Landscape Heterogeneity Effects on Scaling and Monitoring Large Areas Using Remote Sensing Data

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Abstract
Given the increasing rate of landscape change, researchers have realized that managing natural resources sustainably requires knowledge about ecosystems over more than one temporal and spatial scale. Monitoring ecosystem integrity implies sampling over long periods of time and space to identify any significant changes. Subsequently, remote sensing has become integral to many large-scale monitoring efforts. Nonetheless, there remain aspects related to scaling which limit the ability to detect landscape change with a maximal amount of inference. While successive analyses can be used to estimate errors, it is not clear how spatial reorganization resulting from scaling has diluted the signal of the processes embodied within the observed patterns. To achieve a maximal amount of inference, it is first necessary to match three scales: spatial heterogeneity, the scales of the ecological processes creating landscape heterogeneity, and the spatial and temporal resolutions of the image used in the analysis. We discuss the relationship between scale of spatial pattern, image analysis, and scale of process and how their interactions affect large-scale monitoring quality. In particular, we assert that the interactions between pattern and process need to be considered explicitly when designing large-scale monitoring to accurately describe ecological change. This study and others further support the suggestion that monitoring be coupled with spatio-temporal models to elucidate the mapping from pattern to process across scales. It is stressed that future research efforts be directed to understanding the characterization of space-time relationships implicit in pattern and that we move beyond the space-time duality approach to analysis.

I. INTRODUCTION

Currently, there is a concerted effort to develop integrative methods for the assessment and inventory of ecosystems across large spatial scales (see Jensen and Bourgeron [1], Stevens [2]). Indeed, given the increasing rate at which landscapes are changing (Ojima et al. [3]), scientists and managers have realized that managing natural resources sustainability requires knowledge about ecosystems over more than one temporal and spatial scale. Monitoring ecosystem integrity implies sampling over long periods of time using a series of indicators that reflect ecosystem composition and structure in order to identify any significant changes (Noss [4]).

One way to detect such changes is by monitoring landscape spatial pattern using remotely sensed data (O'Neill et al. [5]). Over the past decade, many constraints to acquiring the necessary spatial coverage have been alleviated with technical advances. Satellite imagery now forms the basis for most large-scale inventory and monitoring programmes whose foci range from regional deforestation studies to canopy physiology (Quatttrochi and Goodchild [6], Ehrlinger and Field [7]) and biodiversity (Miller [8]). Modern sensor technology spans over five orders of magnitude affording resolution and spectral flexibility to tailor to specific needs (Atkinson and Curran [9]). The wide variety of available sensor platforms (e.g., airplane, helicopter, ultralight) offer affordable ways to capture spatial variability characterizing a variety of terrains and scales (e.g., riparian corridors; intertidal systems; gopher mounds). Computer technology has improved geographical data manipulation by removing much of the drudgery and obstacles associated with map digitization and data handling. In addition, an entire generation of landscape indices, time series, and spatial statistical methods such as spectral analysis, wavelet analysis, fractals, and geostatistics are commonly employed for quantification of pattern (Turner and Gardner [10], Powell and Steele [11], Rossi et al. [12], Fortin [13], Schneider [14]).

Despite these advances, there remain certain puzzles which limit our ability to detect landscape change with a maximal amount of inference. In order to extract the maximal amount of inference from imagery, it is necessary to match three scales which describe a given landscape: spatial heterogeneity, the scales of the eco-

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logical processes creating landscape heterogeneity, and the spatial and temporal resolutions of the image used in the analysis. While innovations in remote sensing technology and signal processing have improved our abilities to quantify landscape patterns, there is less certainty when it comes to making inference about the processes which govern these patterns. We discuss the relationship between scale of spatial pattern, image analysis, and scale of process and how their interactions affect the quality of large-scale monitoring plans. In particular, we assert that the interactions between pattern and process need to be considered explicitly when designing large-scale monitoring to describe ecological change accurately.

II. MATCHING LANDSCAPE HETEROGENEITY AND SAMPLING SCALES

The major challenge to landscape ecology is the identification of the appropriate scales that govern and describe ecological phenomena (Wiens [15]). Scaling issues have figured predominantly in the ecological literature over the past decade. Entire books continue to be devoted to this subject (e.g., Ehleringer and Field [7], Allen and Hoekstra [16], Edwards et al. [17], Quattrochi and Goodchild [6], Peterson and Parker [18] Levin [19]). Generally, scaling refers to how information is aggregated and translated from one spatial scale to another with a change in extent and grain (Csillag et al. [20]). In the context of landscape monitoring, scaling is implicit in the process of sampling design; an aggregate of samples are collected at one scale (e.g., plot or image resolution) to represent the state of a unit at another scale (e.g., watershed). In most cases, the monitoring targets are considered to be reasonably well understood at the fine-scale (e.g., single tree) but their pattern and behaviour over a larger extents is generally less well defined and understood (e.g., watershed; Bradshaw [21], Stohlgren et al. [22]).

To maximize the analyst's abilities to make such inference at the landscape level and minimize bias, it is important to select imagery which will capture landscape patterns most accurately. In the instances where the landscape varies smoothly or is relatively homogeneous, selecting the best image resolution is fairly straightforward. The "best imagery" is the one whose resolution or pixel size, corresponds most closely to the grain of the landscape, where we define grain as the finest spatial resolution at which observations are made and which constitute ecologically meaningful information (Csillag et al. [20]).

Potential error is first introduced with organization of the on-the-ground information into geometric units; pixel shape and size are unrelated to the nature of the vegetation and landforms of interest. Unless the on-the-ground objects are identically proportioned to image resolution, pixels and polygons represent various compositions (Costanza and Maxwell [23], Hess [24], Bradshaw and Garman [25], Heuvelink and Goodchild [26]). Roughly speaking, though, if the resolution of the image is less than or approximates the grain of the landscape pattern, little error is introduced (Van der Knapp [27], Woodcock and Strahler [28]).

In many cases, however, the landscape under consideration is spatially heterogeneous and composed of a mosaic of patches and patterns of various grains which cannot be matched with image resolution. Large areas generally encompass a range of landscape habitats and geomorphology that result in a variety of spatial patterns. Even small areas such as low-order watersheds can be quite heterogeneous because of the interactions of climatic, geologic, and topographic gradients that generate large differences in vegetation patterns. Subsequently, selecting the "right" resolution is not always so straightforward nor sufficient. For these reasons, it is generally assumed that using imagery automatically introduces a source of error because it involves changing unit and resolution different from the constituents parts of the landscape (Rastetter et al. [29], Quattrochi and Goodchild [6]). The question becomes what steps to take to minimize error propagation. Some of these problems can be ameliorated with classification and smoothing algorithms.

Image classification and smoothing are used to organize the image into ecologically meaningful units such as plant communities. Smoothing is effected to eliminate "noise" where noise is regarded as ecologically unimportant information. Noise is usually regarded as single to small sets of pixels that result from misclassification or the misfit of the landscape pattern to the pattern of the pixels. Ideally, the smoothing procedure eliminates scattered, misclassified pixels and retains only ecologically significant features. However, the degree to which these algorithms increase or decrease accuracy still depends on landscape heterogeneity.

Like image resolution, classification and smoothing change the original on-the-ground relationships by imposing an artificial correlation structure on the data. This mismatch can either mask inherent or generate artificial spatial heterogeneity. The patterns created from image processing may even impose an additional scale of pattern. Depending on the resolution of this window and the scales of landscape heterogeneity, more or less data will be smoothed and reclassified; more specifically, the amount and type of reclassification depends on the fine-scale (i.e., window size or less) spatial distribution of classified pixels and its interaction with the selected smoothing algorithm (Milne and Johnson [30], Milne and Cohen [31]).

Given the inevitability of error introduced by the use of imagery, the selection of the most appropriate sampling dimensions (i.e., pixel resolution, classification and smoothing procedures) argues for making apriori assumptions regarding the scale of spatial autocorrelation intrinsic to the landscape under study (Fortin [13]) and the use of various segmentation algorithms which can be applied prior to classification or as part of the classification process (e.g., (Schröder et al. [32]). Others have proposed methods which try to circumvent the intrinsic problem of pixels. Such methods include rescaling techniques that use a geographic window (i.e., irregular area) based on the variogram range, rather than geometric window (i.e., pixel), to segment remotely sensed images (Franklin et al. [33]).

In any case, the successive rendering of the data from ground information to pixel to polygon propagates errors, the magnitude of which depends on the interactions between landscape heterogeneity and sampling scales (Rastetter et al. [29], Bradshaw [21]). However, while successive image analyses can be used to estimate errors resulting from a mismatch between landscape patterns and the image (Rastetter et al. [29]), there is a further issue: it is not clear how this spatial reorganization has diluted the signal of the *processes* embodied within the observed patterns (Milne and Johnson [30], Bradshaw [21], Milne and Cohen [31]). To infer ecological process from an image accurately, it is necessary to understand the meaning of ecological function of these new units and patterns created by scaling using imagery.

III. MATCHING SPATIAL PATTERN, SAMPLING, AND PROCESS SCALES

It is generally assumed that the scaling which occurs during image analyses retains spatial information as well as the relationship between pattern and the processes which have created them. However, the mosaic of vegetation and landforms observed across a landscape are actually a tangle of overlapping spatially *and* temporally constrained processes. The degree to which ecological patterns and processes can be related, and have feedback effects on one another, depends on several factors which interact to increase or decrease landscape connectivity, that is, how landscape elements are related to one another over space and time. We define this connectivity as the *spatio-temporal coherence* of a given landscape. The spatio-temporal coherence reflects the interactions between the disturbance regime and intrinsic characteristics of a landscape such as geology or the presence of topographic gradients.

Space and time are coupled in the term to emphasize the linked relationship between the spatial and temporal character of a landscape. For example, in the case of desert ecosystems, segments along a stream which are spatially proximal may be quite isolated or disconnected from each other in periods of drought. In contrast, connectivity increases at other times such as periods of high flow: two distal points in the landscape become more connected and their spatio-temrporal coherence increases. Similarly, while the immediate effects of disturbance may occur at one locale (e.g., clearcut), the effects can propagate or emerge across a range of spatial and temporal scales (e.g., sedimentation, fish mortality). As such, these translated disturbance effects can produce significant impacts which are both spatially and temporally distal or displaced relative to the initial disturbance event (Hunsaker and Levine [34], Bradshaw and Garman [25]).

As illustrated in the example below, the relationship between an observed spatial pattern and the processes which have generated it, involve a range of spatial and temporal scales which may or may not congruent. Subsequently, the scale of observed pattern is not necessarily commensurate with the scale at which the responsible processes have acted (Allen and Hoekstra [16]) and it will not always be possible to neatly map pattern to process within the image. This problem is not only an image processing puzzle but a conceptual issue as well. The ability to derive inference is hampered by the fact that inference involves an intrinsic discrepency: spatial information (pattern) is used to infer temporal information (process). This means that to infer causality, it is necessary to first evaluate the significance of spatial pattern relative to the context in which it is derived, namely, the process dynamics, which is defined in the temporal domain. Because it is not possible to have continuous coverage of time, image "snapshots" and ecological knowledge are used to interpolate and infer how processes have created the particular change in landscape pattern. The challenge for imagery-based monitoring is to understand how to identify and quantify the degree of spatial and temporal coherence to help to detect change in spatio-temporal patterns.

This challenge becomes more apparent in the presence of multiple patterns where the rates and types of disturbance occur at very different scales. Such is the case for anisotropic (e.g., spatial pattern varying with direction) or gradient-dominant landscapes such as mountainous terrain and riparian networks. As discussed below, the patterns between stream, riparian and terrestrial ecosystems comprising a watershed are usually very different because the dynamics driving these patterns are characterized by distinct temporal variability (e.g., flooding events in the case of aquatic systems, and fire in the case of hillside slopes). The presence of landscape gradients not only changes spatial pattern but also the temporal information stored within a spatial pattern.

IV. EXAMPLE: SAMPLING IN GRADIENT-DOMINANT TERRAIN

To illustrate more specifically how time and ecological processes can affect sampling design and strength of inference, we look at the problem of sampling downed wood recruitment in two different landscapes. The sampling may be accomplished using high-resolution imagery (e.g., ADAR) or field methods. Consider first a landscape composed of flat terrain (i.e., an absence of topographic gradients) occupied by standing forest where gravity is considered the only force affecting wood recruitment. Assuming no other factors, the amount of downed wood intercepted at a sample point derives from standing trees and vegetation in the surrounding area, the *zone of influence* (Figure 1). The contribution to the sample point decreases in an ever? decreasing probability in the radial direction. The area or volume of input is limited by maximum distance, such as maximum tree height, beyond which no wood will be recruited. Under this scenario, it is assumed that when a tree falls within the zone of influence, it is immediately detected at the sample point. Change in downed wood volume at the sample point will vary as a function of the growth and mortality rates of vegetation and local and regional disturbance regimes which affect the area within the zone of influence (e.g., fire, blowdown).

In contrast, consider downed wood recruitment in a second landscape where there is a topographic gradient such as that characterizing a riparian ecosystem. For the present discussion, downed wood is considered to be primarily derived from the riparian zone. The first striking difference between the two landscapes is that the zone of influence is asymmetric in the riparian zone (Figure 2; Higashi and Burns [35]). The presence of the topographic gradient alters the shape and size of the zone of influence (Figure 3). Further, the sources of downed wood are more complex. The presence of the nested topographic gradients extends the effective source area to the riparian network above the sample point. This pattern builds according to the hierarchical structure of the basin network (Figure 4). For example, wood deriving from areas in the upper reaches of the basin eventually contribute to points lower downstream; wood recruited from the banks in the basin midsection serves as input to stream sections downstream, and so forth. Subsequently, the rate at which downed wood accumulates at a sample point within the basin is influenced by processes at several temporal scales: those that are responsible for creating downed wood at the sample point and those that are responsible for creating downed wood upstream and transporting wood downstream (e.g., landslide and flood events, respectively).

Transport is a potentially complex term because it includes mitigating factors beyond the simple distance

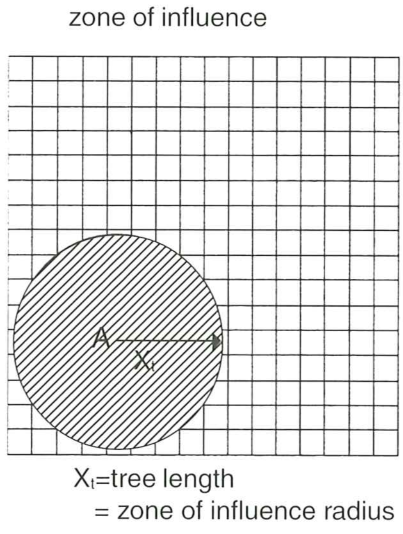

Figure 1. A diagram of the zone of influence at a sample point A for flat terrain.

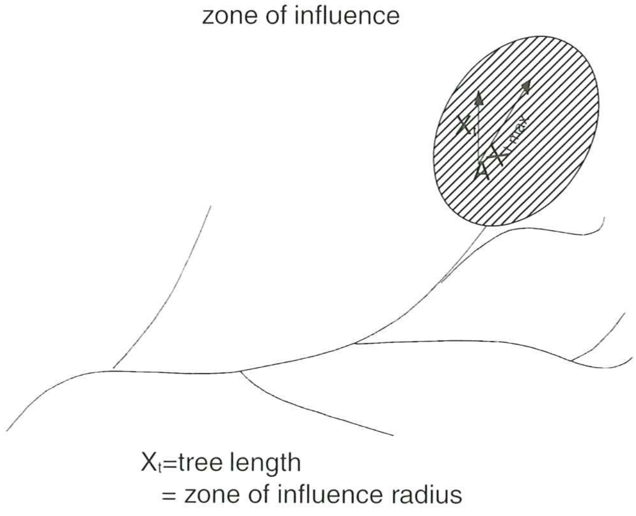

Figure 2. A diagram of the zone of influence at a given sample point along a stream illustrating elliptical shape due to the asymmetry introduced by topographic gradients.

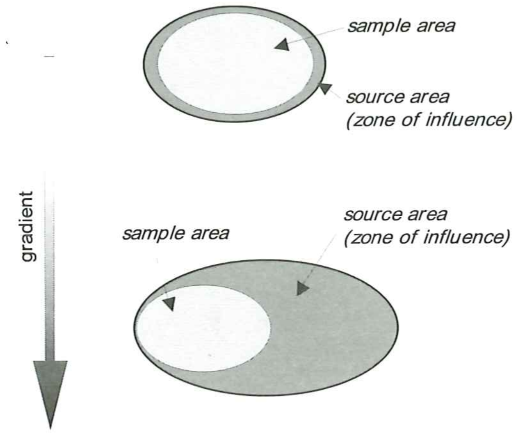

Figure 3. The presence of a topographic gradient creates a spatio-temporal displacement between the sample and source points.

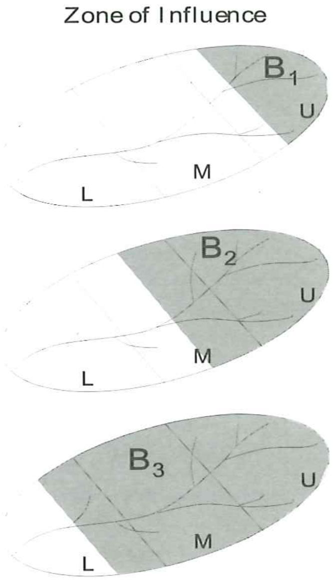

Figure 4. Hierarchical structure of a stream network creates a nested set of gradients and temporal interactions, hence spatio-temporal coherences. The notation *B1, B2*, and *B3* refer to hypothetical sub-basins within the watershed.

between the sample or detection point and location of wood input. It is related to the spatio-temporal coherence of the landscape which is a function of system attributes such as wood retention (e.g., restricted passage by geological formation) and flow variability governed by local and regional climatic regime. For example, several different scenarios may be envisioned. A tree may fall in the water and float downstream immediately to be detected within a very short time period assuming relatively unobstructed movement. On the other hand, a tree may fall or be pulled in by landslides but be retained within the channel until a sufficiently large flooding event occurs and moves it downstream to the point of detection. This is an example of pattern-process feedback effects where landscape heterogeneity (channel pattern) affects the process intensity (transport capacity).

As described in these simple case studies, the concept of spatio-temporal coherence has significant implications for monitoring design and making ecological inference based on spatial patterns. First, as the riparian example described above illustrates, the presence of gradients not only changes spatial pattern but also the temporal information stored within a spatial pattern. Depending on the landscapes spatio-temporal coherence, much of the source area may lie outside the image. In the riparian landscape, changes in spatial pattern are connected temporally by transport rates to upper reaches and potentially lie outside the image extent (Figure 5). Subsequently, the power to detect ecologically-meaningful change *and* the ability to infer causality using image-derived spatial information requires that the spatial coverage be sufficient to encompass the temporal connectivity emerging from the processes. Second, the rates of change at a given monitoring site will depend on landscape spatio-temporal coherence. As such, strength of inference is not consistent across scales; there is a concurrent decrease in the ability to detect change in pattern as spatio-temporal coherence increases. The power to detect pattern can be increased if the period over which sampling occurs is extended (Figure 6).

V. DISCUSSION

The extension of ecological studies to larger-than-traditional scales has necessitated a careful re-examination of the relationship between what is understood about ecological processes and their representation as pattern. Since, in most cases, it is not tractable to census the entire landscape extent, ecologists must choose appropriate sampling designs which represent the landscape most accurately. This requires estimating the sources of variance and choosing sampling units reflecting these processes' dynamics. However, while inference about landscapes characterized by simple spatial patterns may be fairly straightforward and its associated errors manageable using standard image segmentation techniques, inference becomes much less transparent in spatially complex cases. In the case of spatially heterogeneous landscapes, particularly in the presence of landscape gradients, inferring ecological process from image patterns necessitates an explicit treatment of spatio-temporal interactions. The translation of information across spatial scales will vary with landscape heterogeneity and af-

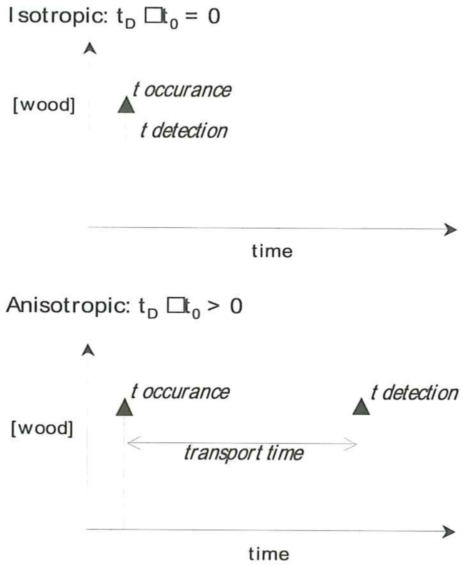

Figure 5. While the distance between points may be the same, the time between onset of change and its detection may differ. The time at which disturbance occurs and is detected is the same for the isotropic case (spatio-temporal coherence is zero), and nonzero for the anisotropic case (spatio-temporal coherence is non-zero).

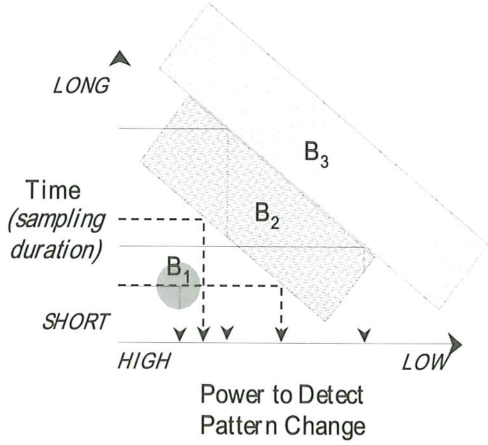

Figure 6. Depending on the degree of anisotropy and sampling duration (i.e., how long a given sampling scheme is implemented), the power to detect pattern change will vary. For example, the power to detect change in the low-order sub-basin *B1* will be greatest when calibrated those disturbances affecting the sub-basin. In contrast, the power to detect change in *B3* may require longer duration of the sampling period in order to capture changes that occur when large flooding events occur connecting the upper and lower basins by transport. The sampling time is represented as an area which corresponds to the range of natural variability.

fect the ability to infer pattern from process (Figures 7 and 8). To this end, we have argued that space and time need to be "re-united" in order to accurately infer process from pattern. This is not a new argument (see Olsen and Schreuder [36], Kareiva [37]) but is less often discussed in the context of remote sensing and GIS studies. The goal of this analysis was to bring the importance of time and its relationship to spatial pattern to the attention of image analysts.

Using concepts such as spatio-temporal coherence, monitoring designs can be calibrated to historic disturbance patterns and intrinsic landscape properties and used to frame the appropriate sampling dimensions necessary to detect change (i.e., range of natural variability; Landres et al. [38]). In this way, spatial pattern, as described by the sampled information, is directly related to process which is captured by the interactions between climate mediated flow and geologically mediated wood retention. By including the intricately related domains of space and time, the commonality, rather than differences between the spectrum of landscapes, including lacustrine, upland, riparian, and aquatic ecosystems and others, is emphasized. The introduction of such concepts as spatio-temporal coherence contributes to building an ecologically-based framework for designing large-scale monitoring which can accommodate the diversity of ecosystems. A common framework for sampling design facilitates an integrated monitoring approach to coordinating across ecosystems and scales. In this light, the following suggestions are offered.

Data comprising spatial patterns created by multiple scales or sources, should be analyzed using quantitative methods and algorithms that retain these qualities. In the case of applying smoothing algorithms to raster or vector data, it is suggested that algorithms be selected to reflect across or multiple-scale interactions (Schröder et al. [32]). In the simplest case, an additional coverage derived from topographic data could be used to weight pixels of varying temporal relatedness. To estimate variables such as downed wood recruitment in a stream network, information is required for sources, processes and rates that are responsible for wood movement. Source information may be derived from of imagery using various platforms (e.g., ADAR) or other surveys as discussed above. Information regarding transport processes and rates may be derived from hydrologic models or records describing streamflow regimes. Sampling may be focussed at a limited set of points within the basin coupled with coarse-scale coverages that describe changes in recruitment sources. Under this scenario, monitoring of wood flux within a basin may be accomplished by integrating plot-scale samples, whose sampling design is calibrated to the range of natural

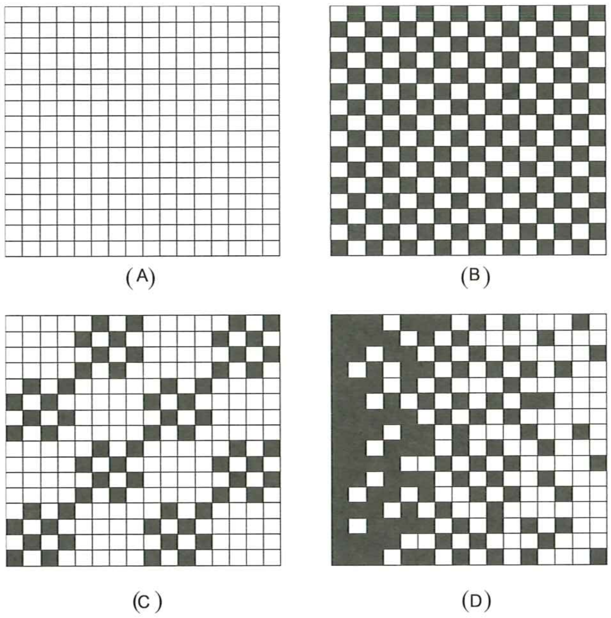

Figure 7. Four simulated landscapes with varying composition and pattern: (A) Homogeneous and by default isotropic; (B) Heterogeneous and isotropic; (C) Heterogeneous and isotropic with nested pattern; (D) Heterogeneous and anisotropic generated by landscape gradient. The distribution of individual cells was stochastically generated with a weighted gradient function.

variability, with basin-scale inventory of standing wood form imagery.

In the absence of information on the processes and rates of change, sampling will have to rely more heavily on fine-scale spatial information that retains information on temporal relationships and seeks to build a quantitative description, both in space and in time, of the rates and patterns of basin dynamics governing wood flux. However, many analyses and sampling efforts are exploratory in nature with the express intent to identify such process interactions through the patterns embedded in the data; the scale and interactions themselves are poorly defined. This study and others further support the suggestion that monitoring be coupled with spatio-temporal models to aid in elucidating the mapping from pattern to process across scales: in particular, develop a more rigorous understanding of "landscape-level processes" (Olsen and Schreuder [36], Kareiva [37]). Finally, it is stressed that future research efforts be directed to understanding the characterization of space-time relationships implicit in pattern and that we move beyond the space-time duality mode of analysis which has dominated western science for centuries (Bradshaw and Bekoff [39]).

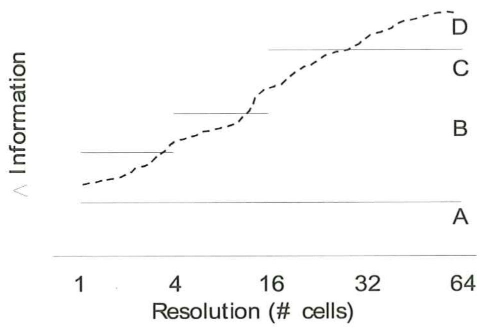

Figure 8. The amount of information changes as a function between the interaction of scaling resolution (i.e., aggregation cell size) and pattern for the four cases in Figure 7. Information is defined in the most general way, as the averaged difference in pixel values between resolution levels.

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