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Issues related to the detection of boundaries

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Abstract

Ecotones are inherent features of landscapes, transitional zones, and play more than one functional role in ecosystem dynamics. The delineation of ecotones and environmental boundaries is therefore an important step in land-use management planning. The delineation of ecotones depends on the phenomenon of interest and the statistical methods used as well as the associated spatial and temporal resolution of the data available. In the context of delineating wetland and riparian ecosystems, various data types (field data, remotely sensed data) can be used to delineate ecotones. Methodological issues related to their detection need to be addressed, however, so that their management and monitoring can yield useful information about their dynamics and functional roles in ecosystems. The aim of this paper is to review boundary detection methods. Because the most appropriate methods to detect and characterize boundaries depend of the spatial resolution and the measurement type of the data, a wide range of approaches are presented: GIS, remote sensing and statistical ones.

Introduction

Historically, ecologists have studied homogeneous regions to characterize and understand ecosystem processes and have avoided the heterogeneous areas between ecosystems. As a result, transition zones have often been ignored or reduced to lines on a map. However, these transitional zones, called "ecotones", are dynamic and play several functional roles in ecosystems dynamics; for example, they control the flux of materials between ecosystems and influence biodiversity (Naiman and Décamps 1990). In fact, because species may be at the limits of their tolerance in these transitional zones, characteristics of ecotones may be especially sensitive to environmental change. Hence, ecotones are dynamic and changes in their location can be used as indicators of environmental changes. For example, the analysis of historic ecotonal shifts can yield information about past climates and culture (Crumley 1993). For these reasons, ecotones have recently become a focus of investigations in landscape ecology (among others, Holland et al. 1991; Hansen and Di Castri 1992; Gosz 1993; Fortin et al. 1996) and global climate change (among others, Risser 1990; Neilson 1991). As interest in ecotones increases (Holland et al. 1991; Hansen and Di Castri 1992; Gosz 1993), there is increased need for formal techniques to detect them (Johnston et al. 1992; Fortin 1994; Fortin and Drapeau 1995). Hence, to better study and understand the functional roles and dynamics of ecotones in ecosystems, we need quantitative methods to identify their location and to characterize them (Fortin and Edwards 2000; Gosz 1993).

In the context of wetland and riparian ecosystems, ecotones are important transition zones; they serve as the aquatic-terrestrial interface that regulates the flux of material and the biochemical processes between these two highly productive ecosystems. Recently, however, these ecotones have been heavily impacted by human activities, which can affect their functional roles in these aquatic and terrestrial ecosystems (Naiman and Décamps 1990). The objective of this paper is to highlight the methodological issues related to the detection and quantitative characterization of ecotones. Hence we discuss the role of geographic information systems (GISs) in linking these techniques and data resources for ecotone detection as well as spatial analysis, image processing, statistics, and modeling that can be used to detect these ecotones. An objective use of these methods will improve understanding of the role ecotones play between ecosystems and of their management. Material presented in this paper evolved from discussions at a workshop on wetland and riparian ecotones[1] and related issues presented by Fortin and Edwards (2000).

Wetland and riparian ecotones

Currently, the conceptual definition (Holland 1988) of ecotones is ‘a zone of transition between adjacent ecological systems, having a set of characteristics uniquely defined by space and time scales and the strength of the interaction between adjacent ecological systems.’ In theory, ecotones can be detected by the high rate of the co-occurance of species from adjacent ecosystems. In practice, because ecotones have often been located subjectively by investigators the comparison of their movement over time has not been possible.

There are biotic and environmental ecotones: biotic ecotones reflect species’ responses to environmental change (sharp or gradual), to species interactions, or to both; while environmental ecotones correspond to sharp physical changes in either moisture, soil, topography, or geology. Biotic ecotones can be identified in terms of the location of high rates of change in species’ abundance or species’ spatial co-occurrence of replacement using presence-absence data. Often, the delineation of a biotic ecotone is used as an indicator of the potential location of a physical ecotone (Fortin et al. 1996). Unfortunately, not all species, or species’ measurements, change exactly at the same location (Naiman and Décamps 1990; Hansen and Di Castri 1992; Holland et al. 1991; Fortin et al. 1996). For example, canopy coverage of trees may provide a different perspective on community structure than individual tree-density measurements (Fortin 1997). Hence, objective statistical methods are needed to compare differences in delineated boundaries (Fortin et al. 1996) as shown in the section ‘Ecotone Detection Methods.’ Furthermore, investigators need to clearly define the criteria, rationale, and scale used to identify ecotones for their specific study.

To illustrate the role of spatial scale, we considered five scales and their associated characteristics that influence ecotone detection (Table 1). Each column of the matrix in Table 1 represents a discrete scale unit chosen arbitrarily but logically with respect to ecotone detection. We concentrate on identifying studies of wetland and riparian ecotones to illustrate these scales.

Wetland-upland interface. These are small, easily traversed areas where the wetland and upland boundaries meet. The boundary, or ecotone, will often fluctuate dramatically depending on season and year, and these fluctuations greatly influence the ecological processes. Johnston and Naiman (1987) found that the dynamics of the wetland-upland interface in Minnesota was greatly influenced by the geomorphological setting and the presence of beaver dams.

Wetland-upland zone. This scale has, as a typical study area, a stream reach with its accompanying riparian forest or a stretch of coastline with its accompanying lowland and upland vegetation. The area can still be traversed by foot but can have a width up to about 30 km. Peterjohn and Correll (1984) and Whigham et al. (1986) have studied the impact of riparian forest and associated ecotones on water quality in Maryland at this scale. Vought et al. (1994) and Gilliam (1994) have reviewed the value of these ecotones in retention of nutrients in riparian buffer strips.

[1] The 3-day international workshop ‘Wetland and Riparian Ecotones in Landscape Dynamics: A Workshop on Applying Theory, Data, and Methods’ was held in Oak Ridge, Tennessee, during September 1990 and was primarily sponsored by the U.S. Man and the Biosphere Program with additional funding from the U.S. Department of Energy and the Environmental Protection Agency.

Table 1. Characteristics of spatial scales in terms of properties associated with ecotone detection.

Study unit	Wetland upland interface	Wetland upland zone	Subwatershed	Watershed	Ecoregion
Map scale, km	50 m-2	2–15	10–40	24–100	50–500
Available resolution, m	1–10	5–20	10–50	10-1-80	30–500
Sharp edge detection, m	2–40	10–80	20–200	20–320	60–2000
Sharp edge mensuration, m	6–200	30–100	20–1000	60–1600	180–10000
Remote sensing platform	Helicopter Low flying plane	Aircraft NHAP SPOT AIRSAR	NHAP SPOT TM AIRSAR	SPOT TM MSS ESTAR	TM MSS AVHRR-1 km
Practical extent, km	4–8	30–60	80–160	200–400	1000–global
Animal	Crayfish Tricoptera	Fish Muskrat	Beaver	Deer Bat	Bobcat
Verification method	Quadrats Ground photos Soil cores Transects	Transects Ground photos Soil cores Plots	Transects Aerial photos Plots	Transects Windshield survey Aerial photos	Transects Aerial photos National inventory

Note: *Study unit* – spatial unit of interest. *Map scale* – scale at which the ecotone being detected would be drawn on a map. *Available resolution* – considering current available remote sensing platforms and technology, available resolution (or grain size) refers to the smallest feature on the ground that can be tractably detected at the particular scale of study. *Sharp edge detection* – related to available resolution, this attribute is an estimate of the minimum width of an ecotone boundary detectable by the technology. Sharp edges can usually be detected reliably within 2 to 4 times the size of the available resolution (i.e., 2 to 4 pixel width). *Sharp edge mensuration* – estimate of the minimum width needed for detection of a gradient within an ecotone boundary. Widths approximately 6 to 20 times the available resolution are needed before reliable assessments of gradients within the ecotone boundary can be detected. *Remote sensing platform* – devices being used to obtain remotely sensed data at the various scales. *Practical extent* – area (on the ground) that can be practically analyzed with current restraints (for most investigators) in computing power, data storage, and wall space on which to mount a map. *Animal* – example of an animal that utilizes the landscape at the specified scale. *Verification method* – methods available for verifying the presence of an ecotone after the detection has occurred via remote sensing.

Subwatershed. At this scale, the areal extent begins to be substantial and satellite imagery begins to be an important source of data. Ecotone studies performed at this scale include the detection, classification, and measurement of ecotones between forest and wetland patches in a glaciated Minnesota landscape (Johnston and Bonde 1989) and the First ISLSCP (International Satellite Land Surface Climatology Project) Field Experiment (FIFE), designed to assess vegetation influence on climate in the Konza Prairie of Kansas (Sellers et al. 1988). Whigham et al. (1988) also demonstrated the importance of wetland type and location within watersheds for nutrient and particulate processing. Corneleo et al. (1996) evaluated the relationships between stressors and contamination in 25 subwatersheds of the Chesapeake Bay.

Watershed. The extent of the watershed scale can vary tremendously, and most of the data available at the subwatershed level are also very useful. Statistical relationships between land cover or land use and water quality within watersheds have been developed for several locations in the United States (Omernik 1987; Osborne and Wiley 1988). Décamps et al. (1988) analyzed the historical human influences on riparian dynamics on a watershed along the River Garonne in southern France. Gosselink et al. (1990) used a landscape approach, with major emphasis on the stream-forest boundary, to assess current conditions and plans for enhanced landscape conservation in a large watershed in northeastern Louisiana. Hornbeck and Swank (1992) promoted watershed ecosystem analysis to study effects of forest harvest practices and past land use across the eastern United States.

Ecoregion. Ecoregions are areas of relative homogeneity in ecological systems (Omernik 1987) and are usually larger than a typical watershed. At the ecoregion scale, ecotones become wider and fuzzier than at the watershed scale. As an example, Iverson (1988) used a GIS to examine the relationship between land-use change and landscape attributes in Illinois. In this study the wetland-upland boundaries were delineated via major soil associations that separate uplands from bottomlands. Although wetland and riparian ecotones are not manifested at the ecoregion scale, we mention ecoregions because of the potential this concept has for improving regional management of environmental resources, especially with respect to the need to assess and predict existing and attainable water quality (Gallant et al. 1989). At level IV of Omernik's ecoregions a river valley, such as the Sequatchie in the Cumberland Plateau of Tennessee, may be uniquely delineated (Griffith et al. 1997). This regional assessment concept has been well developed in Bailey (1996) and applied for the Southern Appalachians (SAMAB 1996).

The dynamics of ecosystem boundaries at regional scales are being examined relative to climate change at several of the Long-Term Ecological Research Program sites (Swanson and Sparks 1990). The Sevilleta site in New Mexico, the Arctic Tundra site in Alaska, the Niwot Ridge site in Colorado, and the North Inlet site in South Carolina all have long-term sampling programs to monitor the environment and have transects of plots crossing ecotones at each site. Gosz (1993) discussed ecotone hierarchies and scales with respect to the Sevilleta site and presented a multilevel, nested sampling design that relates plant-edge ecotones to the dynamics of the biome ecotone. Given the various spatial resolutions of data associated with these spatial scales (field data, aerial photographs, in the following section and remotely sensed images), various methods can be used to detect ecotones as shown in the following section.

Ecotone detection methods

Methods for ecotone detection include spatial analysis (such as GIS and remote sensing) to detect spatial patterns, statistics to quantify and contrast patterns, and modeling to formulate and predict multivariate interactions. Recent advancements in capabilities and increased availability of GISs are key factors in developing approaches capable of dealing with the complexities of ecotones, and allowing performance of spatial analysis, image processing, statistics, and modeling all within the same system. The edge detection methods discussed in this section can often be applied to a variety of data, independent of the resolution of the data or data collection procedures.

Detection of ecotones can be made with field data gathered along transects (one dimension) or across a grid (two dimensions). The type of data will guide the choice of method(s) to be used (Table 2). For instance, two-dimensional sampling can produce a grid of observations (raster format) that can be used to estimate the degree of sinuosity or waviness of an ecotone not possible from one-dimensional transects. Remote sensing is ideal for producing a grid of data (raster format) for analysis, whereas data collected via field work may be limited to transect or point data.

Geographic information systems

The power of a GIS is its ability to synthesize information about spatial phenomena, such as ecotones, by integrating geo-referenced data to show the original data and derived information in new ways and perspectives (Arnoff 1989). An important decision in designing a spatial database for ecotone study is the selection of the underlying geo-reference system and spatial resolution (Table 1). Although the choice of scale may be strongly influenced by existing data, the selection is important for establishing a common system for data integration, for addressing data-quality issues, and for specifying detection limits. An understanding of the precision and accuracy of the data within a GIS is also important. Even though a GIS can mechanically reformat and transform data from different sources into a common system, it is the responsibility of the GIS user to determine the consequences of integrating data that has been collected at different scales, represented by different topological structures, digitized with varying degrees of precision, or containing other sources of errors. Unfortunately, elegantly drawn GIS maps usually do not convey the uncertainty associated with boundaries or contour lines. However, cartographic techniques can be used that provide more information. Clarke et al. (1991) delineated ecological regions and subregions for Oregon and assigned two attributes to each boundary – the relative width of the transition zone and the rank of the importance of the characteristics used to determine the boundary.

This issue of scale and its importance to relationships between landscape structure and process is illustrated by the paper by Hunsaker and Levine (1995). Some literature indicates that land use close to streams (i.e., in riparian zones) is a better predictor of water quality than land use over an entire watershed, whereas empirical evidence from other literature concludes that the upland land uses are as important as near-stream land uses. Hunsaker and Levine (1995) conclude that the seemingly contra-

Table 2. Statistical methods for measuring and characterizing ecotones. The choice of a particular analytical method depends on the type of data available.

Ecotone attribute	Data type		
	Grid data (raster format)	Transect data	Sparse data[a]
Detection	Edge detection algorithms and kernels	Magnitude of first difference	Irregular edge detection
Location	Thresholding of edge operations	Maximum of first difference	Functional criteria
Width	Goodness of fit for location statistic; inverse slope of brightness	Magnitude of first difference	Magnitude of first difference
Evenness	Dispersion of widths along boundary		Dispersion of widths along boundary
Sinuosity	Length of boundary as a function of grid precision; fractal dimension		Length of boundary as a function of grid precision; fractal dimension
Coherence and significance	Boundary statistics overlap statistics (different between boundaries vegetation, soil, etc.)	Coincidence of limits more often than by random chance	Boundary statistics overlap statistics (different between boundaries vegetation, soil, etc.)

[a]Sparse data refers to scattered point measurements taken over the landscape.

dictory results within the literature are a function of the large differences in data resolution and different approaches between studies. Factors that enter into these apparent contradictions are the data resolution of land cover, stream vectors, and digital elevation data and the accuracy of GIS functions to approximate riparian zones (e.g., equal area buffers around coarse-resolution stream vectors or hydrologically active areas for overland flow as defined by topography).

The two major types of GIS data models are raster and vector, each with different functions for detecting ecotones. In raster systems, values are assigned to each cell or pixel in an x,y-grid; most remote sensors generate raster data. Pattern recognition, optimal corridor location, moving window, and most spatial modeling techniques are better suited to raster data. In vector systems, attributes are associated with point, line, and polygon features, and adjacent features are related to each other through topology. Vector systems can more readily calculate lengths, areas, and fractal dimensions; identify adjacent ecosystems; calculate buffer zones; and generate more traditional cartographic products. However, with vector systems, most ecotones are reduced to a line while in fact they should be portrayed as transitional zones (Clarke et al. 1991). GIS functions that may be applied to the detection of sharp or gradual ecotones are those for raster format, such as the image enhancement algorithms that use a filter (moving window) to identify edges. At first these filters were developed to segment remotely sensed images, but lately most raster GISs offer these functions (Burrough 1986; Arnoff 1989; Cornelus and Reynolds 1991). The use of GIS techniques, in combination with image processing, for the quantitative analysis of ecotones are described in Johnston et al. (1992). The specifics of these edge-detection filters are presented in the next section on remote sensing.

Remote sensing

Remote sensing can be used to visualize transitional zones and to detect ecotones based on surface properties (e.g., vegetation, soil type, and soil moisture), especially at the watershed and broader scales. Imagery is available from a variety of remote sensors with a range of temporal, spatial, and spectral resolutions (Table 1). However, it is interesting to note that in the past, image processing has reduced ecotones to simple lines between homogeneous areas. Given this perspective, new image-processing approaches are needed to focus on ecotones themselves.

Extensive work has been done to recognize and classify terrestrial vegetation on the basis of remote-sensing data (e.g., Hardisky et al. 1986; Justice et al. 1985; Butera 1983; Wolter et al. 1995). Ecotones may appear in remotely sensed images as very sharp or more gradual transitions between ecosystems. Useful methodologies for detecting ecotones must be able to handle both cases. Some ecotones are very sinuous and may exhibit disjunct islands beyond the main distribution, and to be useful, the boundary-detection algorithms must be capable of sensing such disconnected boundaries.

Since the 1970s, edge detection (boundaries) has been appreciated as a computational problem and dozens of techniques have been proposed for its solution (Pitas 1993). Although many edge algorithms have been described, it is unlikely that any one is perfect for general application or that any can be directly applied to ecotone detection. Most of the relevant methodological development in image analysis has focused on edge enhancement (visually emphasizing the boundaries in a picture); less attention has been given to methods for edge detection (determining whether a clear edge is present) or localization (finding its position). In the image-processing literature, the term texture refers to the brightness variations of an image. Texture can be described using a structural or statistical approach. In the structural approach, an image is assumed to be composed of primitive elements (groups of pixels) that can be characterized by their shape and size as well as their pattern of repetition. However, because image processing encounters problems similar to those met in field ecology (i.e., misclassification or unclear repetitive patterns) a statistical approach is often preferred. Such an approach consists of analyzing the intensity of the gradient among neighborhood pixels with various techniques, such as autocorrelation functions, autoregressive models, spatial intensity co-occurrence probabilities, textural edginess, and structural element filtering (Pitas 1993).

The major problems in the detection of edges in image processing are noise due to bad resolution; the spatial resolution of the image (this is similar to the situation in field data where the finest level at which an edge can be detected depends the resolution of the samples – pixels, quadrat size, or at the limit, the crown canopy size); the texture that adds itself to the noise; and the intensity of the discontinuities. If the discontinuities do not contrast sufficiently with the background (texture), they are considered as noise.

The most common edge detection methods take into consideration locally neighboring pixels and are called parallel methods because, in theory, all the pixels should be processed at the same time. The simplest methods are the ones that are based on linear differences, such as Sobel and Kirsch operators or local first-order derivatives between adjacent pixels, and are called edge detector kernels or simply edge filters (Pitas 1993). These kernel operators can be either windows of 2×2 or 3×3 pixels. Gradients computed from 3×3 windows are smoother than those computed from 2×2 windows and hence reduce more of the noise. The size of the window is critical, as is the block size in field data, for overcoming noise and for the ability to detect small edges.

These algorithms, based on linear differences and first-order derivatives, detect edges by showing the presence of the highest rate of change between adjacent pixels. When an edge is wide, it is important to detect its starting and ending locations. This can be accomplished by using second-order derivatives, where the derivative values equal zero except at the locations where the boundary begins and ends. Such second-order derivative operators are known as Laplacian operators (Pitas 1993). The major problem with a Laplacian operator is that it is so sensitive to noise that it is necessary to smooth the data first.

There are several other parallel edge detection algorithms: nonlinear ones that use kernels based on polynomials; edge-preserving smoothing techniques with nonlinear filters; global thresholding that segments the pixels based on their spectral brightness; and adaptive filters that correct for random noise as well as additive or multiplicative noisy data related to the image scene (Pitas 1993). Multivariate spatial analysis of spectral data may yield a much fuller picture of vegetation patterns. For subtle transitions to be detected, multispectral images must be exploited fully rather than relying on a single ratio, such as the normalized vegetation index, or any other single scalar derived from the multispectral image. For instance, with a training set in which homogeneous vegetation types and their ecotones are identified from ground truth information, we can use multivariate discrimination to determine the combination of spectral variables that best distinguishes these components of the landscape. There are several ways to combine the evidence for transitions displayed in different wavelengths [e.g., color edge detection and metrics derived from band combinations (DeFries et al. 1995)].

The appearance of vegetation often changes as seasons change, and techniques that can exploit this temporal dimension may be quite useful for detecting ecotones (e.g., Wolter et al. 1995). For instance, deciduous forests go through many phenological changes each season, with different species following different schedules. By comparing repeated images of the same site through time and observing phenological changes, it should be possible to detect ecotones with more precision and to determine their species composition.

Spatial clustering techniques in image analysis are grouped under the heading of image segmentation. They have been used for several decades to carry out automated image analysis in a variety of fields, including remote sensing, medical imaging and industrial imaging. Three broad categories of segmentation techniques have emerged. These are region-growing techniques, edge-detection techniques, and hybrid techniques. Region-growing techniques rely on 'seed' regions which may have been determined ahead of time, either by another algorithm or a human operator, which are then grown outwards using a homogeneity criterion based on spatial contiguity until the regions meet at boundary zones. Boundary techniques, on the other hand, use edge detection methods to identify boundary elements, and then attempt to connect discontinuous boundaries together to form a spatial partition. Hybrid methods use both region-growing and edge detection strategies.

A large variety of segmentation strategies have been developed over the past several decades. There exist at least several hundred different types of segmentation. Aggregation methods, hierarchical strategies, Fourier techniques, context-based methods, methods which statistically iterate towards a better partition, fuzzy set theory approaches, texture-based methods, and so on have all been developed. Although in principle methods have been developed to extract transition zones, these have largely been applied to applications in medical and industrial imaging, and only infrequently to remote sensing data. This is an area where more work might be usefully attempted. Despite the large number of segmentation techniques which have been developed, relatively little attention has been paid to the need to develop error measures for the resulting partitions (Edwards 1995). Beauchemin et al. (1995) surveyed different methods which have been used to characterize the error or uncertainty associated with segmentation techniques. None of these are fully satisfactory, but they do provide some insight into the errors involved.

Over the past several years, the use of image segmentation techniques has evolved towards methods which mimic human vision more closely (Cantoni et al. 1997). Again little effort to study error has accompanied these efforts. Nonetheless, these methods of identifying boundaries and regions in images represent the beginning of a convergence towards the kinds of processes used by humans in photo-interpretation tasks, and may well provide new insights into the sources of error and uncertainty found in the latter (Story and Congalton 1986; Edwards and Lowell 1996).

Statistical methods

The choice of statistical methods to detect ecotones depends on the data available and the question asked (Table 2). Several quantitative studies have addressed the problems of detecting transition zones (Wiens et al. 1985; Cornelius and Reynolds 1991; Johnston et al. 1992). Statistically, a boundary can be defined as the location where the highest rate of change occurs (Burrough 1986). Recently, new methods have been developed that use moving split-window techniques (Figure 1a) to compute the amount of variance in adjacent samples along transect data (Ludwig and Cornelius 1987; Johnston et al. 1992) and the boundary is the location where the value of variance is the highest.

With quantitative regularly spaced data, an edge detection algorithm called 'lattice-wombling' (Figure 1b) can be used (Fortin 1994, Fortin and Drapeau 1995). This algorithm requires that the values of the variable be mapped on the nodes of a rectangular lattice as is the case for remotely sensed data. The rate of change is computed for the first-order partial derivatives of each of four quadrats forming a square (see Fortin 1994, for the mathematical details). When the values in the four quadrats are similar, the magnitude of the rate of change will be close to zero; when the values at the four quadrats change abruptly, the magnitude of the rate of change is high. A boundary is identified from the spatially adjacent locations which are characterized by high values of the rate of change. When several variables are available for study, the mean rate of change is defined as the average of the rate of change for the given assemblage of variables.

When field data are quantitative but irregularly spaced, a triangulation-wombling edge detection algorithm (Figure 1c) is more appropriate (Fortin 1994). Indeed, as mentioned above, field data are usually sampled using either random, stratified or systematic sampling designs, which require less sampling effort than a complete survey of an area. To bypass the regularly spaced data requirement, Fortin (1994) modified the lattice-wombling algorithm in such way as to deal directly with irregularly spaced samples. The algorithm also finds first-order partial derivatives, but rather than using four nearby points that form a square, it uses the three nearest points that form a triangle. The Delaunay algorithm can be used to find the

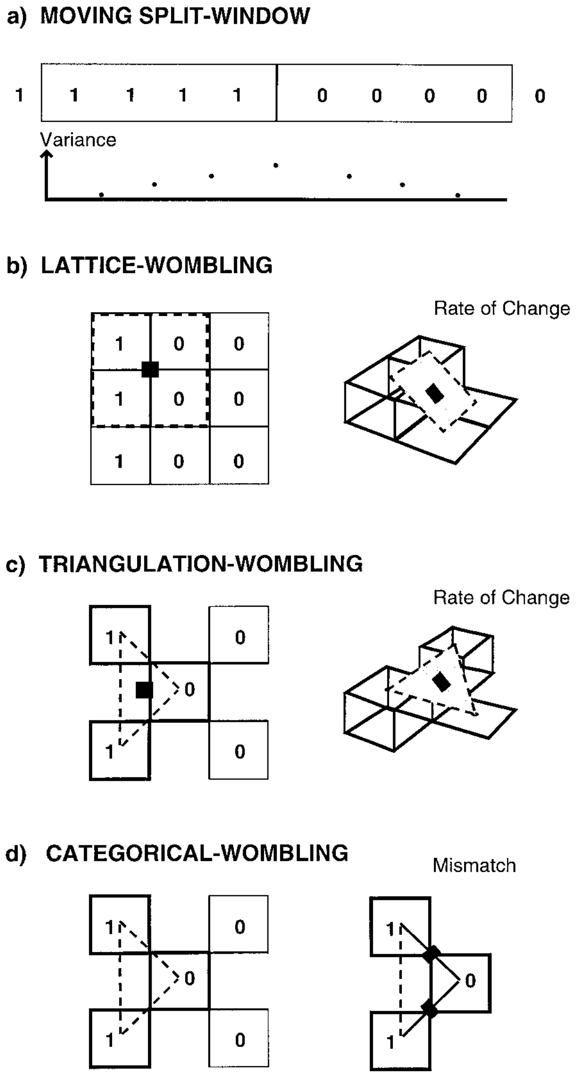

Figure 1. (a) Moving Split-Window computed using a window of 8 sampled where the edge is at the location where the variance is the highest. (b) Lattice-wombling computed for the four adjacent quadrats that forms a square as indicated by the dash line. The number in each quadrat is the quantitative value measured. The filled square indicated the location of the centroid at which the rate of change is computed. The *z*-axis is the quantitative value. The slope of grey plane that fits the quantitative values represents the intensity of rate of change. (c) Triangulation-wombling computed for the three adjacent quadrats that forms a triangle as indicated by the dash line. The number in each quadrat is the quantitative value measured. The filled square indicated the location of the centroid at which the rate of change is computed. The *z*-axis is the quantitative value. The slope of grey plane that fits the quantitative values represents the intensity of rate of change. (d) Categorical-wombling computed for pair of adjacent quadrats that are linked following a Delaunay network indicated by dashed lines. An edge is computed as mismatch between adjacent quadrats and is indicated by the filled squares.

list of nearby samples that form triangles (Upton and Fingleton 1985).

Ecological data include not only quantitative variables, but also semi-quantitative and qualitative ones such as presence/absence of species, type of soil, geomorphologic formation, etc. With such qualitative data, boundaries can be established by computing a dissimilarity, or distance value, using the data of several variables at once, and looking for the highest dissimilarity between adjacent sampled points (Oden et al. 1993; Fortin and Drapeau 1995). With this categorical approach (Figure 1d), qualitative data (or semi-quantitative or quantitative data) are transformed into quantitative coefficients such as dissimilarity measures, or a simple mismatch measure (Oden et al. 1993). To detect boundaries, only the dissimilarities between pairs of spatially adjacent samples are considered. Adjacent samples are defined as those directly connected by the links of a Delaunay network, although other network structures can be used. An overall high dissimilarity value indicates the presence and location of a boundary.

However, as with any statistical analysis, a significance test is needed to establish whether or not the highest rates of change observed are higher than would be expected under a null hypothesis, here which is the absence of a cohesive boundary. Indeed, statistics will always yield numerical results regardless of whether or not they make sense (e.g., edge detection algorithms will always find some rates of change higher than others). Thus, significance tests are needed to ensure that the highest rates of change differ significantly from the random expectation. Such significance tests have been developed for transect data (McCoy et al. 1986) as well for two-dimensional data where observed statistics that reflect the characteristics of boundaries, such as contiguity of the highest rates of change in a long narrow line, are tested against expected values generated by randomizing the original data (Fortin and Drapeau 1995; Fortin et al. 1996).

In general, an ecotone is a multivariate concept that implies the co-occurrence of rapid change for several features, such as density and composition of vegetation and soil moisture. It would be useful to test whether or not different characteristics or measures of different variables have boundaries that coincide. Overlap statistics (Fortin et al. 1996) can be used to assess the degree of spatial relationship between the spatial location of boundaries as detected with different variables. Significance of these overlap statistics should also be assessed using randomization tests (Fortin et al. 1996).

Once located, ecotones can be measured for width, evenness, and sinuosity (Table 2). Width estimation may be an associated output of the location algorithm, or it could be measured by the magnitude of the gradient at points along the ecotone. Transect studies give only point information at selected locations about the steepness of rate of change and width, whereas area studies can give information about the shape of the ecotone, as well as the variation in gradient of change and width. Evenness of the width can be measured by an index of the dispersion of width measures along the ecotone. The degree of sinuosity can be measured by the length of the ecotone per unit area using the fractal dimension (O'Neill et al. 1988). Milne and Johnson (1995) used changes in the multifractal geometry of density classes to support the hypothesis of a spatial phase transition with regard to vegetation gradients or ecotones.

Modeling

The GIS, remote-sensing, and statistical approaches discussed in this paper can be applied to a variety of ecotones. If we know the origin, maintenance factors, or other dynamics associated with an ecotone, we may be able to use that information to build a model that incorporates these processes. Hydrologic modeling of wetland and riparian ecotones are examples of this approach.

Whether the ecotone of interest is between vegetation communities within a wetland or between aerobic and anaerobic soil conditions, hydrology is often the primary factor controlling the location, width, and shape of wetland and riparian ecotones. Therefore, hydrologic models that use spatially defined parameters are useful for detecting wetland and riparian ecotones. In addition, hydrologic models provide a tool for modeling seasonality in ecotone location (i.e., estimate a spatial frequency distribution of ecotone boundary location based on the time of year).

For a hydrologic model to predict locations of ecotones, it is best driven by spatial data. Typical model data include elevation data available from the U.S. Geological Survey (USGS) as Digital Elevation Models (DEM), land use data, and soils data from Nature Resource Conservation Service surveys. Data are converted to a common grid representation within a GIS and linked to the model. The selection of the cell size for the grid determines the size of ecotone that can be modeled (Table 1). Additionally, the spatial nature of the data and model allow output to be mapped for interpretation. Examples of hydrologic models that can be used in this way are TOPMODEL (Beven and Kirkby 1979) and one, which we will call COUNT, developed by Jensen and Dominque (1988).

TOPMODEL uses DEM, soil conductivity, and rainfall data to generate hydrographs for a watershed and to calculate topographic convergence values for each cell within the watershed grid. Topographic convergence is the ratio of drainage area to land surface slope for an individual cell. Cells that have large drainage areas and low slopes have high values of topographic convergence, which means they are more likely to be saturated or have standing water than cells with small drainage areas and steep slopes. Thus, TOPMODEL can model the moisture gradient within a watershed. Topographic convergence and stream network information can be combined with field observations to initially identify possible ecotones. Field transect data on elevation, tree species, etc. can be used to identify the threshold value for topographic convergence where the ecotone occurs between upland and riparian forest. At this point, as many variables as are available, either measured or modeled, can be evaluated or used (e.g., slope aspect, shading). Once determined, a threshold value can be used to classify the cells, indicating the ecotone location and shape as controlled by moisture and other variables found to be useful.

Although riparian ecotones can be approximated using land-use and stream network data with a GIS, the resolution of the stream network is often not fine enough to capture the spatial pattern of hydrologic processes. The model by Jensen and Dominque (1988) can produce stream networks with over 95% accuracy for various types of landscapes based solely on topography. COUNT uses DEM data to estimate the number of cells that contribute hydrologically to any cell within a DEM. The output from this model can be calibrated with field data on overland flow from storm events to identify ecotonal areas that may only be apparent during storm events. The model has been implemented in ARC/INFO GIS (ESRI 1993) as flow accumulation and is used in conjunction with aspect, curvature, and soil-water-holding capacity to derive an integrated moisture index that can delineate transition zones between vegetation types (Iverson et al. 1997). Hunsaker and Levine (1995) effectively used this technique to delineate hydrologically active areas in Texas and model nutrient loadings to streams.

Conclusion

Ecotones, or transitional zones between adjacent ecosystems, are important components of the landscape that have often been ignored in preference for the study of the more homogeneous ecosystems. In this paper, we have discussed the principal issues related to the quantitative detection of ecotones, such as the importance of spatial scales and the edge detection methods used. Recent developments in GISs provide an approach both to analyze spatial data associated with ecotones and to link image processing of remotely sensed data, statistical analysis of field data, and modeling of hydrologic processes. The challenge is to use the available data and techniques in ways that identify the heterogeneous zones as entities rather than simply to reduce them to a line between adjacent patches. A parallel has been drawn between the edge detection and image segmentation methods found in remote sensing and those applied to ecological data. It seems reasonable, therefore, to exploit these cross-disciplinary links to further develop and characterize the delineation of transition zones across a wide variety of sources of data and methods of analysis. This multidisciplinary effort should lead to a greater understanding of ecotone delineation, systematizing the results from smaller studies to a broader context. Research needs include image-processing algorithms for edge detection and enhancement that are capable of sensing disconnected boundaries and exploiting multispectral images. In addition, significance criteria and statistical tests need to be used to quantify the level of change observed in the data relative to random fluctuations. Finally, we need a program of long-term monitoring, in which both field and remotely sensed data are collected by means of sampling designs oriented more toward ecotone detection. Such a database, coupled with techniques presented here, would allow us to more fully understand the role of ecotones in the landscape.

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Appendix A. Data resources

Site- to subwatershed-scale field studies designed to collect data specifically to detect and monitor ecotones are relatively rare. As part of a workshop on wetland and riparian ecotones (Wetland and Riparian Ecotones in Landscape Dynamics: A Workshop on Applying Theory, Data, and Methods, 1990), a questionnaire on existing data relevant to ecotones was sent to over 200 candidate sites, including international biosphere reserves (69), U.S. biosphere reserves (79), long-term ecological reserves (15), environmental research parks (13), and workshop participants (50). Twenty responses were received, and only 11 indicated data appropriate for ecotone studies. Respondents indicated the need for data on wetlands, detailed vegetation maps, long-term monitoring of vegetation composition, and data collected using protocols that allow cross-site comparisons. Generally speaking, very little field data appear to be available or classified as relevant for ecotone studies. An example of available, relevant information is Appendix A in Gosselink et al. (1990), which contains lists of many sources of aerial photos and data for the study of bottomland and hardwood wetland ecosystems and a summary of present and future remote sensing sources by the U.S. Army Corps of Engineers (1993).

Ecotone detection at the watershed and larger scales can effectively use extant data acquired from both aircraft and satellite platforms. Many federal agencies in the United States have highly organized data directories, database systems, and the ability to respond to outside inquiries for data. On-line directories of environmental data can be accessed on the Internet to locate desired data sets and to determine how to acquire them. Some of the major sources of data are summarized below.

The National Aeronautics and Space Administration (NASA) Global Change Master Directory (GCMD) (http://gcmd.gsfc.nasa.gov) "points to" sources of data related to global change programs, which may reside either within or outside of the NASA archive. In this way, a person searching for vegetation classifications, for example, may place an initial inquiry with GCMD and be referred to relevant data sets held by other agencies.

Table A.1. Earth Observing System Data and Information System (EOSDIS) Distributed Active Archive Centers (DAACs) and Affiliated Data Centers

ASF [Alaska SAR (Synthetic Aperture Radar) Facility] DAAC (http://www.asf.alaska.edu/)
Alaska SAR Facility (Fairbanks, Alaska)
Discipline: Polar processes, SAR products

EDC [EROS (Earth Resources Observation Systems) Data Center] DAAC -
(http://edcwww.cr.usgs.gov/landdaac/landdaac.html)
EROS Data Center (Sioux Falls, South Dakota)
Discipline: Land processes

GSFC (Goddard Space Flight Center) DAAC (http://daac.gsfc.nasa.gov/)
NASA Goddard Space Flight Center (Greenbelt, Maryland)
Discipline: Upper atmosphere, global biosphere, atmospheric dynamics, geophysics

JPL (Jet Propulsion Laboratory) DAAC (http://podaac-www.jpl.nasa.gov/)
Jet Propulsion Laboratory (Pasadena, California)
Discipline: Physical oceanography

LaRC (Langley Research Center) DAAC (http://eosdis.larc.nasa.gov/)
NASA Langley Atmospheric Sciences Data Center (Hampton, Virginia)
Discipline: Radiation budget, tropospheric chemistry, clouds, aerosols

NOAA (National Oceanic and Atmospheric Administration) Satellite Active Archive (SAA)
(http://www.saa.noaa.gov/common _www_html/impmess.html)
National Oceanic and Atmospheric Administration Satellite Active Archive (Camp Springs, Maryland)
Discipline: Satellite data (atmosphere, land, ocean, earth sciences, remote sensing)

NSIDC (National Snow and Ice Data Center) DAAC (http://www-nsidc.colorado.edu/NASA/GUIDE/)
National Snow and Ice Data Center (Boulder, Colorado)
Discipline: Snow and ice, cryosphere and climate

ORNL (Oak Ridge National Laboratory) DAAC (http://www-eosdis.ornl.gov/welcome.html)
Oak Ridge National Laboratory (Oak Ridge, Tennessee)
Discipline: Biogeochemical dynamics

The National Oceanic and Atmospheric Administration's (NOAA's) Environmental Services Data Directory (ESDD) (http://www.esdim.noaa.gov/NOAA-Catalog/NOAA-Catalog .html) allows users to search for publicly available environmental data held by public and private sources throughout the world. Data sources include descriptions related to climatology, meteorology, ecology, pollution, geology, oceanography, and remote sensing satellites. ESDD contains descriptions of over 8,000 datasets and NOAA's legacy National Environmental Data Referral Service contains descriptions for over 22,200 datasets.

The U.S. Geological Survey (USGS) Earth Science Data Directory (ESDD) (http://www.usgs.gov/fact-sheets/ESDD/ESDD.html) is a system for readily determining the availability of specific earth science and natural-resource data. It offers on-line access to a USGS repository of information about earth-science and natural-resource databases. The term "earth-science and natural-resource data," as used for ESDD, is an all-embracing term referring to any systematic body of knowledge, automated or not, relating to the Earth, its environment and its energy, mineral, water, land, plant, animal, and other resources. Geographic, sociologic, economic, and demographic databases are among those cataloged. ESDD also provides leads to data for geographic information system (GIS) applications.

The U.S. Federal Geographic Data Committee (FGDC) Clearinghouse Activity (http://www.fgdc.gov/clearinghouse/index.html) is a decentralized system for digital geospatial data. Governmental, nonprofit, and commercial participants worldwide make their collections of spatial information searchable and accessible on the Internet using free reference implementation software developed by the FGDC. The system uses the metadata elements defined in the Content Standards for Digital Geospatial Metadata to provide consistent query and presentation across multiple participating sites.

The Global Information Society initiative is sponsoring the Environment and Natural Resources Management project (http://www.g7.fed.us/enrm/enviro.html) that will use the information infrastructure to address key environmental and natural resources issues of relevance to both developed and developing nations. The objective is to increase the electronic linkage and integration of sources of data and information relevant to the environment and natural resources. The project builds on existing international efforts to create a Global Information Locator service definition, to further interconnect catalogs and directories around the world and ensure their accessibility to developed and developing countries, and to facilitate the exchange and integration of data and information about the Earth for use in a variety of applications. The long-term result will be a virtual library of data and information held in globally distributed electronic sites accessible on emerging electronic networks.

The Earth Observing System (EOS) Data and Information System (EOSDIS) is a comprehensive data and information system developed by NASA under the Mission to Planet Earth (MTPE) Program. EOSDIS manages data from NASA's past and current Earth science research satellites and field measurement programs, and provides data archive, distribution, and information management services. EOSDIS consists of an interconnected network of specialized Data Active Archive Centers (DAACs) that provide search and order services. The DAACs and their areas of focus are listed in Table A.1.

Acronyms related to remote sensing

Acronym	Definition
Agencies:	
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
USGS	U.S. Geological Survey
EPA	U.S. Environmental Protection Agency
EROS	Earth Resources Observing System
Sensors:	
AVHRR	Advanced Very High Resolution Radiometer
MSS	MultiSpectral Sensor
TM	Thematic Mapper
SPOT	Systeme Pour d'Observation de la Terre
CZCS	Coastal Zone Color Scanner
NHAP	National High Altitude Photography
ESTAR	Electronically Scanned Thinned Array Radiometer
AIRSAR	Airborne synthetic aperture radar
Others:	
GIS	Geographic Information System
NVI	Normalized Vegetation Index
DEM	Digital Elevation Model

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