Multiscale Object-Specific Analysis (MOSA): An Integration of Ecological Theory, Remote Sensing, and Spatial Modelling[1]

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Abstract

It is now widely recognized that landscapes are complex systems composed of multiscale hierarchically organized entities that interact within unique spatial and temporal scales. These interactions result in scale-dependent spatial patterns that visually change, depending upon their scale of observation. Remote sensing platforms represent the primary data source from which such landscape patterns can be observed and assessed, but suffer from the modifiable areal unit problem (MAUP). The clearest way out of MAUP is by using *objects*, as objects constitute a non-arbitrary representation of space. Consequently, their aggregation and scaling contains implicit ecological meaning. Therefore, to appropriately monitor, model, and manage our interaction within landscapes, we require a multiscale approach that judiciously integrates ecological theory, remote sensing data and spatial modeling capabilities for the automatic delineation, hierarchical linking, evaluation, and visualization of dominant landscape objects through scale. Furthermore, this approach should be guided by the intrinsic scale of the varying sized, shaped, and spatially distributed *image-objects* that compose a remote sensing scene.

In an effort to achieve this, we present *Multiscale Object-Specific Analysis* (MOSA) as a novel approach for automatically upscaling and delineating multiscale landscape structures from a high-resolution remote sensing image. MOSA is composed of three primary components: *Object-Specific Analysis* (OSA), *Object-Specific Upscaling* (OSU) and *Marker Controlled Watershed Segmentation* (MCS). OSA is a multiscale approach that automatically defines unique spatial measures specific to the individual image-objects composing a remote sensing scene. These object-specific measures are then used in a weighting function to automatically upscale (OSU) an image to a coarser resolution by taking into account the spatial influence of the image-objects composing the scene at the finer resolution. Because image-objects, rather than arbitrary pixels, are the basis for upscaling, the effects of the modifiable areal unit problem (MAUP) are reduced. MCS is then applied to the newly upscaled data to automatically segment them into topologically discrete image-objects that strongly correspond to visually defined image-objects. The elegance of utilizing MCS as a feature detector is that it requires inputs that are automatically and explicitly met by the OSA/OSU outputs. Analysis is performed on an IKONOS-2 image (acquired August, 2001) that represents a highly fragmented agro-forested landscape in the Haut St-Laurent region of south-western Québec, Canada.

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1. Introduction

Landscapes are increasingly regarded as complex systems composed of a large number of spatially heterogeneous components that interact in a non-linear way and exhibit emergence, self-organization and adaptive properties through time (Waldrop, 1992; Prigogine, 1997; Kay and Regier, 2000; Wu and Marceau, 2002). An important characteristic of complex systems is that their hierarchical structure is defined at different critical levels of organization where interactions are stronger within levels than among levels, and where each level operates at relatively distinct temporal and spatial scales (Simon, 1962; Allen and Starr, 1982). Therefore, scale is central to the realization of hierarchy and the organization of landscapes (Levin, 1992).

In general terms, *scale* refers to the spatial dimensions at which entities, patterns and processes can be observed and measured. From an *absolute perspective*, scale corresponds to a standard system, such as cartographic scales and census units, used to partition geographical space into operational spatial units. From a *relative framework*, scale is a variable intrinsically linked to the entities under observation, and corresponds to one's window of perception. Thus every scale reveals information specific to its level of observation (Marceau, 1999). As defined in landscape ecology, scale is composed of two fundamental parts: grain and extent. *Grain* refers to the smallest intervals in an observation set, while *extent* refers to the range over which observations at a particular grain are made (O'Neill and King, 1998). In remote sensing, scale corresponds to the spatial, spectral, temporal, and radiometric resolution of the sensor. Here the term *spatial resolution* is equivalent to grain, while extent represents the total area that an image covers. In this discussion, *small scale* refers to a small area, and *large* or *coarse-scale* represents a large area.

Scale has been recognized as a key component for understanding the structure and the spatio-temporal dynamics of landscapes for more than fifty years and has been the subject of an abundant literature (for a review, see Marceau, 1999; Marceau and Hay, 1999). During this time, two principal challenges have been addressed, respectively known as the *scale* and *scaling problem*. The former refers to identifying the 'natural' or preferred scale(s) at which ecological patterns and processes occur, while the later refers to deriving appropriate rules for transferring data or information across scales (Caldwell *et al*., 1993; Jarvis, 1995). Theoretical frameworks, such as Hierarchy theory (Allen and Star, 1982; O'Neill *et al*., 1986) and the Hierarchical patch dynamics paradigm (HPDP - Wu and Loucks, 1995) have been proposed to express the intricate relationship among pattern, process, and scale explicitly in the context of landscapes, and to provide an operational framework for scaling. Useful concepts such as *scale domain* and *scale threshold* have also been defined. A scale domain represents a segment of the scale spectrum where patterns do not change, or change monotonically with changes in scale, while a scale threshold defines the end or beginning of a scale domain (Meentemeyer, 1989).

More recently, another challenge that has been identified as a mandatory requirement for deciphering the complexity of landscapes is referred to as *multiscale analysis*. The rationale behind multiscale analysis is as follows. Since landscapes are known to exhibit distinctive spatial patterns associated to different processes at different scales, landscape analysis performed at a unique scale is doomed to be incomplete and misleading (Marceau *et al*., 1994a; Hay *et al*., 1997; Wu *et al*., 2000). Furthermore, there is no way of defining *a priori* what are the appropriate scales associated to specific patterns. In addition, scaling requires obtaining information about the patterns (and processes) occurring at a range of scales in order to detect scale thresholds and derive adequate rules for the transfer of information through multiple scales. Thus, it is imperative to develop a multiscale approach that allows dominant patterns to emerge at their characteristic scales, with no *a priori* user knowledge, in order to obtain adequate and complete information about the vertical structure of the landscape.

The idea of multiscale analysis is not new. Wu *et al*. (2000) distinguish between two general approaches for multiscale analysis that have been developed and applied over the last four decades: the *direct* and *indirect approaches*. An indirect approach refers to the use of a dataset acquired or resampled at a series of discrete scales. An example is provided by Marceau *et al*. (1994a,b) who resampled high-resolution airborne data at different resolutions to study the impact of scale and spatial aggregation on classification accuracy results. The principal limitations of the indirect approach are that scales are arbitrarily chosen and do not represent the full vertical continuum of landscapes. Consequently, significant patterns and processes can go undetected or erroneously identified.

In contrast, the direct multiscale approach attempts to capture the dominant patterns as they emerge at specific scales from a unique dataset. A number of computational techniques developed to generate multiscale representations (Starck *et al*., 1998) can be associated to this group. These include fractals (Mandelbrot, 1967), quadtrees (Klinger, 1971), spectral analysis (Platt and Denman, 1975), pyramids (Klinger and Dyer, 1976), wavelets (Daubechies, 1988), beamlets (Donoho and Huo, 2000), scale space (Lindeberg, 1994; Hay *et al*., 2002a), and multiscale object-specific analysis (MOSA) (Hay, 2002; Hay *et al*., 2003).

Among these, the last method exhibits novel characteristics that are of significant importance for multiscale landscape analysis:

- First, MOSA has been developed for the particular spatial sampling context provided by remote sensing imagery. This is important as remote sensing technologies represent an unprecedented means to gather data at a wide range of spectral, spatial and temporal resolutions, which can be used to address a number of challenges related to the scale issue (Marceau and Hay, 1999).

- Second, this approach is based on an *object-specific* framework (Hay *et al*., 1997; 2001). This means that individual *image-objects* rather than arbitrary spatial units are the basis for analysis and scaling. Image-objects are considered as perceptual entities that visually represent objects in an image that are composed of similar digital numbers/grey-tones, and which model real-world entities. Such an object-based approach offers two main advantages. First, it reduces the effect of the modifiable areal unit problem (MAUP). The MAUP originates from the use of arbitrarily defined and modifiable spatial units used to acquire data over a geographical area (Openshaw, 1984). Examples are provided by remote sensing data (Marceau *et al*., 1994a; Marceau and Hay, 1999) and census data. Because these data do not explicitly correspond to geographical entities, but rather are an aggregation of the content of the spatial units, the value of the analysis results based upon them may not possess any validity independently of the units that are used. One way to overcome the MAUP is to focus the analysis on meaningful geographical entities (or objects) rather than arbitrary defined spatial units (Fotheringham and Wong, 1991). An additional advantage of the object-specific approach is that it explicitly considers the hierarchical structure of the landscape by allowing the aggregation of smaller landscape components into the larger objects they are part of at their next scale of expression.

- Finally, this object-specific framework satisfies two major requirements for multiscale analysis (Hay *et al.,* 2002a). First, the generation of datasets that represent a range of 'natural' scales from which objects can be detected. And second, the automatic delineation of individual objects as they evolve through scale.

In an effort to better understand complex landscape behavior through scale, we propose a multiscale approach that judiciously integrates ecological theory, remote sensing data and spatial modeling capabilities for the automatic delineation, evaluation, and visualization of dominant landscape objects through scale. Because there exists no single *optimal* scale for analyzing the myriad different spatial characteristics of landscape components (Marceau *et al.,* 1994 a, b; Hay *et al.,* 1997), we suggest that an effective multiscale approach should be guided by the intrinsic scale of the varying sized, shaped, and spatially distributed 'image-objects' that compose a remote sensing scene, rather than a static (and often arbitrary) user-defined scale of analysis (Hay *et al*., 2001). Based upon these ideas, the objective of this paper is to present a detailed description of Multiscale Object-Specific Analysis (MOSA) as a novel upscaling approach that reduces the effects of MAUP, and automatically delineates multiscale landscape structure from a single scale of remote sensing imagery. This will be accomplished by describing the remote sensing dataset used for analysis, followed by a detailed description of the three components of MOSA – Object Specific Analysis (OSA), Object Specific Upscaling (OSU), and Marker Controlled

Segmentation (MCS). We will then conclude by outlining the overall benefits, limitations, and future research of this approach.

2. Methods

The methodological framework developed in this study represents an integration of techniques and concepts ranging from Landscape Ecology and Computer Vision, to Geographic Information Science. As a result, a number of different computer software programs were employed. Unless explicitly stated, all object-specific code was written by the first author in IDL 5.6 (http://www.rsinc.com/idl), and marker-controlled segmentation code was written in Matlab 5.1 (http://www.mathwork.com).

2.1 Remote sensing dataset

The remote sensing image used in this study is a 500 x 500 pixel sub-image of a panchromatic IKONOS-2 (Geo) scene acquired in August 2001, over a highly fragmented agro-forested landscape in the Haut-St-Laurent region in south-west Quebec, in Canada (Figure. 1). This site is composed of an agricultural matrix textured with forest patches of varying size and shape. Three land-use classes dominate the scene: Agriculture, Fallow land and Forest. In order to illustrate how image-objects evolve through scale over a relatively large extent (i.e., 2 km) while still maintaining a fine level of detail, the panchromatic image was resampled from its original 1 m spatial resolution to 4 m using the object-specific upscaling technique, which is considered a robust upscaling technique (Hay *et al*., 1997).

2.2 MOSA description

MOSA represents an integration of three principal methods: *Object-Specific Analysis* (OSA), *Object-Specific Upscaling* (OSU), and *Marker Controlled Watershed Segmentation* (MCS). In general terms, OSA is a multiscale approach that employs different sized adaptive kernels to automatically define unique spatial measures specific to the individual image-objects composing a remote sensing scene (Hay *et al*., 1997, 2001). These 'object-specific' spatial measures are then used in a weighting function to automatically upscale (OSU) the image to a coarser resolution by taking into account the spatial influence (i.e., area) of the image-objects composing the scene at the finer resolution. Because image-objects, rather than arbitrary pixels, are the basis for upscaling, the effects of the modifiable areal unit problem (MAUP) are reduced in the upscaled image. MCS is then applied to the newly upscaled data to automatically segment them into topologically discrete image-objects that strongly correspond to visual interpretation. The elegance of utilizing MCS as a feature detector is that it requires inputs that are automatically and explicitly met by OSA/OSU outputs. Details regarding each component and their interaction are provided in the following sections.

2.2.1 Object-specific analysis (OSA)

Strahler *et al*. (1986) noted that in a remote sensing image, two fundamental resolution types exist:

1. *Low-resolution* (L-res): where pixels are larger than image-objects; thus, a single pixel represents an integration of many smaller image-objects;
2. *High-resolution* (H-res): where pixels are smaller than image-objects; consequently, a single image-object is composed of many individual pixels.

In object-specific analysis, we are interested in defining the detailed spatial characteristics of individual image-objects. Consequently, an underlying premise of OSA is that all pixels within an image are exclusively considered high-resolution samples of the image-objects they model, even though, both high- and low-resolution (L-res) samples exist in a single image. This is because pixels represent the fundamental primitive from which all image-objects are generated. Thus individual pixels are required to define the larger image-object(s) they are a part of.

OSA thresholds and heuristics

Hay *et al*. (1997) observed that when plotting the variance of digital values generated by sampling image-objects within increasingly larger kernels, the resulting plots produced curves with distinct breaks, or ‘thresholds’ in variance as the analyzing kernel contacted the image-object’s edges (for a more detailed discussion, see Hay *et al.*, 2001). After many hundreds of experiments on different sized, shaped and spatially arranged image-objects ranging from text, human faces, unique sized and shaped geometric shapes, to trees, roads and fields in H-res airborne imagery, it became apparent that the kernel size defined at these thresholds strongly corresponded to the known size (i.e., area) of specific image-objects. As a result, the shape of these variance curves was used to create a set of robust heuristics that define the spatial extent (i.e., kernel area) where an individual pixel is spectrally related to the image-object it is a part of. Rather than a single threshold value being used for all sizes of analyzing kernels, we have defined three robust threshold values that are representative of the pixel/image-object relationship over of a specific range of scales. In fact, a single threshold value does not work for all scales, thus supporting the concept of scale domains.

The primary OSA heuristic is composed of three different percentage values, each of which represents the difference in variance defined between two concurrent kernels over a specific range of kernel sizes. If the difference in variance between the two kernels is less than or equal to the heuristic threshold value, processing is stopped. When a ‘threshold’ is reached, the corresponding *mean*, *variance* and *area* values are also recorded for the pixel under analysis within the specified kernel. This dynamic process is then applied to all the remaining pixels within the original image (O_I), resulting in the generation of corresponding Variance (V_I), Area (A_I), and Mean (M_I) images. These three images are referred to as the first *image-set* (IS_1) (i.e., $V_{1,}$ $A_{1,}$ M_1), and this form of adaptive-kernel processing is referred to as *object-specific analysis*.

The *variance image* is essentially a gradient or edge image. Bright tones correspond to high variance values, thus the edge between two or more image-objects, while dark tones indicate low variance, or homogeneity, thus more ‘object-like’. The *area image* defines the spatial influence, i.e., the kernel size or number of pixels ‘spectrally related’ to the pixel under analysis. Dark tones represent small area values, which correspond to object centers, while bright tones represent large area values. The *mean image* is composed of an average of the H-res pixels that constitute part of individual objects assessed at their respective scales; thus the mean image is a model of what the scene looks like at the next level of (non-linear) multiscale analysis.

The OSA kernel

For simplicity and convenience, object-specific analysis was initially conducted using odd sized square kernels i.e., 3 x 3, 5 x 5, etc (Hay, 1997). However, based on the relationship between 2D Gaussian filters and mammalian vision (Hay *et al.*, 2002a), and the diagonal bias inherent to square kernels, a square approximation of a round kernel was developed and used (Hay *et al.*, 2001). To further improve the sensitivity of this kernel for defining complex edges, two different sized ‘round’ kernels are currently assessed within the same kernel diameter. This new filter set has resulted in improved sensitivity to object edges, faster processing and the minimization of the diagonal bias inherent to square kernels (Hay and Marceau, 2004).

2.2.2 Object-specific upscaling (OSU)

The unique area values defined for each pixel by OSA are used as part of an inverse area weighting scheme to upscale an image to a coarser resolution. The resolution of the upscaled image can either be defined manually according to user requirements, or automatically by statistical properties of the objects composing the image. Because both of these upscaling forms take into account object-specific weights, they are referred to as *object-specific upscaling*. In the following section, we report on the automated method.

The OSU resampling heuristic

An important premise of OSA is that spatially dominant objects should have greater 'influence' in the upscaled image than smaller objects. We intuitively recognize this attribute when we move away from a local scene. Smaller objects seem to disappear while larger objects persist. An explanation for this is partly found in Slater (1980). If an object is less than ¼ the size of the instantaneous field of view (IFOV) of the sensor, its influence in the corresponding pixel is equal to the point spread function (PSF) of the sensor – which in modern sensors is typically very small. In essence, if the object of interest is less than ¼ the size of the smallest resolvable component in the scene, the sensor is unable to visually detect it. From an object-specific perspective, this translates as: if an image-object is composed of fewer pixels than the smallest kernel can discern, its spatial characteristics cannot be defined.

Since the ¼ resampling heuristic describes how the signal of real-world components are modelled by a sensor, we adopt it for automatically defining appropriate minimum upscale resolutions in the following manner:

$$\text{upscale\_res} = \text{pixel\_size} + (\text{pixel\_size} \;\text{x}\; \text{min\_win} \;\text{x}\; \text{res\_heur}) \qquad [1]$$

where:

- *upscale_res* represents the length (i.e., diameter) of the square upscale kernel defined in pixel units that are equivalent to those of the original image;
- *pixel_size* initially is the value 1, where it represents a single pixel in the original image (regardless of its spatial resolution);
- *min_window* represents the smallest sized kernel. In the case of a square 3 x 3 kernel, this value is 3 (i.e., the square root of the total number of pixels in the kernel). However, in the new 'round' kernel, the smallest analyzing kernel is composed of five pixels (that make a cross in a 3 x 3 window), consequently the min-window value equals the square root of 5 (i.e., $5\wedge^{0.5}$);
- *res_heur* equals 0.25 (i.e., ¼) as previously discussed.

Based on Equation 1, the first upscale_res equals 1.559 [i.e., 1 + (1 x $5\wedge^{0.5}$ x 0.25)]. That is, each pixel in the first upscale image has a grain equal to 1.559 pixels in the panchromatic image. This represents a spatial resolution of 6.24 m (i.e., 4 m x 1.559 pixels). The extent of the new upscale image is obtained by dividing the length of the original image (i.e., 500 pixels) by 1.559, resulting in 321 pixels. Essentially, the upscale kernel is used as a mask to generate a weighted area value for each pixel in the following manner. Beginning at the origin, the upscale kernel is overlaid on the corresponding A_I, and each area pixel (within the mask) is divided by the sum of all area pixels in the mask. This generates a fractional area weight that sums to one. Each area weight (in the mask) is multiplied by its corresponding original grey value, and then summed. This summed value represents the new area weighted upscale value that corresponds to the original pixels in the upscale mask. The non-overlapping upscale kernel is then applied to the remaining data resulting in a new upscale image. The placement of the upscale mask (i.e., beginning at the origin) is completely arbitrary and thus subject to the aggregation problem; however incorporating object-weighted values reduces this. For more detail on the inverse area weighting see Hay and Marceau (2004).

To determine the upscale resolution for coarser scales, this process is iterated using *upscale_res* as the new *pixel_size*. Thus, the next upscale_res equals 2.43 [i.e., 1.559 + (1.559 x 3 x 0.25)]. That is, at the second upscale iteration, a single upscale pixel is now equivalent to 2.43 pixels - with a spatial resolution of 9.72 m (i.e., 4 m x 2.43 pixels), and an image extent of 206 pixels. When applied for two more iterations, the resulting upscale resolution, and grain and extent of the upscaled images are defined in Table 1.

Iterative OSA and OSU

Based on promising results from early research, Hay *et al*. (1997) recognized that the application of OSA/OSU rules revealed patterns that accurately correspond to the spatial extent of objects at their next (coarser) scale. This led to the hypothesis that by continuously applying object-specific rules to the M_I generated at each OSA iteration, new spatial patterns will emerge that represent dominant landscape objects, and that these patterns will correspond to real-world objects through a wide range of scales (Hay and Marceau, 1998).

To test this hypothesis, Hay *et al*. (2001) developed an iterative multiscale framework that represents a nested hierarchy of two image-sets (IS_t), each of which possesses membership in a unique scale domain (SD_n). They recognized that there is often a range of scales between the end point of identifiable scale domains where certain image-objects exist and the point where new image-objects emerge at their next scale of expression (see Hay *et al*., 2001 for an in-depth discussion). To exploit this information, the initial framework was modified as follows (see Figure 2 for an overview): at the first OSA iteration (*t = 1*), every pixel in the original image (O_I) is locally assessed within progressively larger kernels until a local *maximum* variance (OSA_{vmax}) threshold is reached. When applied to the entire image, this process generates the first image-set (i.e., V_1, A_1, M_1) - as previously described. In the second iteration (*t = t + 1*), each pixel in the newly generated M_1 is locally assessed until a *minimum* variance (OSA_{vmin}) threshold is reached. The resulting images become the second image-set (i.e., V_2, A_2, M_2) where they represent the beginning scale of all newly emergent image-objects.

Recall that minimum variance indicates that pixels are very similar, thus the corresponding image structures are most ‘object-like’. As a result, odd-numbered OSA iterations define scales that represent the spatial extent or ‘end’ of objects, while even-numbered OSA iterations define the beginning scale of all newly emergent image-objects. Consequently, data within the even-numbered OSA iterations (i.e., $IS_{2, 4, 6\ldots}$) are selected for upscaling (OSU) as they contain the new image-objects we are interested in. For example, within IS_2, OSU is applied to the newly generated Mean image (M_2), resulting in a new Upscale image (U_1) (Figure 3). U_1 is then considered the new base image, and the entire OSA/OSU process is repeated on the new images, until the number of pixels composing them is too small for further processing. If upscaling were applied to the original IKONOS image several iterations further, we would eventually end up with the Upscale data set being represented by a single pixel with a 2000 m spatial resolution.

The result of this iterative object-specific analysis and upscaling approach is a nested hierarchy of image-sets (IS_t), each composed of two V_I, A_I and M_I that have membership in a unique scale domain (SD_n), where n indicates the location of each scale domain within the nested hierarchy (Figure 4). Within each SD_n, all images share the same grain and extent, and represent the result of multiscale analysis specific to the image-objects composing them. However, all images in a SD_n have a coarser grain than those of the previous SD_{n-1} (due to upscaling), though they share the same extent (i.e., the same ground area) through all image-sets. This effect is illustrated by the Upscale images in Figure 3. The combination of all SD_n generated from a single image is referred to as a *scale domain set* (Table 1).

2.2.3 Marker-controlled segmentation (MCS)

Once OSA/OSU processing has been completed, and a multiscale dataset has been generated, MCS is used as a feature detector to automatically delineate and label individual image-objects as they evolve through scale. MCS is a watershed transformation technique that detects regional similarities as opposed to an edge-based technique that detects local changes (Beucher and Lantuéjoul, 1979; Meyer and Beucher, 1990). The key characteristics of this technique are the ability to reduce over-segmentation due to noise by placing ‘markers’ or ’seeds’ in user-specified areas, and to define regions (i.e., image-objects) as closed contours.

The MCS procedure

The general feature detection procedure associated with MCS involves three steps. First, an edge detector is used to enhance intensity variations in an image. This type of detector is typically referred to as a 'gradient operator', and the resulting image is the 'gradient image' (G_I). Second, a relevant marker set is obtained and applied to this gradient image. Third, watersheds are delineated from this combination of markers and edges.

Pre-processing with a median filter

In MOSA, the general procedure is slightly different than previously described. A detailed visual inspection of each V_I, A_I, M_I reveals that a significant amount of salt and pepper (isolated high or low) pixel values exist in each image (Figure 4). Typically, such signals will lead to over-segmentation when a watershed transform is applied to them. Thus, a 3 x 3 median filter is first applied to each of the V_I, A_I, and M_I, prior to watershed processing. All subsequent feature detection is then applied to these images. Median filtering is a nonlinear operation that replaces each point with the median of the one- or two-dimensional neighborhood of a given width. It is similar to smoothing with a boxcar or average filter but preserves edges larger than the neighborhood, while simultaneously effectively reducing salt and pepper noise (Lim, 1990).

Recall that in OSA, we are interested in the spatial/spectral relationship between pixels and the image-objects they are a part of, thus no pre-processing or smoothing of the original image is performed. Consequently, the maximum H-res content is maintained in the O_I. However, in the object delineation portion of MOSA, we are no longer interested in individual pixels, but rather unique pixel groups that represent specific image-objects. When we take this into consideration, along with the fact that the smallest object-specific kernel resides within a 3 x 3 pixel window, and that edges larger than this are preserved, median filtering is an excellent and effective approach for defining the spatially dominant pixel groups that make up the image-objects within each scale domain image.

Generating new gradient images

While a significant amount of edge information visually exists in each Variance image (Figure. 4), discretizing these edges for use as gradient images for MCS is not trivial due to their representation by a wide range of grey-tones. Therefore, rather than using the variance images as gradient images (G_I), as previously done (Hall and Hay, 2003; Hall et al., 2004), new gradient images are generated for each scale domain by subtracting the Mean image from the corresponding resolution Upscale image (U_I) and defining the absolute value of the result. For the gradient images displayed in Figure 5, the following equations were used:

$$G_2 = abs\ (O_I - M_2) \qquad [2]$$

$$G_4 = abs\ (U_1 - M_4) \qquad [3]$$

$$G_6 = abs\ (U_2 - M_6) \qquad [4]$$

Where $G_{2,\ 4,\ 6}$ represent the newly generated Gradient images, *abs* represents the absolute value, O_I represents the original IKONOS panchromatic image, $M_{2,\ 4,\ 6}$ represent the newly generated Mean images, and $U_{1\text{-}2}$ represent the newly generated Upscale images (Figure 3). All MCS processing is applied to the (median filtered) datasets generated by OSA/OSU at their native grains and extents as defined in Table 1.

This method for generating new gradient images is similar to the technique in mathematical morphology where external contours (i.e., object edges) can be created by defining the difference between the original and the dilated image. Other contours can also be created by the difference between the original and the eroded image, and the dilated and the eroded image (Haralick and Shapiro, 1992). However, in each of these cases, a fixed (typically arbitrarily) sized structuring element must be defined for erosion and or dilation, which directly influences the shape of the resulting contours. In the case of OSA, each M_l represents the result of a dynamically sized and shaped structuring element (i.e., the object-specific kernel) that is specific to the different sized, shaped and spatially arranged image-objects within each scene. By using the absolute value, all *difference*, or *changed* values are represented by relatively large (i.e., bright) grey tones that exist within the tails of each G_l histogram.

Image-object markers

Object markers are automatically generated by combining regional minima from the corresponding variance and area images using a logical AND operation. More specifically, the regional minima algorithm (*imregionalmin* available in Matlab) is first applied separately to the V_l and A_l of each SD_n. In this algorithm, regional minima are connected components of pixels (i.e., 8-connected neighbors) with the same intensity value, whose external boundary pixels all have a value greater than this intensity value. The resulting dataset is a binary image, where values equal to one represent regional minima. Variance minima values represent areas of low heterogeneity that conceptually correspond to object centers. Area minima indicate that the object-heuristics for the pixel being assessed were met within a small analyzing kernel and also correspond to object centers. Based on an extensive visual analysis of the images in each SD_n, it became evident that the local Area minima represent both image-object centers and the edges between two or more image-objects. Hay *et al*. (2001) refer to these edge locations as *edge-objects*. That is, both image-objects and edge-objects are typically composed of (relatively) small area values. Thus, exclusively using markers derived from Area minima - as done in earlier studies (Hall et al., 2004; Hall and Hay, 2003) - does not provide optimal results. Fortunately however, only image-objects are composed of both (relatively) small area, and (relatively) small variance values. Thus to ensure that image-objects, rather than edge-objects are defined as markers, the AND logical operator is applied to the regional Area minima and the regional Variance minima datasets. This produces a combined binary marker dataset, where only identical values (i.e., ones) are defined. For additional information see Hay and Marceau, (2004).

Imbedded markers and watershed analysis

To define individual image-objects, the new (combined) marker sets were 'imbedded' within the corresponding gradient image. More explicitly, the location of each marker set was defined within the appropriate gradient image using the Matlab *imimposemin* function. This function modifies the intensity image using morphological reconstruction so the intensity image only has regional minima wherever the binary (marker) image is nonzero. The Matlab watershed algorithm (Vincent and Soille, 1991) was then applied to each 'imbedded' image. This resulted in the generation of 10 watershed images (W_l), each containing 'empty' polygons [three of which ($W_{2, 4, 6}$) are overlaid on their corresponding M_l and illustrated in Figure 5). It is important to note that only empty watershed boundaries (i.e., individual polygons) that separate individual image-objects are generated by this algorithm. They still need to be filled.

Object labeling

Each pixel in the Mean images (Figure 4) represents a member of a newly detected image-object. Since these images are generated from average values calculated within unique threshold kernels, they represent the dominant image structure defined at a specific spatial resolution within a unique scale domain (Hay *et al*., 2001). Therefore, each newly defined – though empty – watershed polygon is used as a mask to generate a value equal to the average of the corresponding M_l pixels located within its perimeter (see *Labeled MCS Images* in Figure 5). In essence, each watershed polygon now spatially represents the average grey-tone, and areal extent of a unique image-object. This step is referred to as *object labeling* and represents the final step in the automatic delineation of discrete multiscale objects as illustrated in each of the three scale domains in Figure 5.

3. Discussion and conclusions

In this paper, we have presented multiscale object-specific analysis (MOSA) as a hierarchical framework for the multiscale analysis of remote sensing imagery. This non-linear framework integrates ecological theory, Object-Specific Analysis (OSA), Object-Specific Upscaling (OSU), and Marker Controlled Watershed Segmentation (MCS) for automatic multiscale scene generation and feature extraction. A unique characteristic of this framework is that it allows dominant image-objects to emerge at their respective scales, and in addition, it requires no *a priori* scene information. In summary, this framework exhibits the following characteristics.

- Object-specific analysis can be applied to any digital data regardless of whether it is considered high resolution (i.e., sub-meter – 5 m), medium resolution (5 – 30 m) or low resolution (greater than 30 m). The ability to define image-objects is dependent upon the relationship between the size of the image-objects composing a scene, the spatial resolution of the pixels that compose the image-objects, and the size/shape of the analyzing kernel. Thus, if coarse grain data are used (i.e., TM, MODIS, AVHRR), then the spatial characteristics of relatively coarse grain image-objects will be defined.
- The underlying ideas and heuristics are conceptually simple, are based upon strong empirical evidence, and follow many concepts of Complex Systems and Hierarchy theory.
- The OSA kernel represents a close approximation of an isotropic filter (i.e., a square approximation of a round kernel with no preferential orientation), thus reducing the diagonal bias common in square kernels. In addition, we have defined and incorporated three robust empirical scale-dependent threshold conditions that are representative of the pixel/image-object relationship over an explicit range of scales, thus supporting the concept of scale domains.
- OSA/OSU allows for upscaling between objects and within an image hierarchy, where it incorporates the idea of a ‘generic’ point spread function in relation to object size for determining an appropriate upscale resolution for the next iteration of processing (Hay *et al.,* 2001).
- OSU incorporates object-specific weights, thus minimizing the effects of the modifiable areal unit problem (MAUP).
- Land-cover classifications have been shown to improve with the addition of object-specific datasets as additional logic channels (Hall et al., 2004).
- OSA/OSU has been statistically proven to produce better-upscaling results than cubic convolution, bilinear interpolation, nearest neighbour and non-overlapping averaging (Hay *et al.,* 1997).
- MCS is well documented in the literature, and watershed segmentation algorithms are commonly available in popular image processing packages.
- Decomposability is possible by mapping each OSA/OSU image to corresponding Mean and Area dataset; thus the ability exists for explicitly tracking information over scales in a bottom up, and top down approach (see Hay and Marceau, 2004 for detailed information).
- One of the greatest limitations of the MOSA is that it has not yet been tested over a large number of different landscapes, or by a significant number of researchers. However, further testing and validation are underway. In addition, no commercial software is available and its object modeling is done empirically. Thus, the results of multiscale analysis require validation against field data, which becomes difficult if not impossible as scales become coarser. However, OSU takes into account the relationship between the pixel size and the image-objects from which the original OSA heuristics were developed. Thus at fine scales, results visually model known image-objects very well. Therefore, a precedent exists on which to base results at coarser unverifiable image-scales.
- While the incorporation of MCS into MOSA represents an elegant feature detection solution that capitalizes on the explicit object information inherent to the Variance, Area and Mean datasets, further refinement of automatically defined marker sets is required – particularly for coarser scale delineation.

Currently there is no integrated topological solution in MOSA for hierarchically linking and querying delineated image-objects through scale; however, an extended goal of MOSA includes not only automated object-specific feature detection as described here, but also the classification (Hall et al., 2004) and linking of image-objects through scale (Hay *et al.,* 2003). At present, we are developing a topological mechanism similar to that described by Hay *et al.,* (2002b) for the linking and querying of multiscale *Scale-Space* blobs. Once completed and implemented in MOSA, the spatial characteristics of individual image-objects can be assessed using spatial statistics and landscape metrics to evaluate how landscape components (i.e., image-objects) become fragmented and/or connected to each other through scale.

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List of tables

List of figures

Table 1. Information resulting from generating a scale domain set (SD_n)

SD_n	IS_t Components	OSA_t	OSU_n	Upscale Resolution (O_I pixels)	Grain (m^2)	Extent (pixels^2)	# Pixels
	O_I			1.0	4.0	500	250000
SD_1	$IS_1 = V_1, A_1, M_1$	1			4.0	500	250000
	$IS_2 = V_2, A_2, M_2$	2			4.0	500	250000
	U_1		1	1.559	6.24	321	103041
SD_2	$IS_3 = V_3, A_3, M_3$	3			6.24	321	103041
	$IS_4 = V_4, A_4, M_4$	4			6.24	321	103041
	U_2		2	2.430	9.72	206	42436
SD_3	$IS_5 = V_5, A_5, M_5$	5			9.72	206	42436
	$IS_6 = V_6, A_6, M_6$	6			9.72	206	42436
	U_3		3	3.789	15.16	132	17424
SD_4	$IS_7 = V_7, A_7, M_7$	7			15.16	132	17424
	$IS_8 = V_8, A_8, M_8$	8			15.16	132	17424
	U_4		4	5.907	23.88	85	7225
SD_5	$IS_9 = V_9, A_9, M_9$	9			23.88	85	7225
	$IS_{10} = V_{10}, A_{10}, M_{10}$	10			23.88	85	7225

Figure 1.

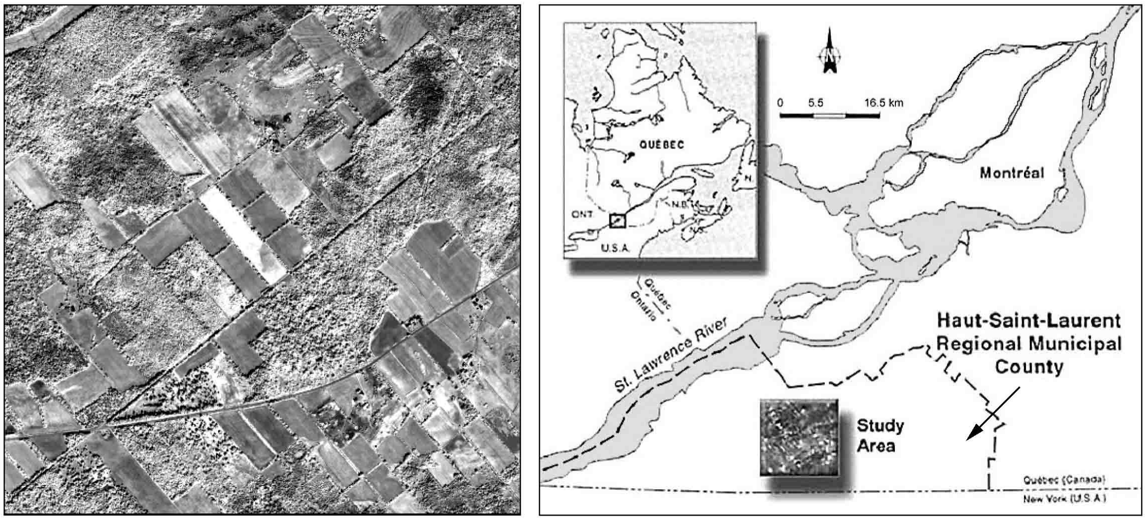
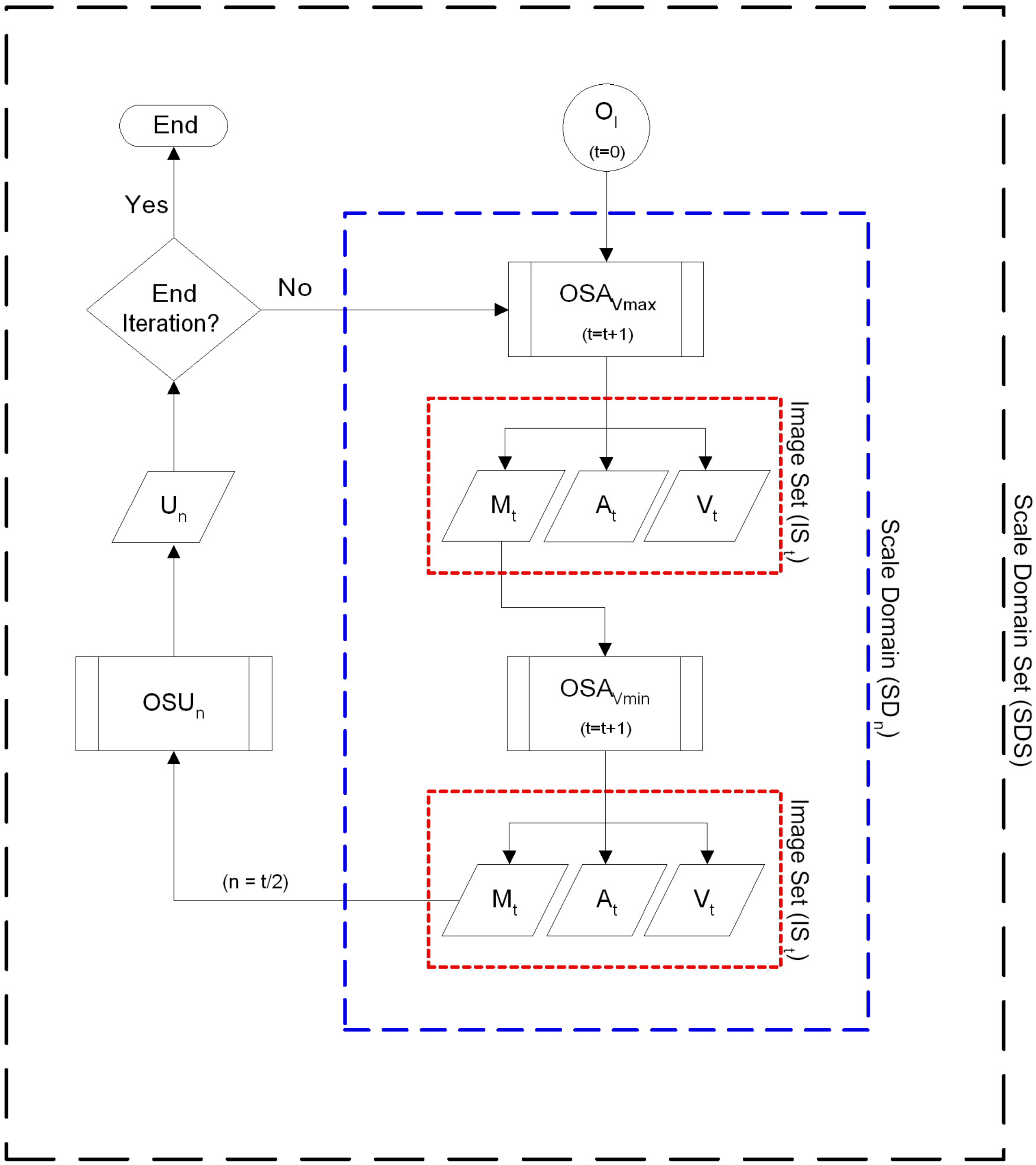
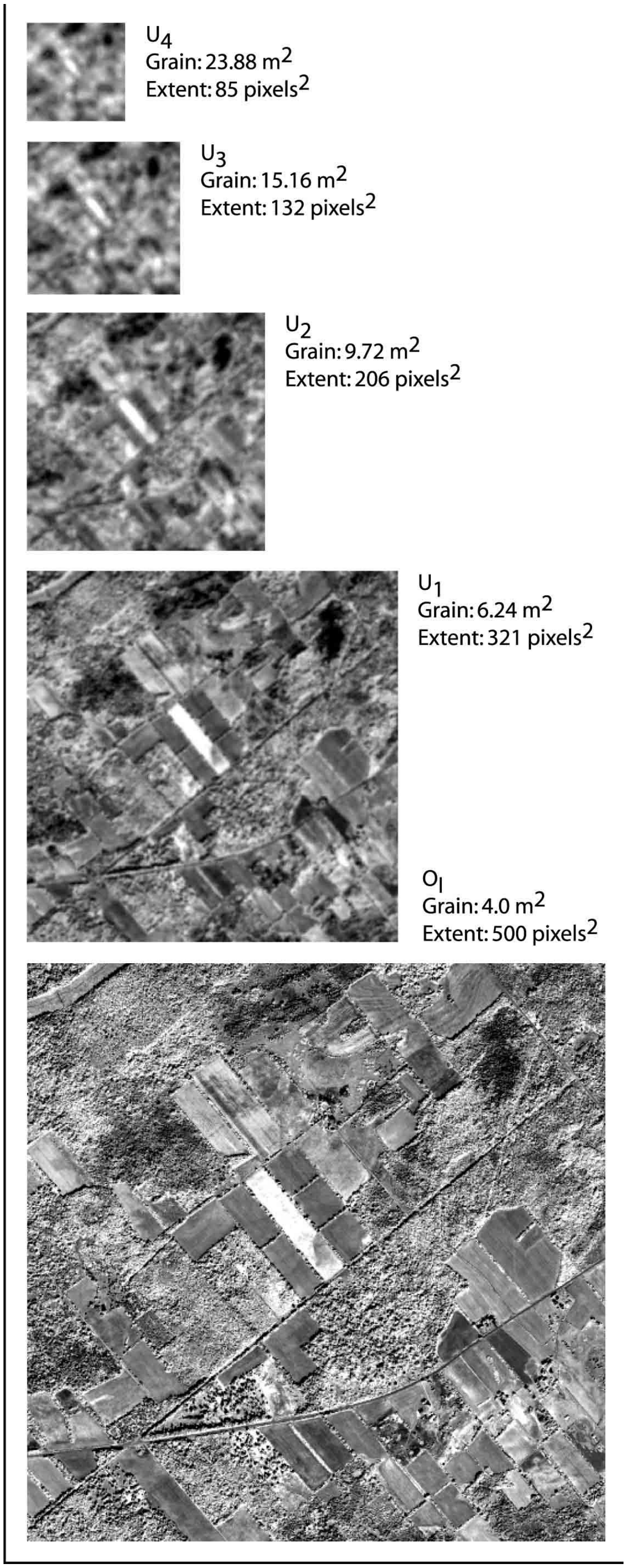

QUÉBEC
ONT.
N.B.
U.S.A.
Québec
Ontario
0
5.5
16.5 km
Montréal
St. Lawrence River
Haut-Saint-Laurent
Regional Municipal
County
Study
Area
Québec (Canada)
New York (U.S.A.)

Figure 2.



End
Yes
End Iteration?
No
U_n
OSU_n
(n = t/2)
O_I
(t=0)
OSA_Vmax
(t=t+1)
M_t
A_t
V_t
Image Set (IS_t)
OSA_Vmin
(t=t+1)
M_t
A_t
V_t
Image Set (IS_t)
Scale Domain (SD_n)
Scale Domain Set (SDS)

Figure 3.



U_4
Grain: 23.88 m^2
Extent: 85 $pixels^2$
U_3
Grain: 15.16 m^2
Extent: 132 $pixels^2$
U_2
Grain: 9.72 m^2
Extent: 206 $pixels^2$
U_1
Grain: 6.24 m^2
Extent: 321 $pixels^2$
O_l
Grain: 4.0 m^2
Extent: 500 $pixels^2$

Figure 4.

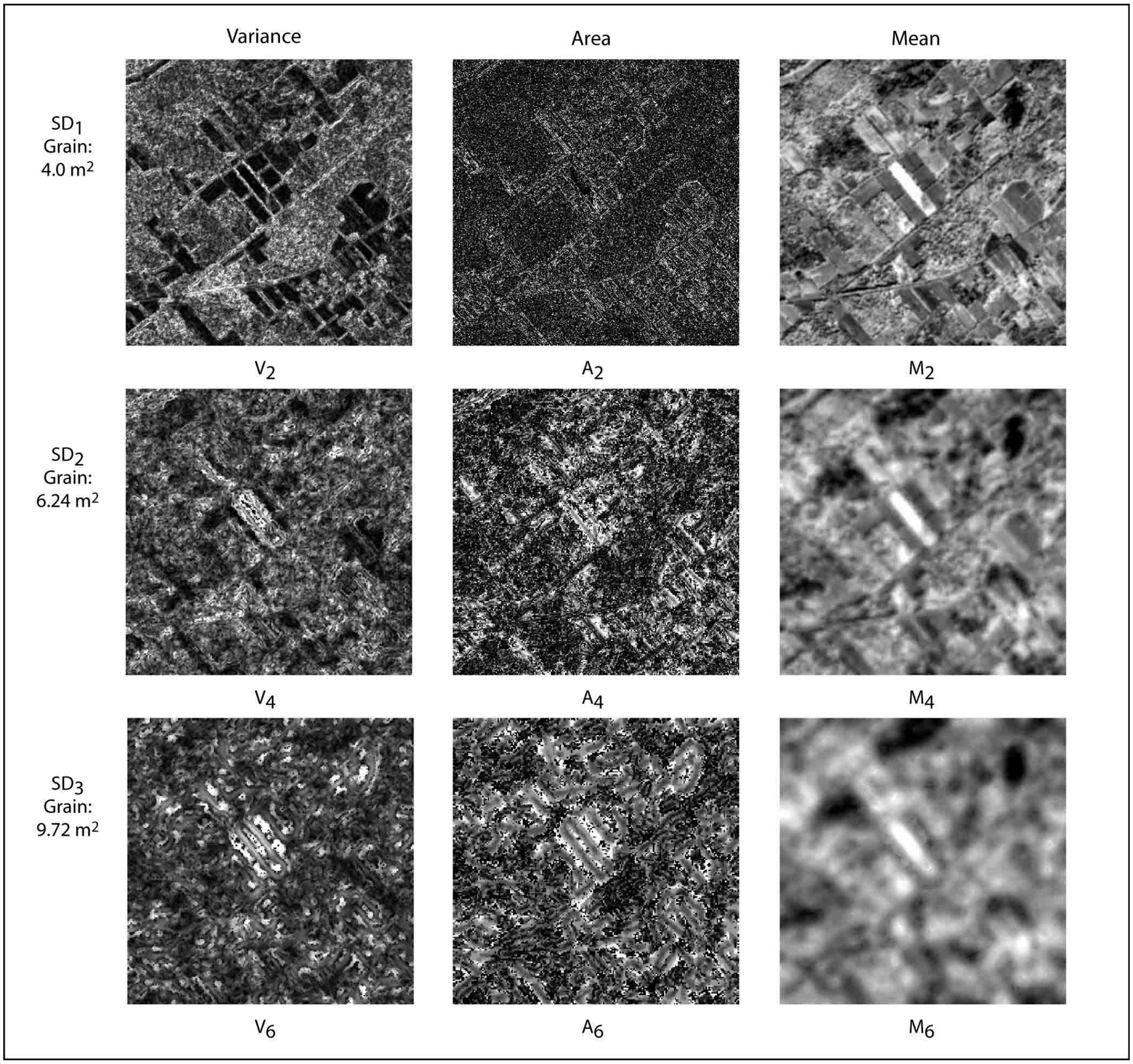
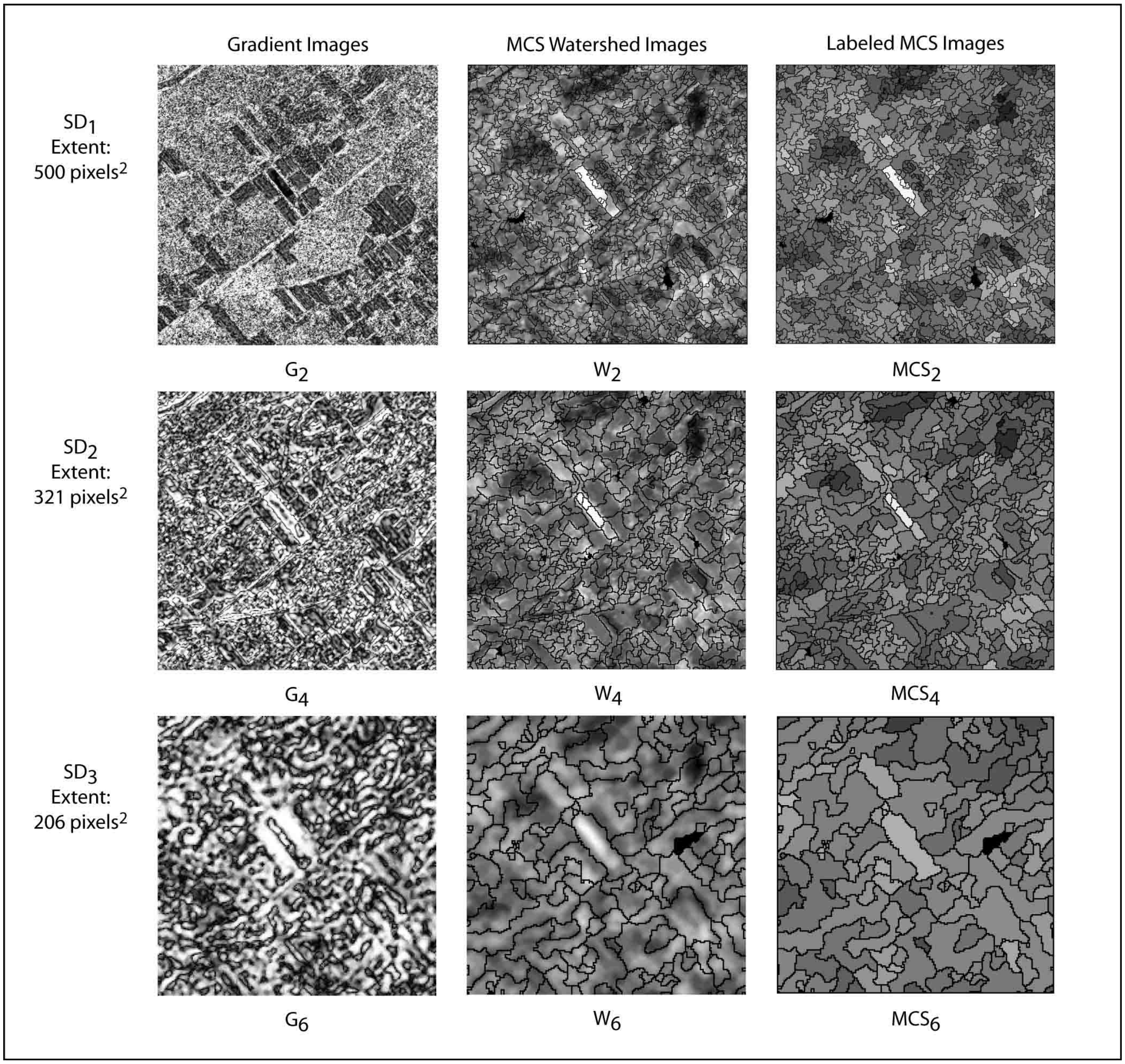

Variance
Area
Mean
SD1
Grain:
4.0 m2
V2
A2
M2
SD2
Grain:
6.24 m2
V4
A4
M4
SD3
Grain:
9.72 m2
V6
A6
M6

Figure 5.


Gradient Images
MCS Watershed Images
Labeled MCS Images
SD1
Extent:
500 pixels2
G2
W2
MCS2
SD2
Extent:
321 pixels2
G4
W4
MCS4
SD3
Extent:
206 pixels2
G6
W6
MCS6