once decomposed, certain groups or bands of frequencies can be emphasized relative to others, and recombined to produce an enhanced image. The Fourier transform is used to remove periodic noise or restore images because noise information is easier to identify in the frequency domain than in the spatial domain (Jensen 1996).

Scale-space filtering decomposes and describes spectral frequencies with respect to scale. The wavelet transform is the most common scale-space filter used in processing satellite imagery in the earth sciences. Wavelet transforms are capable of decomposing an image at different scales with different or multi-resolutions (Schowengerdt 1997). Scale-space filters such as the Laplacian-of-Gaussian (LoG) and Difference-of-Gaussian (DoG) zero-crossing filters are used predominantly in fine-resolution image processing and machine or computer vision, and have not been widely applied in processing coarse-resolution digital imagery. The LoG filter uses the second derivative of a Gaussian function to indicate changes between negative and positive values, or the zero crossing (Schowengerdt 1997). The basic Gaussian convolution filter is circularly symmetrical; any cross-section through its center yields a weight profile that has the form of a Gaussian or normal curve. Using Gaussian filters of successive scale factors, it is possible to decompose an image into its constituent spatial components whereby high spatial frequencies correspond to small-scale structure and low frequency to large-scale structure. Local maxima are detected and can be linked across scales to describe structure at multiple resolutions (Crowley and Parker 1984).

Similarity between pixels, or groups of pixels, is a fundamental concept behind many image-processing algorithms. Texture analysis characterizes the spatial distribution of spectral values. The most common technique uses a co-occurrence matrix although a variety of approaches has been developed and tested (Haralick et al. 1973). Some refinements to texture analysis have been introduced that decompose the image into small units of local texture information, or texture units. These are analyzed against the frequency distribution of all texture units, or texture spectrum (He and Wong 1991).

Applications in Landscape Ecology

Much of the current research in landscape ecology uses the patch model to generate thematic landscape data using standard image classification techniques. Refinements of the thematic data are accomplished in several ways. One is to use a combination of vegetation maps with environmental variables such as geology, elevation, slope, and aspect. The spatial correspondence between these variables can enhance vegetation classification (Franklin 1987, Davis 1990). However, environmental variables do not correspond equally well in all vegetation types and their inclusion may not successfully classify an entire landscape (Frank 1988). Other studies classify and represent thematic data as probability surfaces. Likelihood and typicality probabilities (derived from modifying maximum likelihood algorithms) have been used to identify vegetation gradients between woodland and heath land (Wood and Foody 1993). Texture analysis was used to classify areas relative to a value for a specific forest type (Gulnick et al. 1993). The resulting classification indicates the relative composition at the margins of specific forest types. Fuzzy k-means classification produces similar results in pixels that are classified as having different levels of class membership that produces 'fuzzy' boundaries in various widths (Foody 1992).

Edge detection techniques have successfully produced edge boundaries for forest areas (Johnston and Bonde 1989, Fortin 1994) and soils (Webster and Wong 1969). These techniques are applied at fine-scales using field collected data. Applying edge detection to large-scale data requires that data first be categorized. As described above, techniques to classify remotely sensed data can be subjective and current techniques have not been adequate or satisfactory for landscape issues such as boundaries. Though various techniques have been applied in boundary detection, a need to develop new image processing approaches to characterizing ecotones is recognized (Fortin at al. 2000).

DIRECTION FOR FUTURE RESEARCH

Combining different scales of observations and their interactions with a focus on linkages between domains of scale has been recognized as an important research challenge (Meentemeyer and Box 1987, di Castri and Hansen 1992). Gosz (1993) recognizes a need to identify appropriate technologies to address interactions between adjacent systems as cross-scale influences and incorporate a multi-scale perspective in performing landscape studies at several scales (Gosz 1991). This has been expressed as a need to integrate the gradient approach with the patch perspective and define boundaries and change across scale (Pickett and Rogers 1995). Examining patches and mosaics across several scales of resolution is one approach to unifying the gradient and patch unit models. Investigating landscape dynamics using remotely sensed data across broad geographic extent has been particularly challenging. In the past, image processing has reduced ecotones to simple lines between homogeneous areas (Fortin et al. 2000). As our knowledge about natural phenomena has advanced, it becomes evident these simple models inadequately convey how landscape elements and the environment interact (Naveh

and Lieberman 1994, Burrough 1996). Current techniques for processing remotely sensed data can be subjective and have not been adequate or satisfactory for landscape studies. There is a serious need to develop new image processing approaches that focus on landscape dynamics and scale issues (Fortin et al. 2000). This thesis will explore satellite imagery processing techniques to objectively develop landscape heterogeneity models across multiple scales based upon detectable spectral patterns representing vegetation distributions.

METHODS

GENERAL APPROACH

Techniques using filters in a moving-window analysis were explored to develop a method for objectively identifying and defining landscape features at multiple scales. These techniques were applied to a Landsat Thematic Mapper (TM) scene using its spectral values as variables to characterize landscapes. The spectral values represent a measure of the reflectivity or absorptive properties of the ground features within a ground instantaneous field of view (GIFOV). Each picture element (pixel) carries a discrete spectral value corresponding to the GIFOV. When the pixel arrays are displayed as an image, ground features and regions can be distinguished based on the overall variations in spectral values through visual interpretation of tone, texture, form, and context of pixel combinations. As a digital raster model, algorithms applied over the TM scene using moving windows can summarize image properties and organize values into landscape units through objective and replicable means. Borrowing from scale-space theory, Difference-of-Gaussian (DoG) filters of increasing size were used to smooth fine scale (high frequency) data within a Landsat Thematic Mapper (TM) scene. New pixel values were calculated as a function of neighborhood size, weighted values in the DoG kernel, and contrast between neighborhood pixel values. Each DoG iteration was processed using standard edge detection techniques to combine individual pixels into groups and define the landscape units. The results of the landscape unit classification were assessed against actual ground features as represented by aerial photographs and established regional classifications of the area.

STUDY AREA

The study area is situated in central Oregon, and lies between latitudes 45° 00′ N and 44° 30′ N and longitudes 122° 00′ W and 120° 45′ W. The Cascades Range traverses the western portion of the study area in a north/south orientation, the high desert region dominates the central portion of the study area, and portions of the Ochoco Mountains occupy the far, eastern side of the study area (Figure 2).

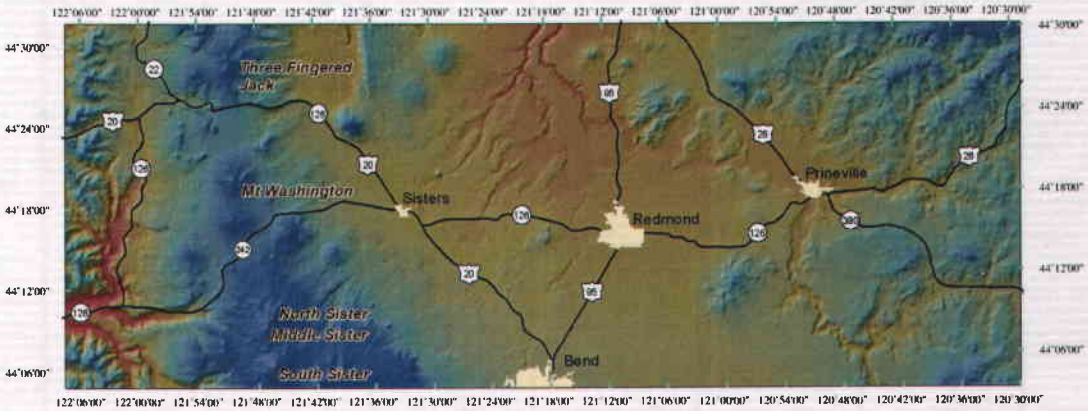

Figure 2. Study area location.

The study area includes eight Level IV ecoregions (Omernik and Gallant 1986) (Figure 3), which roughly correspond with physiographic provinces described by Franklin and Dyrness (1973) (Figure 4).

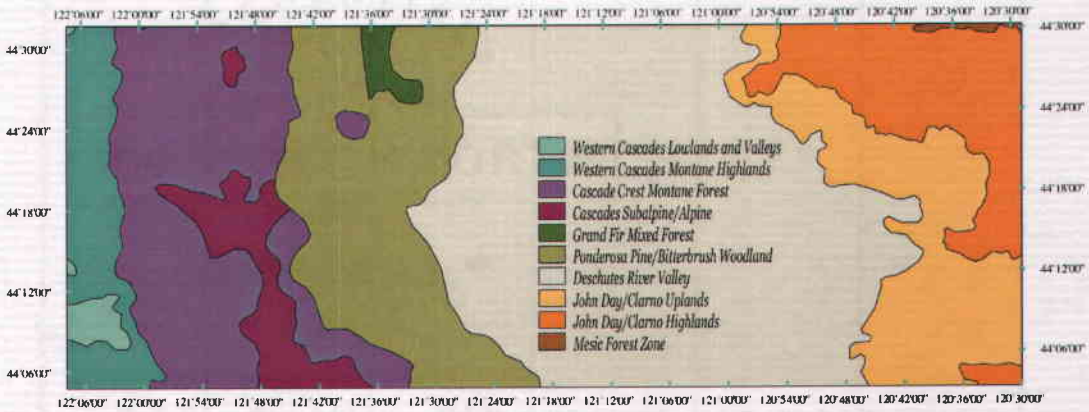

Figure 3. Level IV ecoregions of Oregon (Omernik and Gallant 1986).

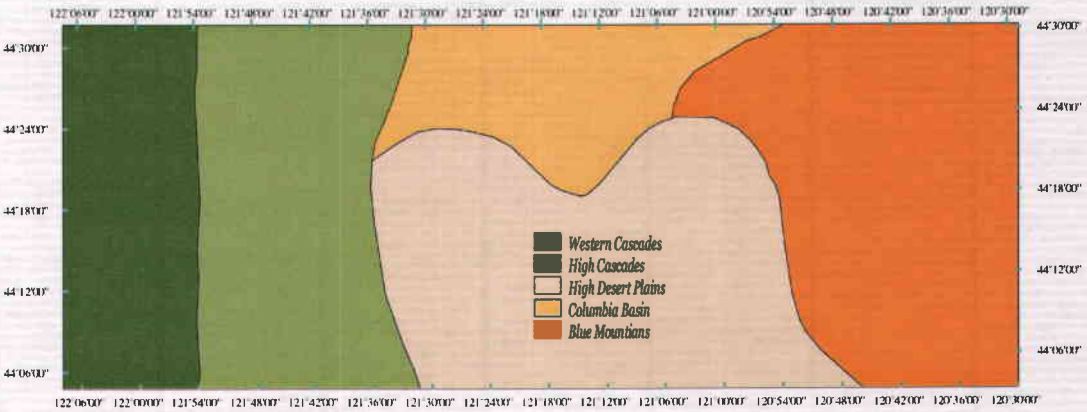

Figure 4. Physiographic and geological provinces within the study area (Franklin and Dyrness 1973).

A strong east/west gradient exists across the study area. Two climatic regions can be described for the area based upon the primary distribution of airmasses during the winter and summer months. Within the most western portion of the study area frequent intrusions of airmasses from the Pacific occur during winter and summer whereas the area east of the Cascades is influenced by interior airmasses (Mitchell 1976). The orographic effects of the Cascade Range on prevailing westerly winds from the Pacific Ocean strongly influence the broad distribution of vegetation. Apart from these major patterns, complex terrain can strongly influence local precipitation patterns and contributes to patterns of natural diversity (Mock 1996). A transition from a more maritime to a more continental climate occurs within the study area.

IMAGERY AND IMAGE STATISTICS

A Landsat TM scene (path 45, row 29) acquired 13 September 1995 was used for this investigation. The image had previously been resampled from 30-meter by 30-meter to a 25-meter by 25-meter pixel size using cubic convolution and was georectified. A correlation matrix was built for the seven TM bands to aid in determining which bands would provide the most useful data for the study (Table 1).

Table 1. Correlation Matrix for TM Bands 1 Through 7

Band	1	2	3	4	5	6	7
1	1.00000	-	-	-	-	-	-
2	0.97322	1.00000	-	-	-	-	-
3	0.95936	0.97843	1.00000	-	-	-	-
4	0.30404	0.37454	0.28585	1.00000	-	-	-
5	0.76101	0.80111	0.83962	0.42466	1.00000	-	-
6	0.70984	0.72254	0.78155	0.11627	0.80450	1.00000	-
7	0.81641	0.83563	0.89094	0.21683	0.94918	0.87925	1.00000

Bands 1 through 3, representing the chlorophyll absorption bands, are all highly correlated. This suggests that the bands carry very similar information and data loss would be minor when using only one of the three bands. Band 3, the red chlorophyll absorption band (0.63-0.69 μm), is one of the more important bands for vegetation discrimination (Figure 5). It generally displays vegetation health on the basis of chlorophyll absorption. The degree of absorption is represented in the gradient of lower values (darker areas) to higher values (lighter areas). The lightest areas indicate presence of senescent vegetation or bare soil or rock. Band 3 is affected less by atmospheric attenuation than bands 1 and 2 and therefore tends to provide more contrast between spectral values.

Figure 5. TM band 3 image of the study area.

Within the group of infra-red bands (4 through 7), band 4 shows the lowest correlation with band 3 and could be useful in identification of land features through data discrimination between these two bands. Band 4, typically referred to as the near infra-red (NIR) band, provides good representation of biomass, and is generally used for soil-crop discrimination (Figure 6).

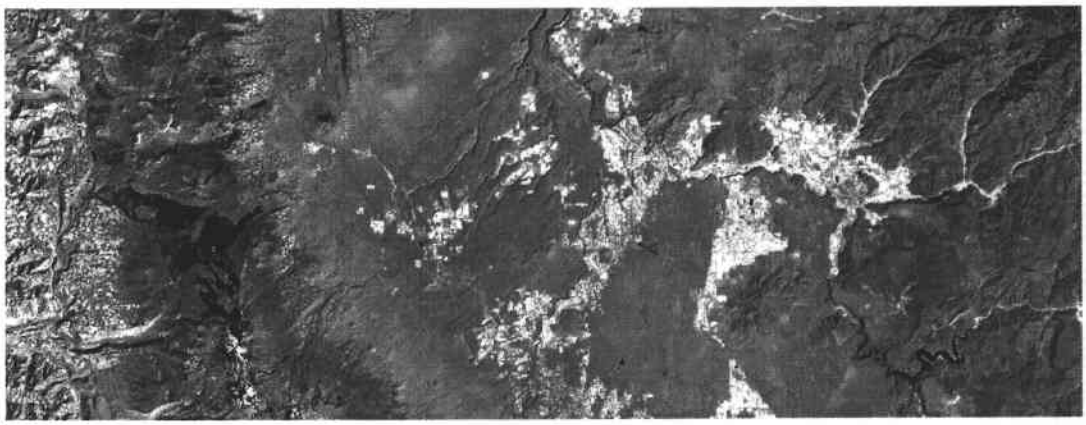

Figure 6. TM band 4 image of the study area.

A visual comparison between bands 3 and 4 reveals how land features are represented differently. Of particular interest to this study, is how vegetation in the Ochoco Mountains (east/right side of the image) and the Cascades (the west/left side of the image) is represented with varying degrees of detail in the two bands. Each band carries relatively unique information that can be observed visually, and is confirmed by low correlation values shown in Table 1.

The two bands were ratio transformed to 1] reduce data dimensionality into one single data layer, 2] reduce effects of topographic shading, and 3] provide increased contrast. The ratio transform was performed using the equation:

$$M_{NIR,red} = (\rho_{NIR} - \rho_{red}) / (\rho_{NIR} + \rho_{red})$$

This modulation for the NIR and red bands is commonly referred to as the normalized difference vegetation index (NDVI). The low reflectance of red light and high reflectance in NIR of healthy, vigorous vegetation results in high NDVI values. NDVI values that are near zero and decrease into negative values represent non-vegetated areas. High NDVI values are represented as light shades and low NDVI values as dark shades in the band-ratioed image (Figure 7).

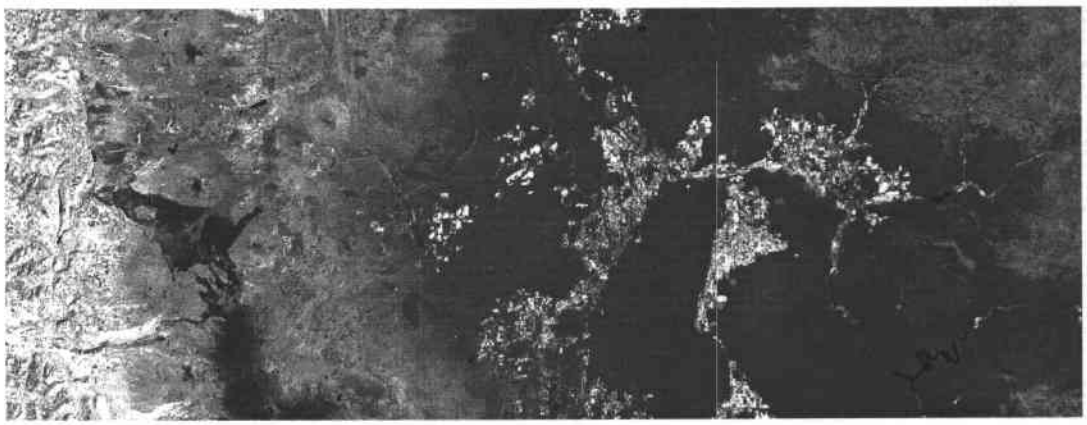

Figure 7. Normalized difference vegetation index image of the study area.

SPATIAL FREQUENCY ANALYSIS

A series of 1-D Gaussian functions was calculated as:

$$g = e^{-\frac{1}{2}\exp}$$

where exp = x^2 / σ^2 in which x = distance and σ = standard deviation to represent scale. The function yields a weight profile that has the form of a Gaussian or normal curve (Figure 8).

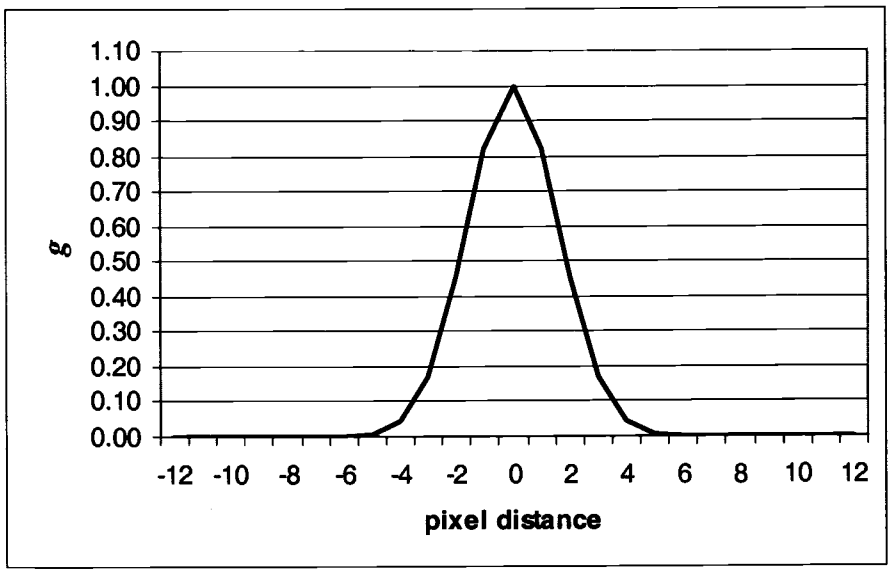

Figure 8. 1-D Gaussian function.

The 1-D Gaussians functions were each normalized to sum to 1, and a 2-D Gaussian function was created by duplicating values from the *x*-axis to the *y*-axis and multiplying values from each axis to generate *xy* values and produce the 2-D Gaussian function (Figure 9). The difference between two 2-D Gaussian functions having different σ values was calculated to produce the $DoG_{\sigma 1,\sigma 2}$ function (Figure 10).

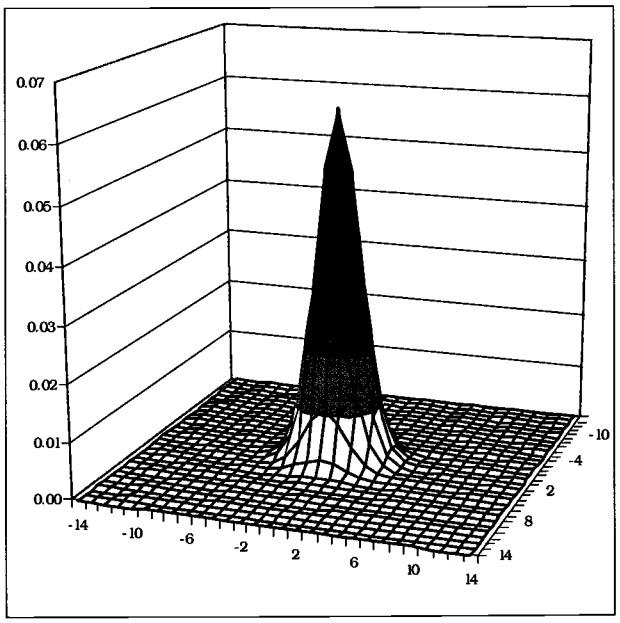

Figure 9. 2-D Gaussian function.

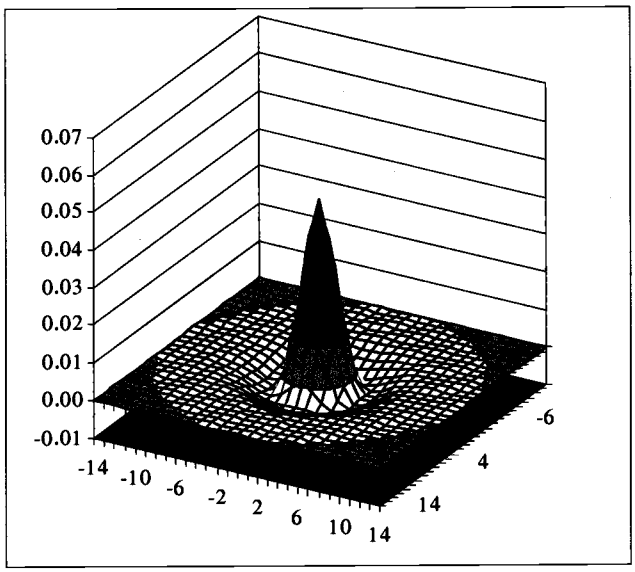

Figure 10. Difference-of-Gaussian function.

The $DoG_{\sigma 1,\sigma 2}$ values were then used to construct kernels (or filters) to use in a moving window operation (Figure 11). Each DoG filter was passed over the NDVI image of the study area on a pixel-by-pixel basis. The values in the underlying

image pixels were multiplied by the corresponding filter values and the summed value for the neighborhood was assigned to a pixel in an empty data set, positionally identical to the central neighborhood pixel on the NDVI image.

$DoG_{0.9,1.1}$

0.0000	0.0000	0.0000	- 0.0001	- 0.0002	- 0.0001	0.0000	0.0000	0.0000
0.0000	- 0.0001	- 0.0005	- 0.0017	- 0.0024	- 0.0017	- 0.0005	- 0.0001	0.0000
0.0000	- 0.0005	- 0.0034	- 0.0077	- 0.0086	- 0.0077	- 0.0034	- 0.0005	0.0000
- 0.0001	- 0.0017	- 0.0077	- 0.0004	0.0190	- 0.0004	- 0.0077	- 0.0017	- 0.0001
- 0.0002	- 0.0024	- 0.0086	0.0190	0.0650	0.0190	- 0.0086	- 0.0024	- 0.0002
- 0.0001	- 0.0017	- 0.0077	- 0.0004	0.0190	- 0.0004	- 0.0077	- 0.0017	- 0.0001
0.0000	- 0.0005	- 0.0034	- 0.0077	- 0.0086	- 0.0077	- 0.0034	- 0.0005	0.0000
0.0000	- 0.0001	- 0.0005	- 0.0017	- 0.0024	- 0.0017	- 0.0005	- 0.0001	0.0000
0.0000	0.0000	0.0000	- 0.0001	- 0.0002	- 0.0001	0.0000	0.0000	0.0000

$DoG_{0.8,1.2}$

0.0000	0.0000	- 0.0001	- 0.0003	- 0.0004	- 0.0003	- 0.0001	0.0000	0.0000
0.0000	- 0.0002	- 0.0012	- 0.0033	- 0.0046	- 0.0033	- 0.0012	- 0.0002	0.0000
- 0.0001	- 0.0012	- 0.0064	- 0.0145	- 0.0166	- 0.0145	- 0.0064	- 0.0012	- 0.0001
- 0.0003	- 0.0033	- 0.0145	- 0.0031	0.0358	- 0.0031	- 0.0145	- 0.0033	- 0.0003
- 0.0004	- 0.0046	- 0.0166	0.0358	0.1382	0.0358	- 0.0166	- 0.0046	- 0.0004
- 0.0003	- 0.0033	- 0.0145	- 0.0031	0.0358	- 0.0031	- 0.0145	- 0.0033	- 0.0003
- 0.0001	- 0.0012	- 0.0064	- 0.0145	- 0.0166	- 0.0145	- 0.0064	- 0.0012	- 0.0001
0.0000	- 0.0002	- 0.0012	- 0.0033	- 0.0046	- 0.0033	- 0.0012	- 0.0002	0.0000
0.0000	0.0000	- 0.0001	- 0.0003	- 0.0004	- 0.0003	- 0.0001	0.0000	0.0000

$DoG_{0.7,1.3}$

0.0000	0.0000	- 0.0001	- 0.0003	- 0.0006	- 0.0008	- 0.0006	- 0.0003	- 0.0001	0.0000	0.0000
0.0000	- 0.0001	- 0.0005	- 0.0020	- 0.0049	- 0.0065	- 0.0049	- 0.0020	- 0.0005	- 0.0001	0.0000
0.0000	- 0.0003	- 0.0020	- 0.0087	- 0.0195	- 0.0234	- 0.0195	- 0.0087	- 0.0020	- 0.0003	0.0000
0.0000	- 0.0006	- 0.0049	- 0.0195	- 0.0099	0.0470	- 0.0099	- 0.0195	- 0.0049	- 0.0006	0.0000
- 0.0001	- 0.0008	- 0.0065	- 0.0234	0.0470	0.2305	0.0470	- 0.0234	- 0.0065	- 0.0008	- 0.0001
0.0000	- 0.0006	- 0.0049	- 0.0195	- 0.0099	0.0470	- 0.0099	- 0.0195	- 0.0049	- 0.0006	0.0000
0.0000	- 0.0003	- 0.0020	- 0.0087	- 0.0195	- 0.0234	- 0.0195	- 0.0087	- 0.0020	- 0.0003	0.0000
0.0000	- 0.0001	- 0.0005	- 0.0020	- 0.0049	- 0.0065	- 0.0049	- 0.0020	- 0.0005	- 0.0001	0.0000
0.0000	0.0000	- 0.0001	- 0.0003	- 0.0006	- 0.0008	- 0.0006	- 0.0003	- 0.0001	0.0000	0.0000

Figure 11. DoG Filters.

A binary map was created from the DoG filtered image by dividing the pixel brightness value (BV) by its absolute value using the formula $BV_{x,y} \div | BV_{x,y} |$, resulting in values of either 1 or –1 and essentially building an edge map. Edges were created wherever the BV transitioned between negative and positive values

and the image was thereby segmented into discrete areas or zones. These zones where related back to the original NDVI image and zonal values (ZV) were calculated using the following function:

$$ZV_z = (x_g - x_z) - \sigma_g$$

where x_g = the global mean for the NDVI image, x_z = the mean for BVs within the zone, and σ_g = the standard deviation for the NDVI image. For display purposes, the resulting values were adjusted to positive values and multiplied by a factor of 10 to redistribute values as whole integers.

RESULTS

BROAD-SCALE REGIONALIZATION

The DoG $_{0.9,1.1}$ filter differentiated the study area NDVI image into 149,806 elements. These elements were categorized into 90 zones with zonal values of 0 through 96 (not all values are represented). The zones exhibited a clumped distribution tending to be clustered as opposed to being evenly distributed across the study area. Based upon the observed clusters, zones 0 though 16, 17 through 25, 26 through 28, 29 through 41, and 42 through 66 were aggregated into six regions These regions roughly correspond to Omernik level IV ecoregions (Figure 12). Study area zonal values greater than 67 were generally related to agricultural areas.

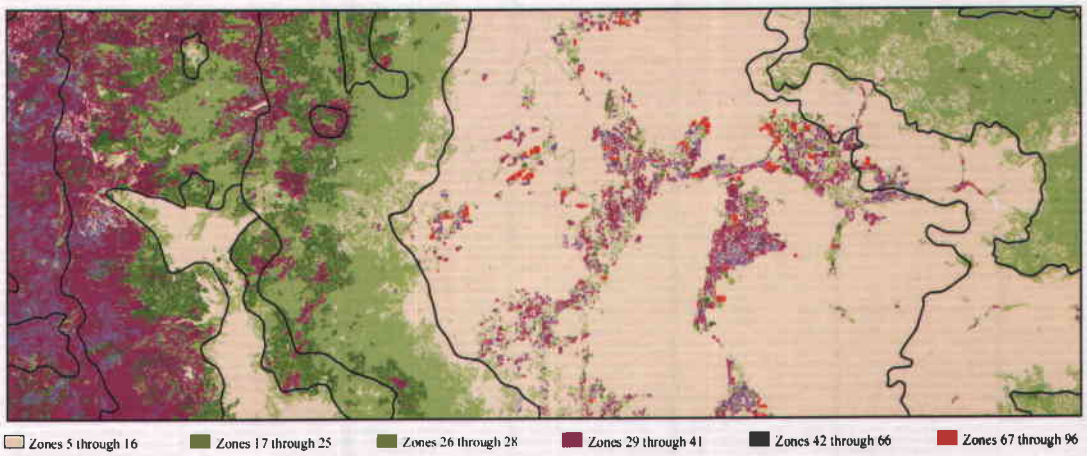

Figure 12. DoG $_{0.9,1.1}$ regionalization.

The DoG-derived regionalization of the study area cannot be compared directly to level IV ecoregions since the DoG regionalization is based solely on NDVI values, whereas level IV ecoregions were interpreted and delineated using numerous parameters from various data sources. Discrepancies between the two landscape

characterizations are expected. The comparison serves to demonstrate general agreement of transitional boundaries, overall orientation of known environmental gradients, and to serve as a point of reference in comparing DoG products across multiple scales.

The DoG $_{0.8,1.2}$ filter differentiated 110,896 elements and categorized 96 zones with zonal values 3 through 98. Aggregating zones using the same criteria as were used with the $DoG_{0.9,1.1}$ product resulted in similar regions but with a general shift in regional perimeters (Figure 13). The shift appears as a decrease of zone values along regional perimeters primarily between zones 17 through 25 and zones 5 through 16 (i.e., the John Day/Clarno Uplands and John Day/Clarno Highlands, and the Ponderosa Pine/Bitterbrush Woodland and Deschutes River Valley). Minor shifts are also evident between other zones including 26 through 28, 29 through 41, and 42 through 66. Counter to this trend, an increase in value occurs in portions of zones 17 through 25 or otherwise referenced as the central and west-central areas of the Deschutes River Valley and the Cascades Subalpine/Alpine ecoregions.

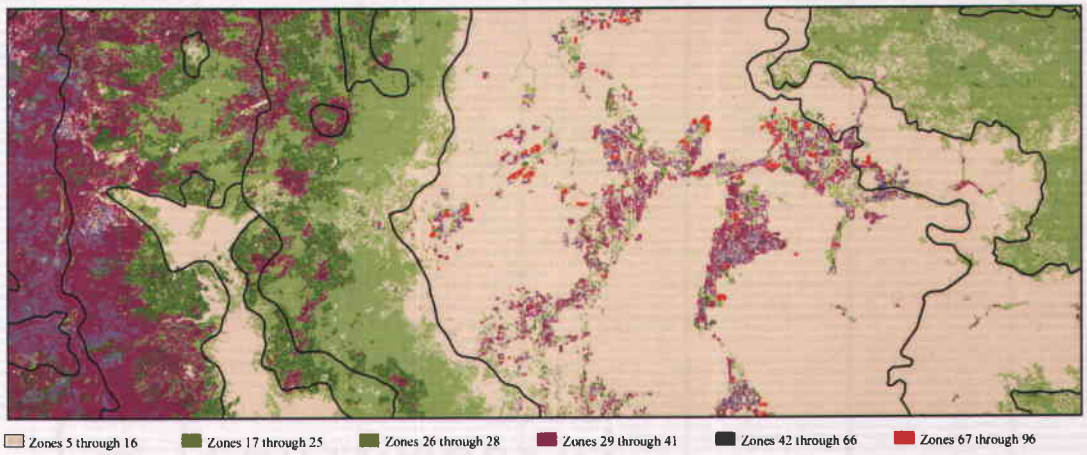

Figure 13. DoG $_{0.8,1.2}$ regionalization.

The DoG $_{0.7,1.3}$ product resulted in 176,430 elements that were categorized into 92 zones with zonal values of 3 through 96. The differences in the DoG $_{0.7,1.3}$ product suggest a general trend of decreasing values in zones 17 through 25 (Figure 14).

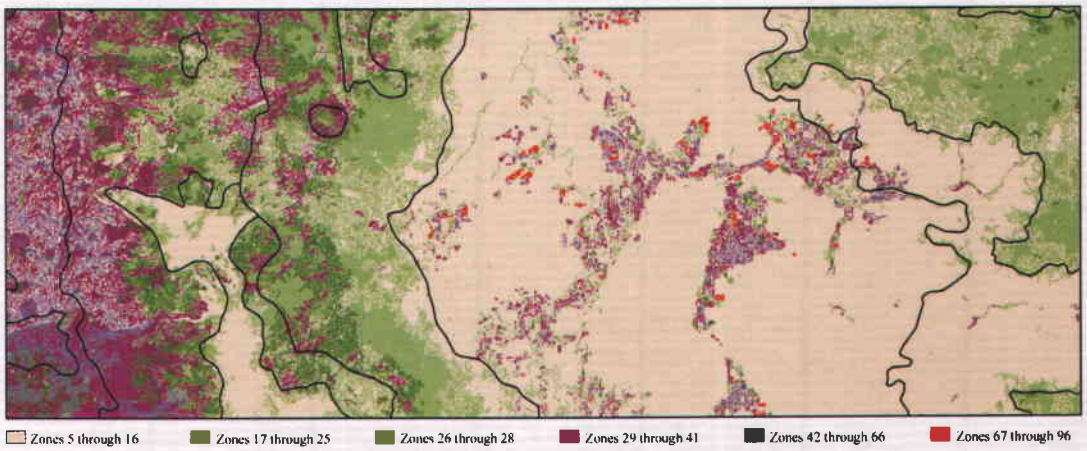

Figure 14. DoG $_{0.7,1.3}$ regionalization.

While the decrease in values in zones 17 through 25 for both the DoG $_{0.8,1.2}$ and DoG $_{0.7,1.3}$ products is perhaps the most obvious conclusion from visually comparing the above three images, closer inspection reveals there is a general, consistent shift in pixel values from high to low values across all zones and more inconsistent local shifts from low to high value. Additionally, a sudden and far-reaching influx of low values (zonal values 5 through 16) is evident in zones 29 through 41, and 42 through 66 in the DoG $_{0.7,1.3}$ product, suggesting a misrepresentation of the region.

Using the aggregation of zonal values 5 through 16 as an example, these pixel value shifts (or zone migration) are relatively minor for DoG $_{0.9,1.1}$ and DoG $_{0.8,1.2}$ products but result in a major excursion in the DoG $_{0.7,1.3}$ product (Figure 15).

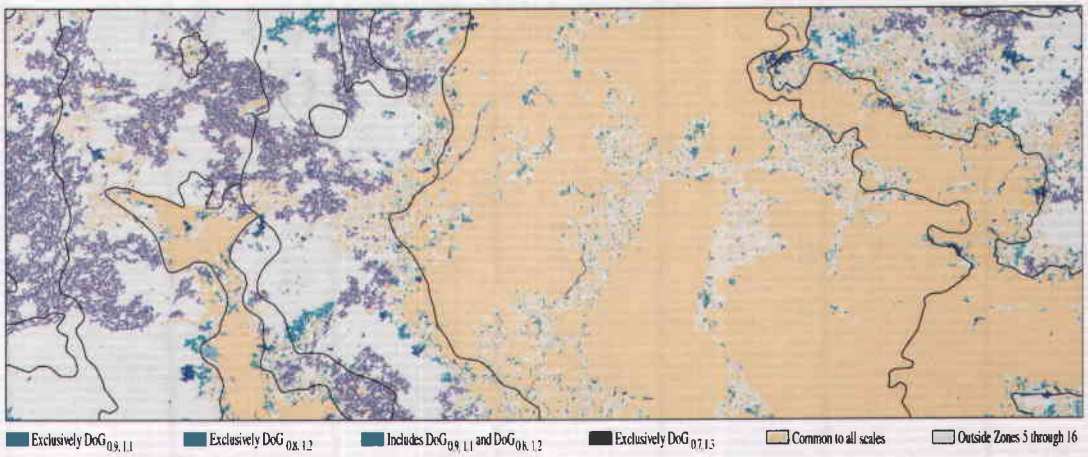

Figure 15. Example of zone migration.

LOCAL-SCALE IMAGE SEGMENTATION

The representation of regions is contingent upon the level of accuracy in differentiating landscape elements and the subsequent classification of zones. Overlaying polygon boundaries of the zones identified in the DoG $_{0.9,1.1}$ on an ortho-rectified aerial photograph, visual observation reveals a reasonable differentiation of objects within the photograph (Figure 16). A closer observation of zones classified 14 through 59 within the clearcut area reveal that object boundaries are not entirely accurate (Figure 17).

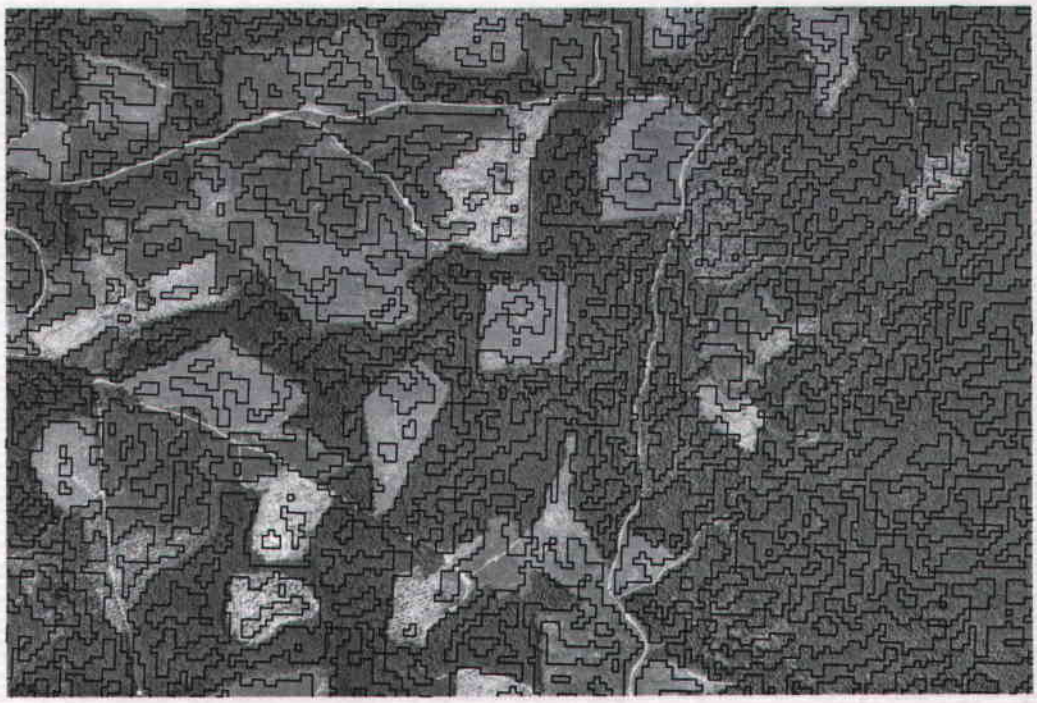

Figure 16. DoG $_{0.9,1.1}$ image segmentation example in forest and clearcut areas.

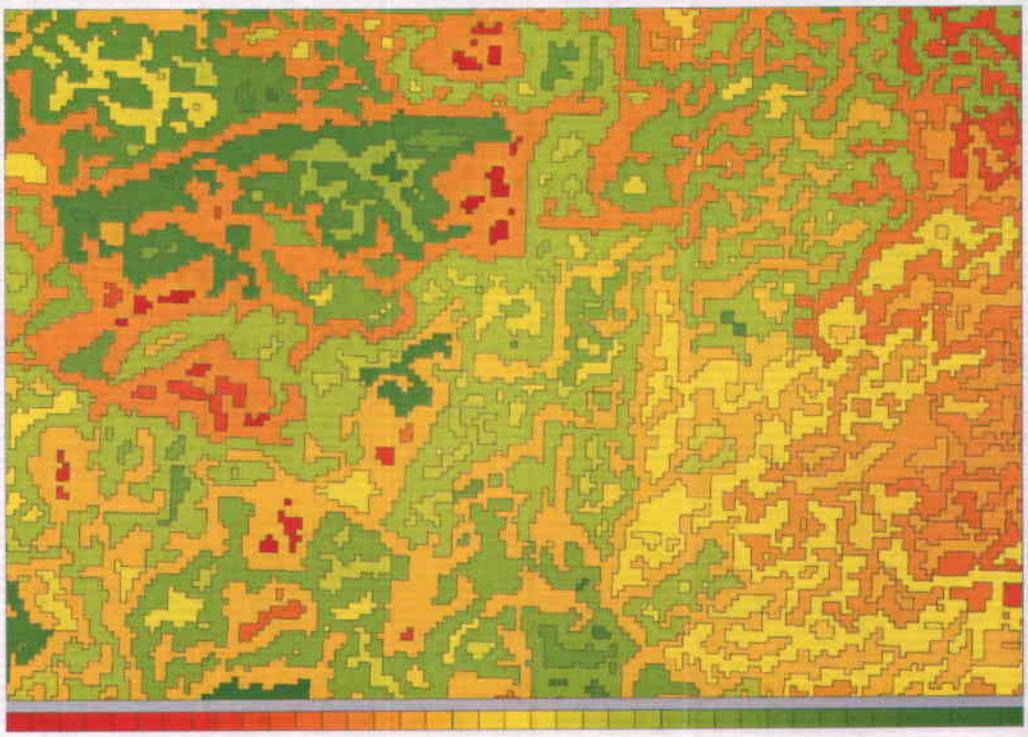

Figure 17. DoG $_{0.9,1.1}$ zone classification example in forest and clearcut areas.

The DoG filter failed to detect edge pixels along portions of objects' boundaries and thus created boundaries that wander and polygons that incorporate pixels unrepresentative of the object. The two resultant errors are maldelineation of objects and miscalculation of zonal values. It is, however, difficult to determine the level of error in the filter from these results and the above comparison. Edge (i.e., object boundary) representation was derived from medium resolution (30 x 30 meter) satellite imagery and is being compared to finer resolution (1 x 1 meter) photography. However, using the aerial photographs as a point of reference, a comparison of boundaries from DoG $_{0.8,1.2}$ and DoG $_{0.7,1.3}$ products show inconsistent results in defining landscape objects (Figures 18 and 20). Boundaries in the example shown in figure 18 for the DoG $_{0.8,1.2}$ object, seem to relate less to actual object boundaries and more to defining even distributions of pixel values, as evidenced by relatively even distance between lines demarcating edges. This is more clearly shown by the zones classified using the DoG $_{0.8,1.2}$ filter (Figure 19).

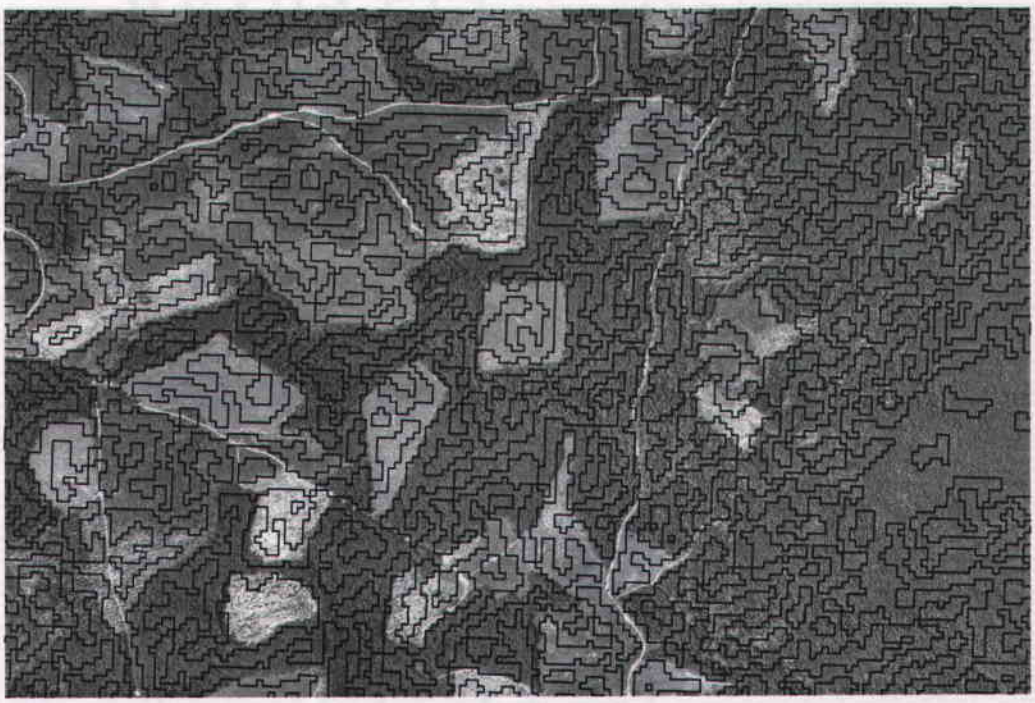

Figure 18. DoG $_{0.8,1.2}$ image segmentation example in forest and clearcut areas.

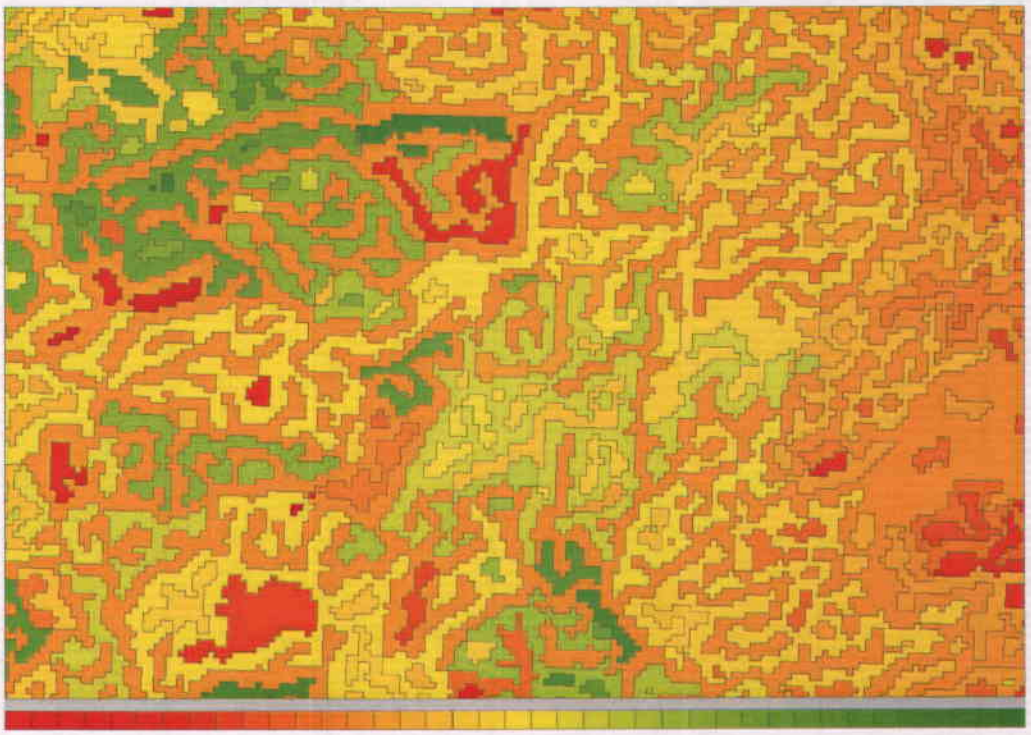

Figure 19. DoG $_{0.8,1.2}$ zone classification example in forest and clearcut areas.

The example of the DoG $_{0.7,1.3}$ product in figure 20 follows the DoG $_{0.8,1.2}$ product in scaling up from the DoG $_{0.9,1.1}$ product and shows an edge or boundary pattern more consistent with the DoG $_{0.9,1.1}$ product. Major boundary locations appear to be maintained with nearly imperceptible generalization of objects between scales. However, error in detecting edge pixels along portions of object boundaries is particularly evident in zone classification of the DoG $_{0.7,1.3}$ product (Figure 21). Wandering boundaries incorporated pixels unrepresentative of the object and the calculation of zonal values 14 through 59 resulted in an unrealistic change in zones across scales.

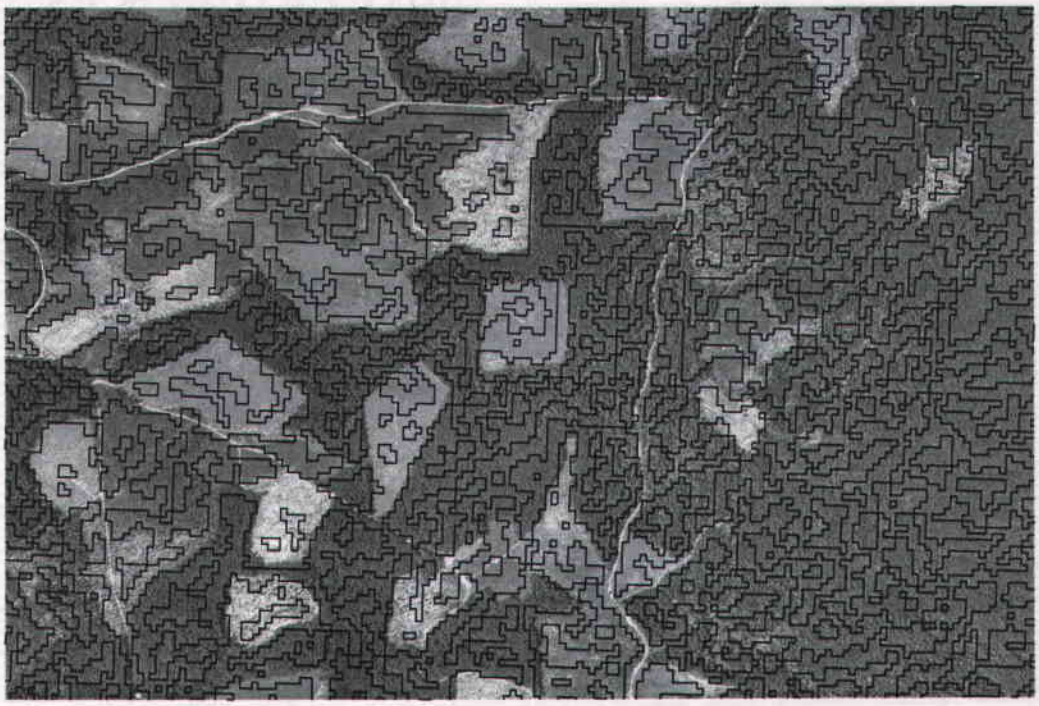

Figure 20. DoG $_{0.7,1.3}$ image segmentation example in forest and clearcut areas.

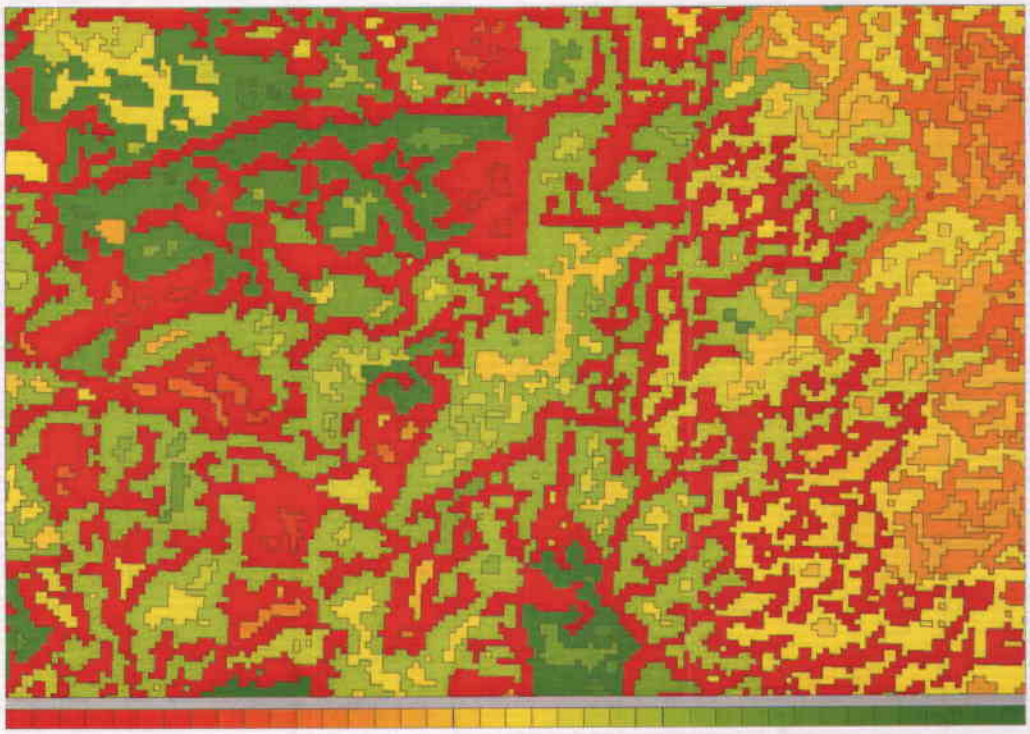

Figure 21. DoG $_{0.7,1.3}$ zone classification example in forest and clearcut areas.

Another example, in an ancient lava flow area, again demonstrates a reasonable image segmentation using the DoG $_{0.9,1.1}$ filter (Figure 22). However, as in the previous example, there are cases where edge pixels were not detected, resulting in either delineations wandering across actual boundaries or loss of complete polygons (i.e., objects were not detected and defined). What appears as a clearly distinct lava area in orthophotography is not represented by zones classified with values of 8 through 64 (Figure 23).

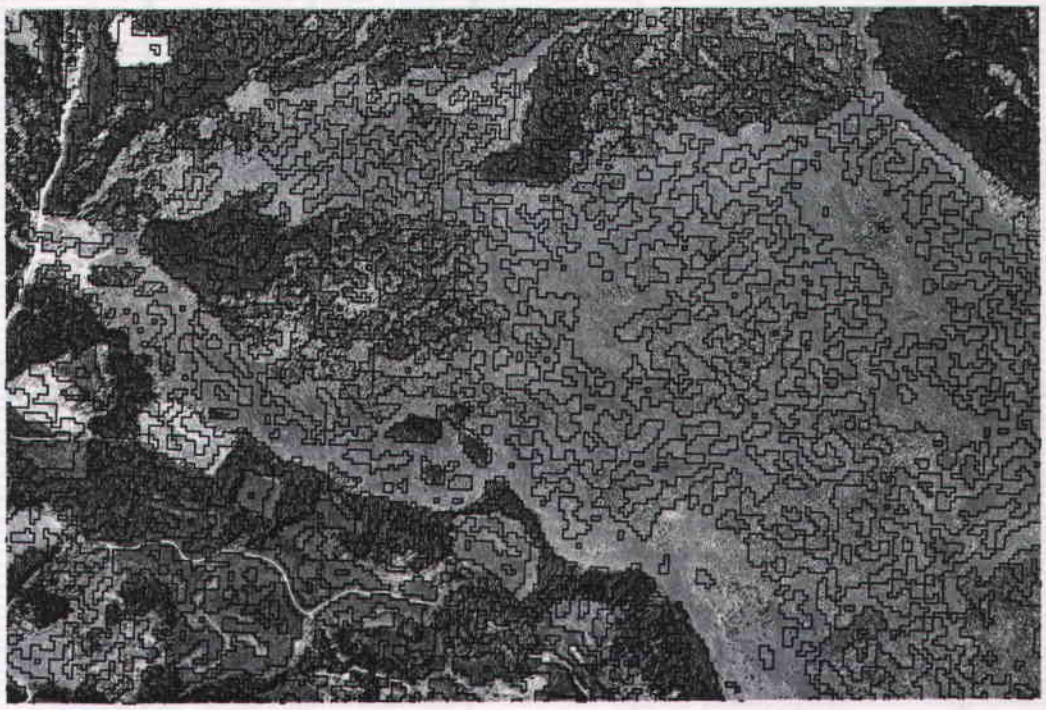

Figure 22. DoG $_{0.9,1.1}$ image segmentation example in a lava flow area.

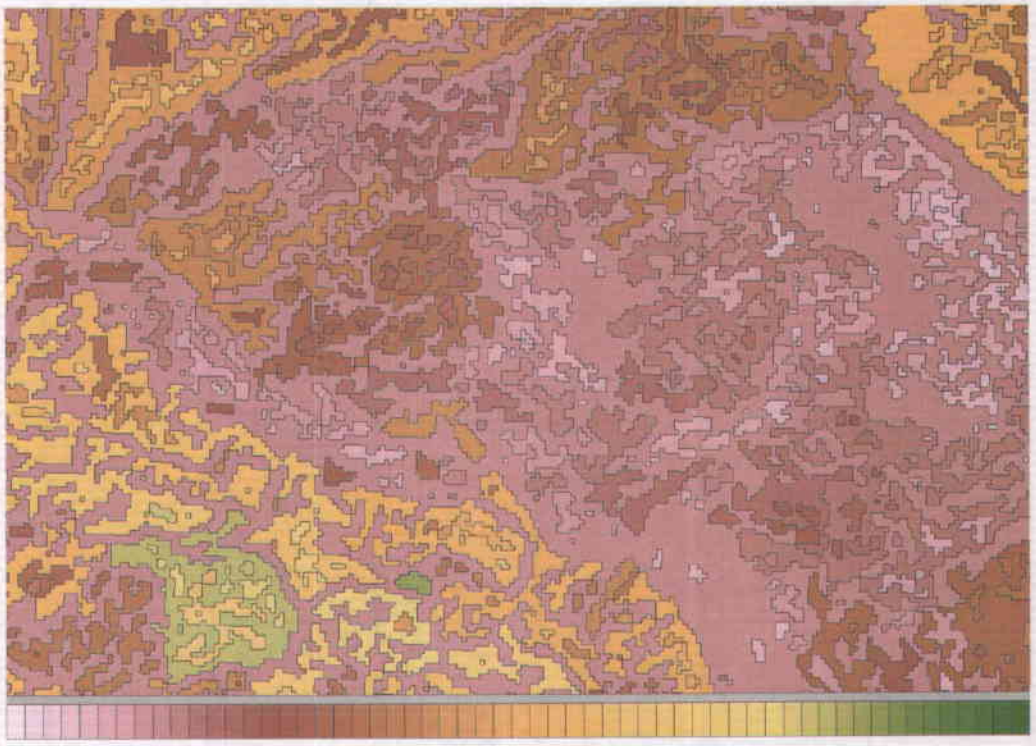

Figure 23. DoG $_{0.9,1.1}$ zone classification example in a lava flow area.

The DoG $_{0.8,1.2}$ image segmentation within the lava flow area (Figure 24) displays the same tendency of segmenting values within relatively even distributions across the image as in the previous example for results displayed in figure 18. Zone classification, ranging in values of 8 through 64, does not appear to realistically define landscape objects as perceived on orthophotography (Figure 25).

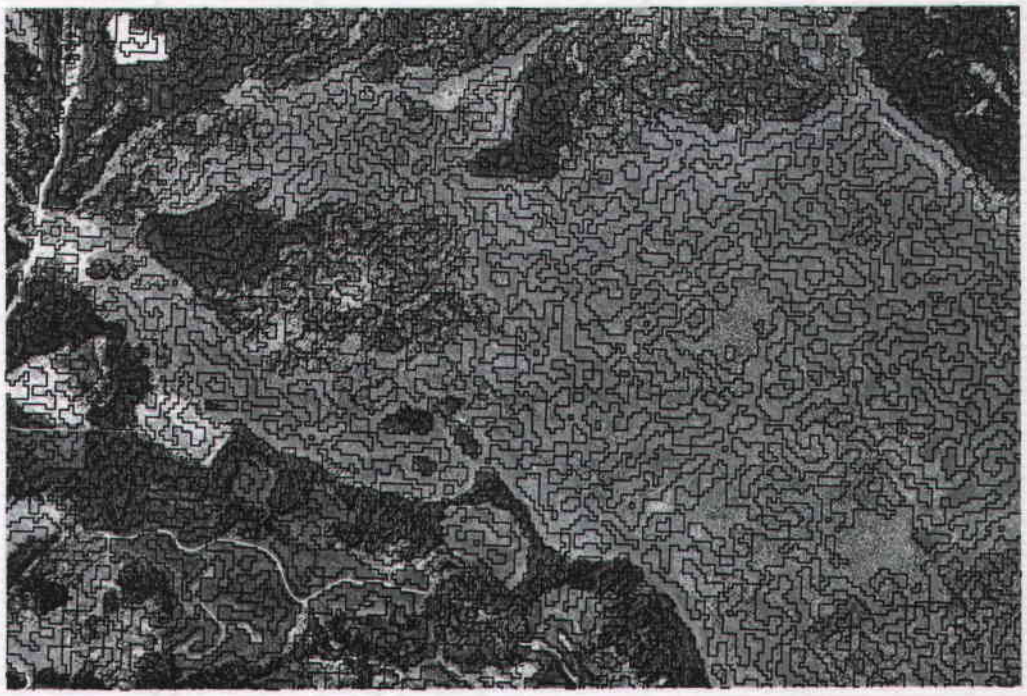

Figure 24. DoG $_{0.8,1.2}$ image segmentation example in a lava flow area.

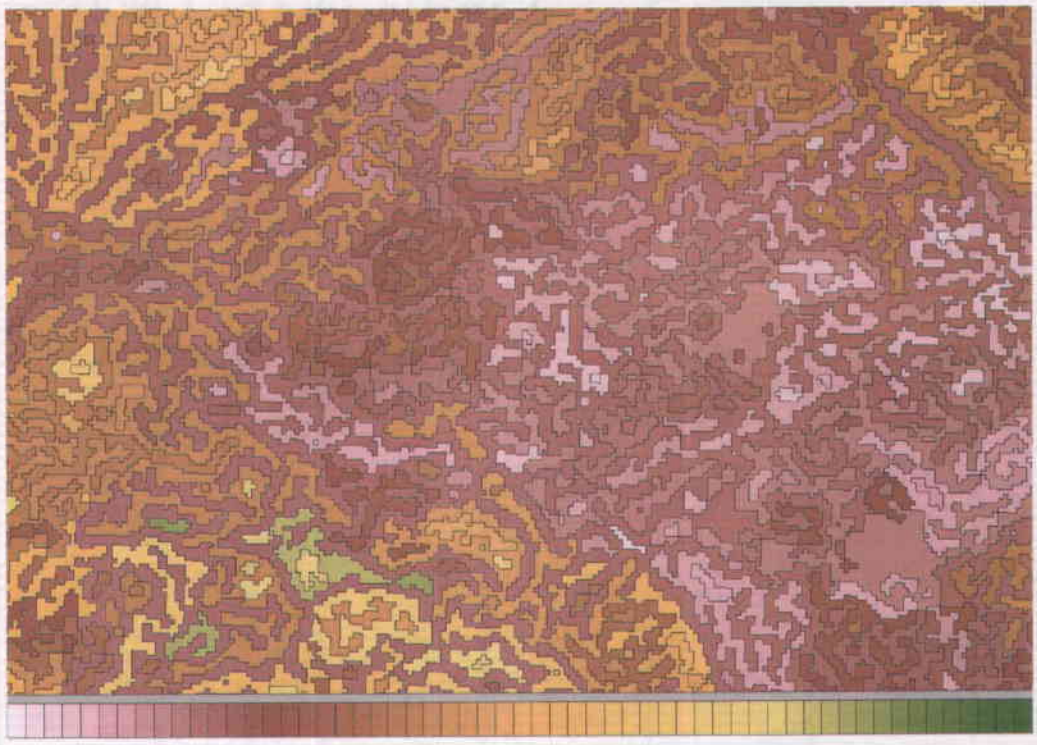

Figure 25. DoG $_{0.8,1.2}$ zone classification example in a lava flow area.

The DoG $_{0.7,1.3}$ image segmentation (Figure 26) appears to be very similar to the DoG $_{0.9,1.1}$ image segmentation (Figure 22). As with the previous forest stand and clearcut area example, the generalization of features across scales is largely imperceptible. However, in detailed comparison of the zone classification, one can observe that objects have been redefined (Figure 27). Objects that were not identified in the DoG $_{0.9,1.1}$ image segmentation are identified in this example of the DoG $_{0.7,1.3}$ image segmentation and vice versa. In addition, though errors of delineations wandering across actual boundaries are less obvious in the lava flow area example, the results reported for DoG $_{0.7,1.3}$ derived regions (see Figure 15) indicates that subtle, though far reaching, edge detection errors were generated in the region represented by zones 5 through 16 at the lava/forest interface.

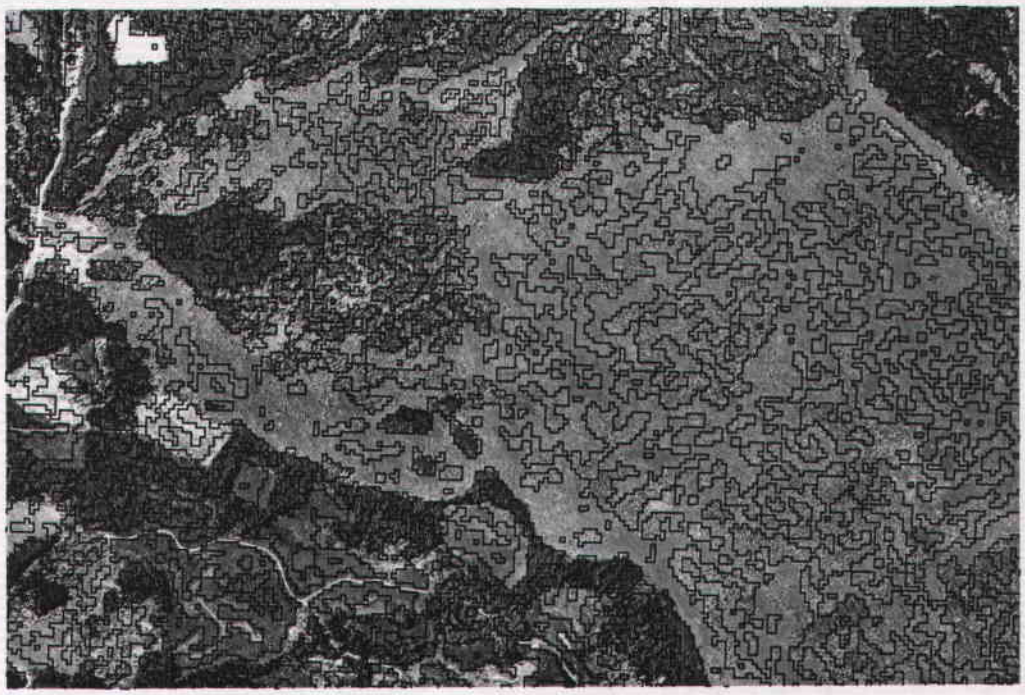

Figure 26. DoG $_{0.7,1.3}$ image segmentation example in a lava flow area.

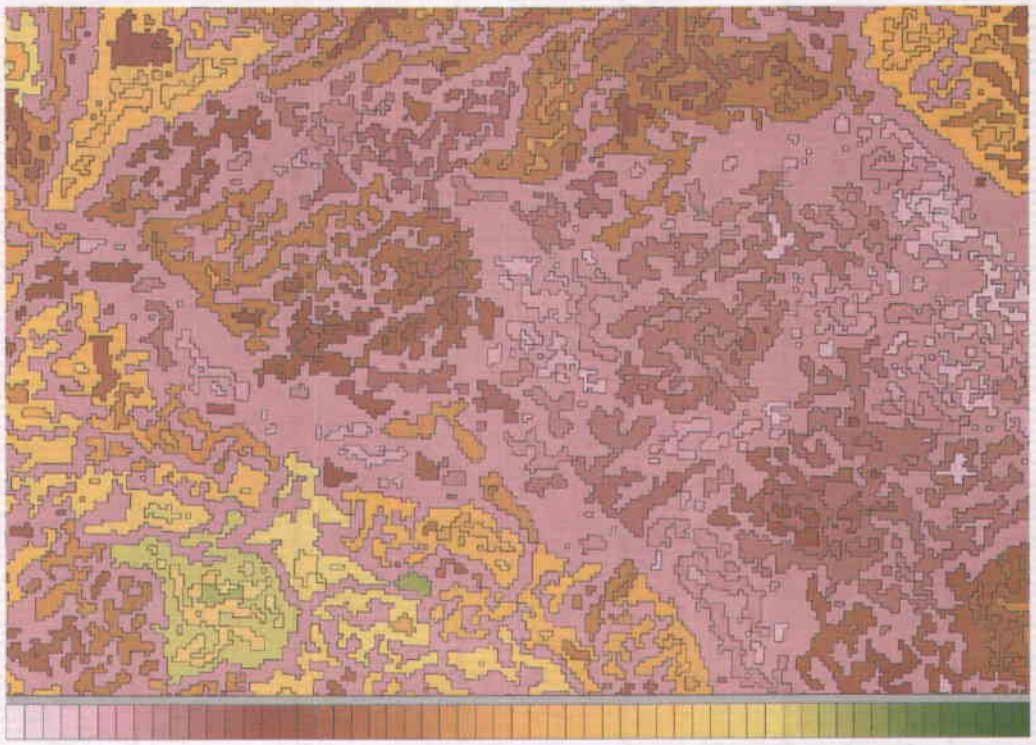

Figure 27. DoG $_{0.7,1.3}$ zone classification example in a lava flow area.

DISCUSSION

THE DIFFERENCE OF GAUSSIAN APPROACH

The application of DoG filters, as described in Methods and presented in Results, failed to accurately delineate local scale landscape objects within the study area. These edge detection errors in turn adversely affected the identification of broader scale landscape regions.

Local Feature Delineation and Regionalization

Errors were generated from each of the DoG filters applied, and increased with the size of the filter. As neighborhood size (i.e., the extent of the pixels contained within the filter) increases there is a greater likelihood that the neighborhood contains more than one edge and/or edge anisotropy. Woodcock et al. (1988b) experienced similar problems, related to anisotropy, in characterizing shapes on scanned aerial photographs. Most edge filters are 3-pixels by 3-pixels in size, thereby evaluating single pixels surrounding the central pixel or pixel of interest. The smallest DoG filter applied in this study was 9-pixels by 9-pixels in size and, though weighted to place more influence in pixel values closer to the central pixel, may have generated errors when multiple edges and/or a single edge deviated from a simple vertical, horizontal, or diagonal orientation within the neighborhood being evaluated. These errors could be corrected by adjusting the size of the DoG filter. However, there are likely to be lower limits to creating an effective DoG for differentiating landscape objects. The minimum filter size applied in this study was not adequate in boundary detection and it is unknown whether a smaller and more effective filter can be constructed. Because of these critical filter size limitations,

it is unlikely that a series of sequential DoG filters could be generated and applied as proposed in this study. It may, however, be possible to produce multi-scale landscape representations by applying a single DoG filter, if one can in fact be constructed (see discussion above) over images that are successively smoothed with a simple Gaussian filter. Further study should explore whether size limitation would entirely preclude the use of DoG filters in segmentation of landscapes. Optionally, LoG filters could be used in lieu of DoG filters. The LoG filter, the second derivative of Gaussian, uses a single σ value as opposed to σ pairs as with the DoG filter. The single σ value of the LoG filter makes scale unambiguous.

Characterization of Transitions

Interscale transitions at biome boundaries were unexpectedly represented as a gradient of NDVI values as opposed to being represented as nested objects, generalized with increasing scale. The modified approach of a DoG/Gaussian combination, as described above, is likely to produce similar results (i.e., migrating biome boundaries represented as gradients). It was expected that biome boundaries would be more persistent than those between landscape elements within the biomes. In other words, it was expected that the biome boundary would not migrate under the range of spatial scales applied in this study, but rather, be redefined solely on the basis of the resolution of landscape units that were aggregated to form regions. Boundaries within regions were expected to migrate as the landscape units coalesced into ever more generalized structures. This would be consistent with theory of hierarchical environmental constraints, the relationship of pattern and process with scale, and strength of interactions at the boundary interface (Schumm and Lichty 1965, di Castri et al. 1988, Delcourt and Delcourt 1992, Gosz 1993). Furthermore, the representation of transitions as nested objects would be more applicable in studies investigating the distribution of landscape

units at regional boundaries in relation to geomorphic facets or ecotopes (Walter 1984, Neilson 1993) or distributions of landscape units throughout a region in relationship to the regional core and boundaries (see Griggs 1914, Neilson 1991, Delcourt and Delcourt 1992, Neilson et al. 1993). The representation of transitions as gradients would be difficult to relate to specific factors driving the gradient in spatially explicit analyses. Objects would be preferred to explain transitions using a mechanistic model.

AN ALTERNATE APPROACH

Apart from using DoG/Gaussian combinations as described above, watershed segmentation may be an alternate approach to developing landscape heterogeneity models. Watershed segmentation treats an image as a topographic surface, a gradient magnitude is calculated, and 'topographic relief' is produced. The peaks around depressions, or areas of lower values, define the 'watershed' boundaries (i.e., object boundaries). Though the watershed technique typically results in over-segmentation, objects can be hierarchically merged over numerous scales. The watershed segmentation technique uses slope between adjoining pixels to define relief, therefore, edge detection error related to window size is not an issue. However, rules would be required to merge image segments into definable objects and thereby introduce an element of subjectivity into the process in relation to how the objects are defined. In developing rules to merge elements, it is important to consider the ecological legitimacy of units that evolve from the combination of the fine-scale elements (Pickett et al. 1989, King 1990). Nevertheless, the procedure would produce numerous outcomes, in the form of nested objects that could be assessed across scales.

POTENTIAL SOURCES OF ERROR

Data quality affects study results and the spectral and geometric quality of the remotely sensed data applied in this study may have influenced the image segmentation to some degree. The spectral and geometric quality of remotely sensed data is affected by various factors. Mal-function or mis-calibration of the remote sensing detectors generates error in collecting and recording the energy emitted from the area being scanned. The paths of the transmittance of energy also affect spectral quality. The atmosphere affects solar irradiance as it travels to the target and again after it has been reflected by the target or GIFOV. Reflectance may bounce into the GIFOV and sensor from surrounding terrain or features, particularly in areas of complex topography. Collectively, these paths of radiance to the sensor deliver a total radiance that may not accurately represent the energy actually being emitted by the target. Geometric distortion of the remotely sensed image arises from changes in the orientation or velocity of the remote sensing system or platform in relation to the area being scanned. Other sources of geometric distortion relate to the curvature of the earth or topography.

Techniques can be applied to correct or compensate for errors in remotely sensed data. This study did not identify errors specific to the TM data used, therefore, analyzing for error and developing strategies in the study approach to address those errors may lead to improved results. A better understanding of specific errors in the data would facilitate the assessment of filter performance.

CONCLUSION

In landscape studies, investigations into relationships between pattern and process can be undertaken at any level (scale of observation) and the quality of the data reflects directly on the study results. Remotely sensed data, in the form of satellite imagery, is an important information source for studies in landscape ecology at broad geographic extent. However, current approaches in processing this data can provide highly subjective input, over-simplify the systems being studied, and arbitrarily affect the outcome of the study. Additionally, data representing multiple scales of observation are required for investigating landscape dynamics and linkages between domains of scale. The image processing techniques explored in this study demonstrate the potential to objectively generate multi-scale landscape heterogeneity models from TM satellite imagery. The series of DoG filters used in this study, with σ pairs of 0.9 and 1.1, 0.8 and 1.2, and 0.7 and 1.3, failed to accurately define landscape elements at a range of spatial scales when applied to TM data. However, this study does set a foundation and provide direction for future inquiry into scale space applications for remotely sensed data in the field of landscape ecology. Modification to the process used in this study, or an alternate image segmentation approach using watershed analysis, could successfully provide techniques for use in objectively identifying landscape features at multiple scales. Future research should include not only further investigation into the application of DoG and LoG filters, but also statistical methods to test zonal values and aggregate zones. Refinements to the approach, leading to improved accuracy in feature identification, would generally provide an important contribution to studies in landscape ecology in which patch units are a significant component of the study. The approach would generate unbiased, objective delineations of landscape objects for intra-scale studies, allowing realistic comparison of results between separate studies and geographic regions. More specifically, the scale space approach would facilitate inter-scale studies to investigate the evolution of landscape entities and

patterns across scales of domains. Though statistical approaches, such as the semivariogram , can be used to identify domains of scale, no GIS techniques have been developed to study scale issues in a spatially explicit manner. The scale space approach, as introduced in this thesis, shows promise and future research will advance the approach towards practical application.

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