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Research article

Landscape metrics with ecotones: pattern under uncertainty

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Abstract

Landscape metrics are in widespread use, but previous research has highlighted problems over scale and error in the reliability of the metric values. This paper explores the variation of metric values when it is hard to distinguish exactly where one land cover type changes into another; when the ecotone is not an abrupt transition, but has a spatial extent in its own right. The values of metrics are explored in a landscape classified, using satellite imagery and the fuzzy *c*-means classifier, into fuzzy sets so that every location has a degree of belonging to all classes. The result is that any ecotone can be characterised by a variety of metric values depending on the degree to which a location is in any particular land cover class. The values recorded show some similarities, however, to those for an interpretation of the same landscape with abrupt changes, but the nature of that similarity varies unpredictably between metrics and classes. This analysis provides a limited degree of reassurance for those using metric analysis where the boundaries may have spatial extent, but much further work is required to establish an improved description of metrics under this condition.

Introduction

Landscape ecology in the North American tradition (Wiens 1997) is founded on the idea that the spatial arrangement of phenomena in the landscape is a principal determinant of ecological process and landscape health (Forman and Godron 1986; O'Neill et al. 1986; Turner 1989). Central to this tradition has been the design of metrics of landscape pattern (Turner and Gardner 1991), the exploration of the properties of those metrics (Riitters et al. 1995; Cain et al. 1997), and attempts to relate those properties to ecological process (Turner 1989).

Metric analysis of landscapes is based on a Boolean division of the landscape, inherited from traditional maps and cartographic conventions, which has remained embedded in much thinking about spatial information (Fisher 1998). In a Boolean map any location can be allocated to one and only one landscape class. Conceptually there is no possible doubt about the outcome, and therefore the spatial boundaries are sharp. In many spatial phenomena, especially those of the natural environment, prototypes of classes (such as different types of land cover, soil, vegetation, etc.) can be identified and have clear spatial extent. At the transition between classes, however, it may not be possible to clearly and unequivocally identify the position of the boundary (Burrough 1996). The boundary can then be described as indeterminate or vague. Furthemore the indeterminacy can be in both the attribute and the spatial domains.

The problem of indeterminate boundaries has been explored by a number of writers in the description of vegetation communities (Roberts 1989; Moraczewski 1993a; Moraczewski 1993b). If a plant community is defined by the presence of a certain proportion of a plant, then is it reasonable to identify a different community because there is 1% less than that proportion? Recognition that an ecotone is indeterminate means that in the zone of transition between classes, locations belong to both communities to a degree. The study of indeterminate spatial boundaries is concerned with those transition zones where doubt over the placement of any Boolean boundary is not a question of error in the placement, but of indeterminacy of the boundary.

In managed agricultural landscapes neighbouring communities tend to be very different, and the change between them to be spatially abrupt leading to the Boolean model of space being a reasonable approximation of the landscape. In areas of natural and semi-natural vegetation this is not the case, and more or less broad zones of transition may exist.

Recent research in geographical information science has explored the modelling and representation of indeterminate boundaries (Burrough and Frank 1996). Boundaries may themselves occupy space, instead of being infinitely narrow as in the Boolean model of space; the ecotone itself is actually a 2 dimensional object, not a 1-dimensional line. Interestingly, the recent volume on *Spatial Uncertainty in Ecology* (Hunsaker et al. 2001) does not treat this topic; the main treatment of ecotones in that book assesses the accuracy of hard boundary detection, and methods for precisely locating a hard boundary (Fortin and Edwards 2001) not ecotones as spatial entities in their own right. In this respect it reflects a body of research reported in a number of papers on optimal boundary location (Fortin 1994; Fortin and Drapeau 1995; Loehle et al. 1996; Fortin et al. 2000).

The purpose of this paper is to examine whether metrics used in landscape ecology are significantly and predictably effected by a model of the landscape that explicitly accommodates the spatial indeterminacy of the change from one class to another in the ecotone. We model gradual ecotones between land cover classes as indeterminate boundaries. Specifically, the question addressed here is does the extent of this ecotonal area have a significant effect on the values of landscape metrics.

In the next section we explore the importance of the ecotone in the landscape, representations of indeterminate boundaries, and the consequences of representing the indeterminacy on the allocation of a location to categories in the Boolean model. Next, we introduce a study area used to examine the problem identified, and discuss the methods employed in that case study. We then explore results of that analysis and conclude with a series of warnings.

We believe that the issues raised in this paper have been ignored to date in landscape ecology, but are at least as important as the widely recognised problem of scale (Levin 1992; Wickham and Riitters 1995; Bissonette 1997; Wu et al. 2002) and the more recently studied issue of error (Hess 1994; Hess and Bay 1997; Fortin and Edwards 2001; Shao et al. 2001).

Background: Boolean and fuzzy regions

Many metrics for describing landscape pattern have been suggested in the literature, and implemented in well known packages such as Fragstats (McGarigal and Marks 1995), Apack (Mladenoff and DeZonia, n.d.) and r.le (Baker and Cai 1992). All the metrics are designed to operate on a Boolean landscape where any location is a member of one and only one landscape class. This approach to mapping categorical information is embedded in the production of paper maps, and has a long history (Fisher 1998). With computer databases and storage increasingly replacing the paper map, there is no longer any necessity for the Boolean assignment of locations to single classes, and it is possible to store the similarity of locations to many classes. Many researchers advocate this more general model, and a number of alternative approaches have been explored in the Geographical Information Science literature (Foody 1992; Foody 1996; Burrough and Frank 1996; Fisher 2000a; Fisher 2000b).

Foremost among alternatives is the application of fuzzy set theory (Foody 1992; Foody 1996; Wang and Hall 1996; Fisher 2000b), which is grounded in the concept of vagueness. In the Boolean Set any location is represented as having a membership of 1 in one and only one of the candidate classes and 0 in all others classes. In fuzzy set theory as applied to mapping, all locations have a membership represented by a real number between 0 and 1 in all classes. If the value is 1 then there is a very strong similarity between the concept of that class and the properties at the location, whereas if the value is 0 then there is effectively no similarity between the two. Fisher (2000a) and Robinson (2003) present recent reviews of fuzzy set application in Geographical Information Science. Fuzzy sets have been suggested as useful in describing boundary conditions (Wang and Hall 1996), and particularly in the classification of remotely sensed images (Robinson and Thongs 1986; Fisher and Pathirana 1990; Foody 1992; Foody 1996; Zhu, 2001). The key justification for the application of fuzzy set theory to remotely sensed imagery is twofold (Fisher 1997). First, sub-pixel objects (either within pixel or linear features which may cross pixels) are ignored in the traditional classification of satellite imagery based in Boolean logic. For example, a pixel may be classified as cover type X and may indeed be occupied by a large proportion of that cover type, but cover type Y may also be present over a significant proportion of the pixel. Second, the concept of gradual transitions or intergrades, which occupy space, are ignored in a Boolean classification, but a location may have similarities to the properties of a number of different mapped concepts such as habitats. It is apparent that the issue of gradual transition, which is accommodated by the fuzzy model of space, is a direct analogue of the gradational ecotone of landscapes.

The consequences of a fuzzy model of space on metrics of landscape pattern may not be immediately apparent. For illustration, consider a region with three classes of land cover named A, B and C, and assume that we have a fuzzy classification of the area so that each grid cell has a fuzzy memberships for each of the three classes. A Boolean classification of the area can be achieved by identifying the class associated with the maximum fuzzy membership within any pixel; a cell with memberships $\mu_A = 0.8$, $\mu_B = 0.1$, $\mu_C = 0.1$, can be assigned to Boolean class A. On the other hand, a Boolean classification makes no distinction between that and another cell with $\mu_A = 0.4$, $\mu_B = 0.3$, $\mu_C = 0.3$, although the membership of A is less than the total membership of the other classes. Notice also that these two cells have very different levels of membership in Class A without any distinction being made in the Boolean classification. Indeed, cells with equal degrees of belonging to Class B may be assigned to a different class; consider one cell with $\mu_A = 0.5$, $\mu_B = 0.4$, $\mu_C = 0.1$, and another with $\mu_A = 0.3$, $\mu_B = 0.4$, $\mu_C = 0.3$, which would be assigned to class A and B respectively. In short, the uncertainty (fuzzy) information shows that the variability of memberships within a class can be greater than those between classes, and all such information is ignored in the Boolean assignment.

To extend these observations into two dimensions, Figure 1 shows that a single pattern of islands in a Boolean classification (Figure 1A) can relate to more than one fuzzy pattern (Figure 1B and C). It can either reflect real islands (patches with fuzzy boundaries but with no similarity to the class being mapped in most of the intervening area; Figure 1B), or apparent islands where a ridge of low membership links the two patches (Figure 1C). The degree of similarity of the ridge to the patches may be sufficient to serve at least as a corridor between the two islands for species movement. It may even be sufficiently similar to be acceptable as a habitat for some species (flora or fauna) exploiting the cover type. In the Boolean model, however, it will not be recorded. Figure 1D and E show real patches in a landscape (taken from the analyses discussed below). It is possible to see zones of low membership forming large, but varying size inlets in the outline of obvious patches, as well as islands which are linked by a ridge, and those which are not.

If the boundary of a fuzzy patch cannot be precisely determined, then properties of that patch such as area and perimeter are hard to specify (Fonte and Lodwick, in press). The consequence of these phenomena on landscape metrics has not been explored in the literature and may be important for all indices, from the number of patches to edge length and diversity indices. Furthermore, an acceptable habitat for some species may be defined by 0.5 membership of a class while others may live in areas where the class has a membership of only 0.3. For example, if the fuzzy membership reflects the occurrence of a specific species then the very presence of that species in a cell may be important and so any degree of membership, even very small, in a mapping class associated with that species might be important to exploring its spatial distribution and that of associated species. Others may use a particular land cover class as a corridor when membership is small, but not live in it. Therefore, a variety of questions arise about the use of indices when class is viewed as vague and measured by partial membership.

Study area

To explore the behaviour of ecotones under uncertainty, it was necessary to identify a landscape of semi-natural vegetation. For this study, we decided to work on a region in the Bolivian savannah-forest transition zone (from 66.31°W 14.83°S to 66.45°W to 14.83°S; Figure 2), following previous work in the area by one of the present authors and colleagues (Millington 1996; Wellens et al. 1999; Wellens et al. 2000). This is a relatively simple landscape dominated by the three principal cover types (forest, permanently inundated savannah and seasonally dry

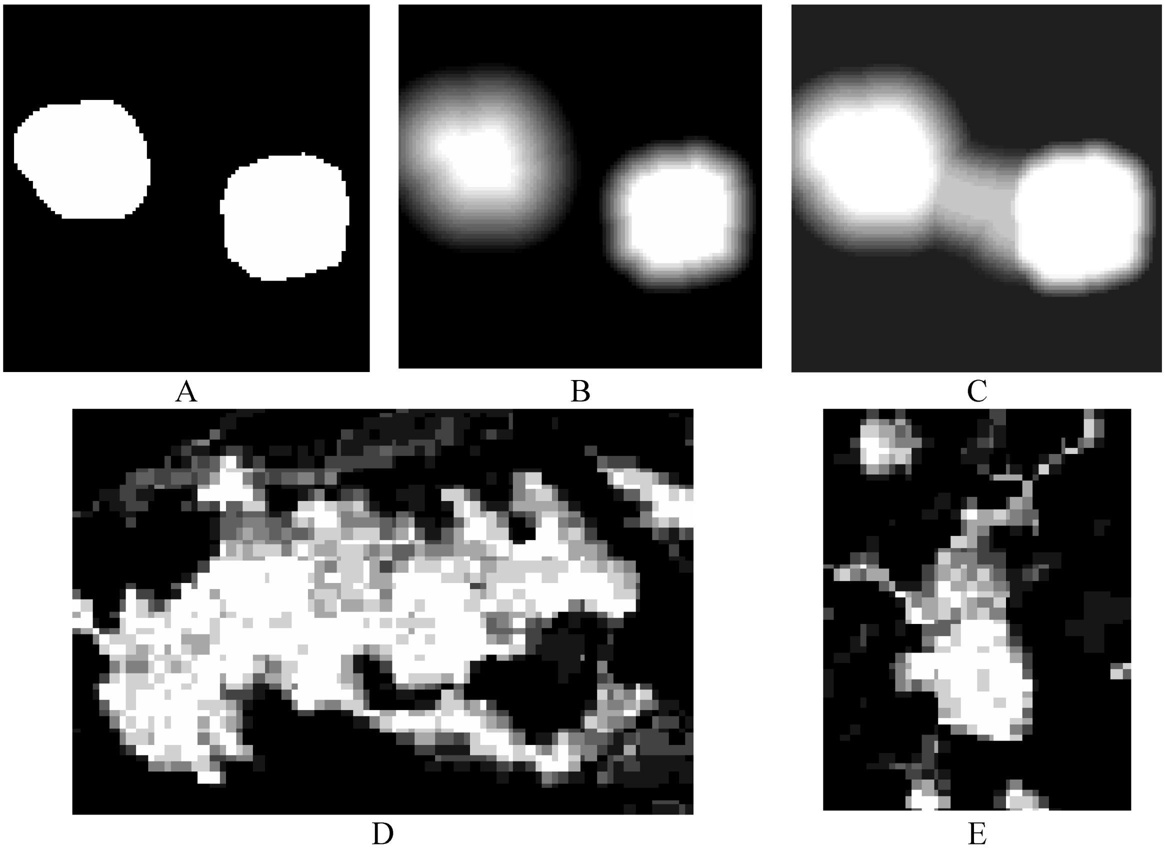

Figure 1. Boolean islands of the cover type of interest (A) can be derived from either true islands (B) or islands of higher membership linked by a ridge of low but useful membership (C). The outlines of actual islands show ridges and inlets of different levels of membership (D and E). White indicates fuzzy membership 1 and black 0.

savannah) although water (rivers and lakes) and human-made covers (urban areas, air-strip, highway, ranches) are also present.

Three Landsat TM images were available for the area, taken in August 1985, December 1986 and July 1989. Two of these are from dry seasons (1985 and 1989) and one from a wet (1986). The 1985 and 1986 images were geometrically corrected to the 1989 image using 2nd order polynomials. A subscene was then selected in an area where the landscape is dominated by savannah and forest, avoiding areas of urbanisation.

Methodology

Fuzzy processing

A number of approaches have been suggested for parameterising fuzzy memberships of cover types in an area. In this study we used the reflectance in 5 bands of the TM images, as multivariate inputs to an implementation of the fuzzy c-means algorithm (Bezdek et al. 1984). Fuzzy c-means is a non-hierarchical clustering strategy based in the well known k-means clustering approach (Legrendre and Legrendre 1998-354), but re-written to derive fuzzy memberships based on the similarlity of an observation to the mean values of classes located in the multivariate space. The applicability of this to satellite imagery has been explored previously (Robinson and Thongs 1986; Fisher and Pathirana 1990; Foody 1992; Foody 1996), although some recent studies of fuzzy cluster-

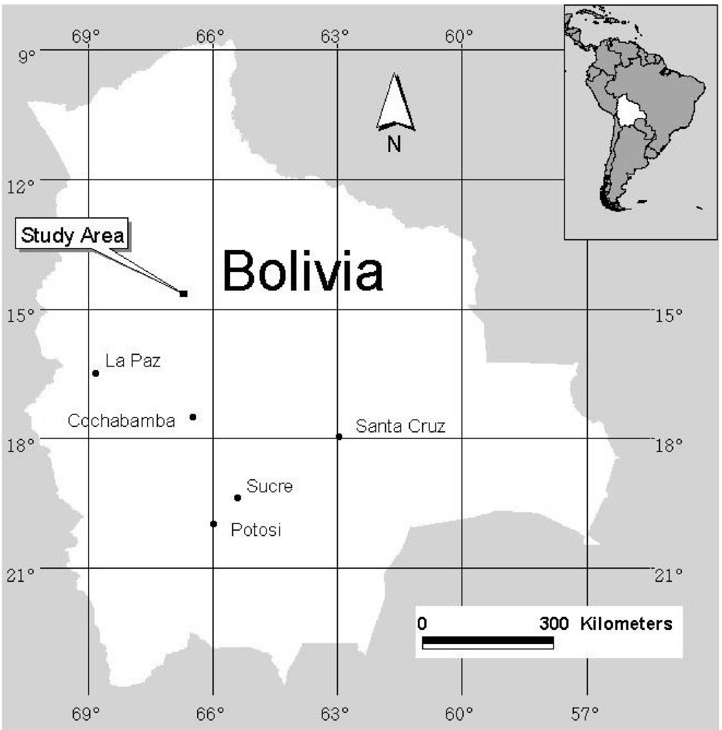

Figure 2. Location of the study area in Bolivia.

ing of satellite imagery have used neural networks (Foody 1996). We executed multiple experiments varying key parameters of the algorithm (Bezdek et al. 1984; Robinson and Thongs 1986; Fisher and Pathirana 1990; Foody 1992; Foody 1996). We found that the landscape was described by four clusters which could be associated with the following cover types:

1. forest
2. inundated savannah,
3. dry savannah, and
4. a complex mixture of water and human-made features (roads and ranches).

Only the first two are discussed in detail below.

For every pixel fuzzy *c*-means yields one real number fuzzy membership per land cover class per pixel. For analysis by landscape metrics these need to be converted to Boolean images (hard or crisp sets). This is achieved by the method of alpha-cuts (α-cuts). An alpha cut is the area delineated by a contour of equal membership, giving a crispened (Boolean) version of the fuzzy set where any location with a membership greater than or equal to some threshold, α, is defined as being within the set (coded as 1), and all other locations outside the set (coded 0). By varying the value of α it is possible to develop a series of alternative hard (Boolean) versions of the fuzzy set (Figure 3). The system of α-cuts is used by Fonte and Lodwick (in press) to examine the area of a fuzzy spatial entity. In the work reported here, we used values of α in the range from 0.05 to 0.95 in steps of 0.05, giving 19 different Boolean hardenings of the fuzzy. Figure 4 shows 9 such α-cuts for the forest cover type in 1985.

The fuzzy membership value 0.5 is sometimes taken as the basis for converting a fuzzy set to a Boolean set, so called *crispening* of a fuzzy set. The value is known as the crossover point, and below, reference is made to this value and the associated crossover α-cut.

Each landscape metric studied here was evaluated for each of the 19 α-cuts. The range of values of the landscape metrics of the α-cuts are compared to the values derived by the area defined as forest by a maximum fuzzy membership class for the fuzzy *c*-means image; for a particular pixel the rule records the class associated with the largest fuzzy membership. We call this the maximum fuzzy membership

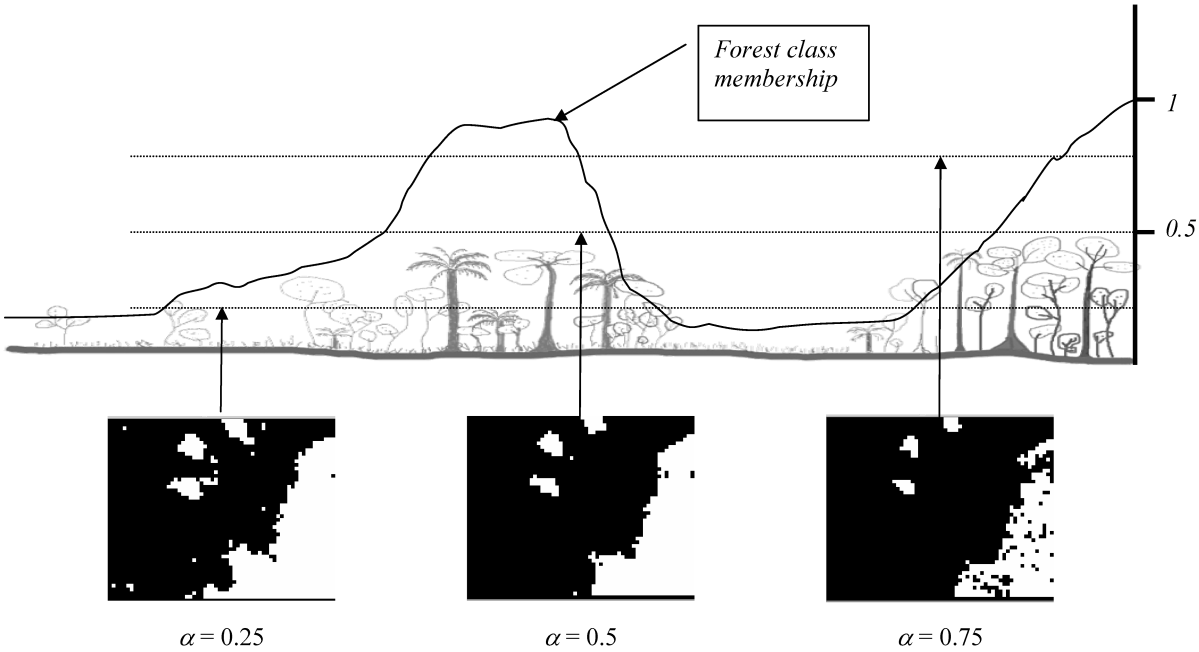

Figure 3. Cross-sectional schematic of vegetation in relation to expected forest class membership. α-cuts from the 1989 image are shown in which white represents forest and black is non-forest .The α-cuts correspond to forest class membership at 0.25, 0.5 and 0.75.

class to recall maximum likelihood classification, and we use it in preference to a different classification, perhaps a maximum likelihood classification. The maximum membership classification has the greatest chance of being similar to an α-cut image of that class, as it is based on the same class prototypes and therefore the same spectral signatures for classes. Any Boolean classification is, however, unlikely to correspond to any α-cut image (crossover or otherwise), because the latter are based on contours of equal membership in a multiclass classification. The maximum fuzzy membership class represents the view of the area that would most commonly be used to calculate landscape metrics in a study of the landscape ecology.

Discussion focuses on forest and inundated savannah. The ecotone of forest to either savannah type is generally narrow and relatively well defined, but that of inundated and dry savannah is more diffuse and broad. Therefore the discussion here focuses on the forest and only one of the savannah types (inundated). Dry savannah is not discussed further here.

Landscape metrics

As has been noted by previous researchers, there are a large number of landscape metrics defined and implemented in the standard packages, especially Fragstats (McGarigal and Marks 1995). Many metrics provide useful results for binary landscapes such as the α-cuts analysed here, but measures dependent on the number of cover types present, such as diversity and evenness, do not. Therefore these last metrics are ruled out from the analysis presented here. Various researchers have shown that many metrics are confirmatory, and it is possible to focus on a small number of representative metrics (Riitters et al. 1995; Cain et al. 1997). As in those earlier studies, the total number of possible metrics was reduced by an exploratory Principal Components Analysis on a large matrix of landscape metrics for all α-cuts for the four cover types at the different dates. The results of the current analysis are in line with the previous work.

Five components explain nearly 95% of the cumulate percentage of the total variance in the dataset, and therefore subsequent discussion focuses only on representative metrics from these four components. The Area Weighted Mean Shape Index (AWMSI) and the Total Core Area Index (TCAI) represent Component 1. Other components are typified by only one metric each. Component 2 is associated with Largest Patch Index (LPI). Component 3 with Mean Patch Size (MPS), Component 4 with Mean Shape Index

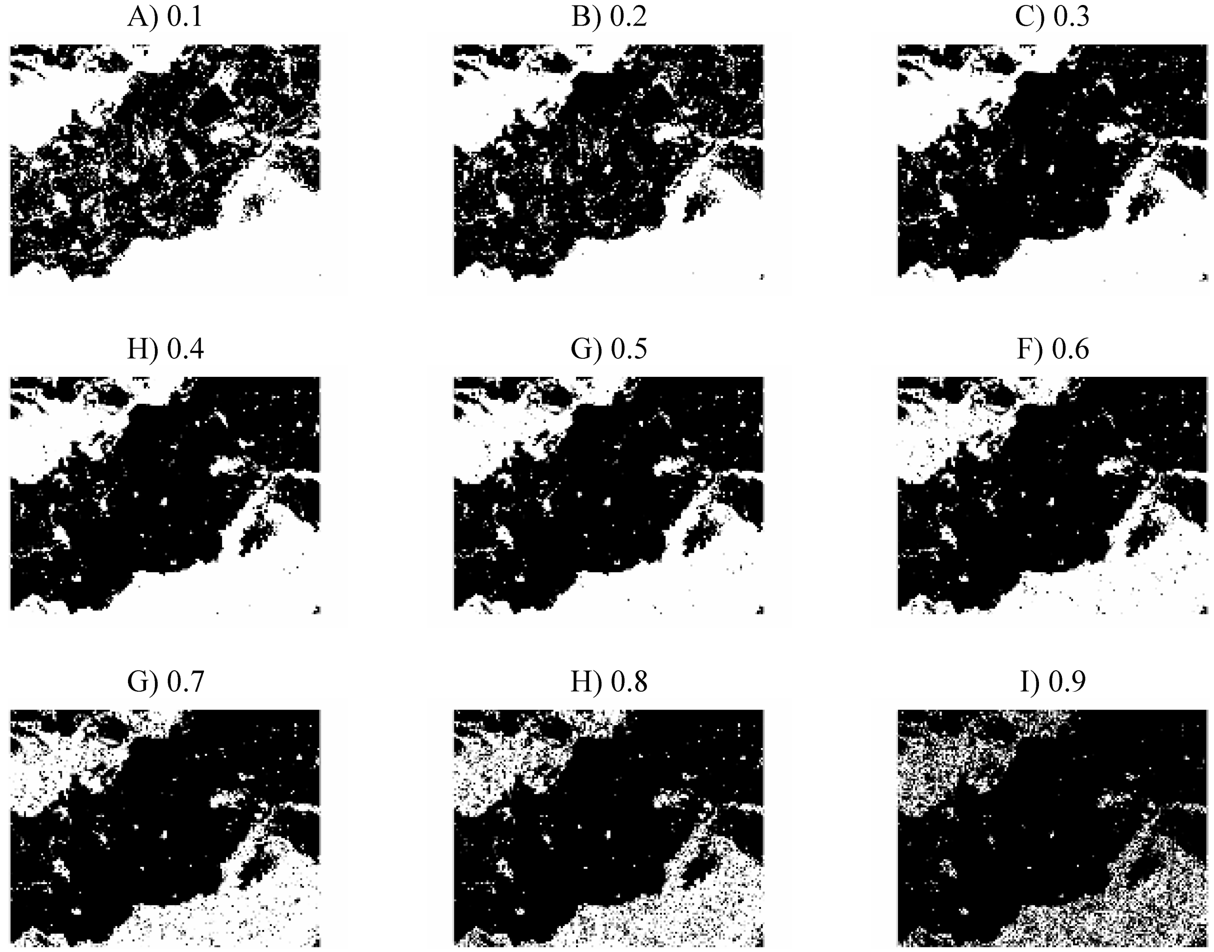

Figure 4. α−cuts of the forest class in 1985. The cuts are derived from a fuzzy classification to 4-clusters, and shows the extent of the forest class in white at each 0.1 cut. The numbers 0.9 to 0.1 indicate the α−cut values for image. White represents forest, and black non-forest.

(MSI), and Components 5 with Nearest Neighbour Standard Deviation (NNSD).

Results

General patterns

Figure 4 presents the sequence of 9 α-cuts for the fuzzy forest class. In Figure 4 the image for $\alpha = 0.9$ shows that locations with a strong affinity to the image-characteristics of the forest class are patchy and occupy a small area of the total scene. At $\alpha = 0.9$ the distribution of the forest class includes small contiguous areas and many isolated patches, and within the contiguous areas of forest to the northeast and southwest there are many patches of non-forest. Examination of the images for $\alpha = 0.8$ and $\alpha = 0.7$ shows that the nuclei of isolated patches (islands) increase in size and become more continuous, while the core forest areas are infilled. A few new islands emerge to the northeast of the area especially in the $\alpha = 0.9$ to $\alpha = 0.8$ change. As the α level decreases, this infilling of the core areas, emergence of new islands, and expansion in the area of forest continues up to $\alpha = 0.3$. In $\alpha = 0.2$ and 0.1 areas with very little affinity with forest start to be included in the area of forest. This is highlighted by the inclusion of roads as forest at very low fuzzy memberships, $\alpha = 0.1$, and many new islands are apparent in the image for $\alpha = 0.2$.

For comparison, Figure 5A and B show the extent of forest and inundated savannah, respectively, derived from the maximum fuzzy membership class in the 4 class FCM classification of the area. As noted

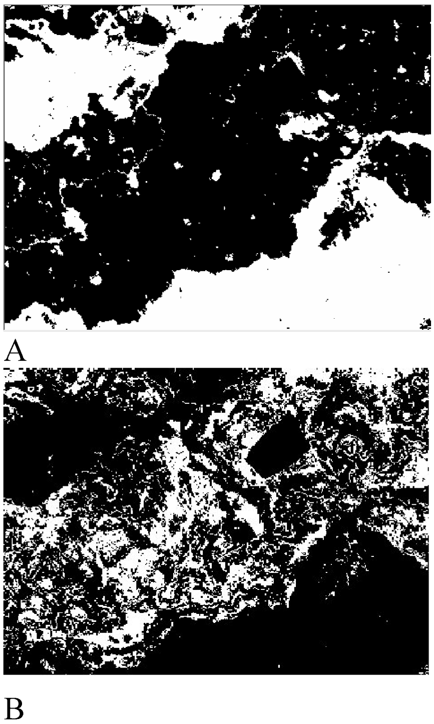

Figure 5. Maps showing in white the extent of the maximum fuzzy membership class A) forest and B) inundated savannah.

above there are many methods for deriving such Boolean maps of the landscape which would be derived from a traditional classification (such as that from the maximum likelihood classifier), and although these are derived from the fuzzy membership data they bear no relationship to any of the α-cuts. As is necessary in the maximum membership (likelihood) class method, a decision as to the class of a pixel is made even for those located in the most diffuse ecotone. In the graphs in Figure 6 to 11, values of landscape metrics for the maximum fuzzy membership class are shown as horizontal lines. Each line represents a single value and is included as a line for convenience in comparison with the α-cut values.

Area weighted mean shape index (AWMSI)

In the fuzzy images for the forest and inundated savannah classes for all dates AWMSI varies with the level of fuzzy membership but the profiles across the range of α-cuts have different patterns. Graphs of α-cut versus membership for 1986 are shown in Figure 6. Similar graphs for other years show the same patterns. In the forest class, the smallest membership (0.05) has a relatively high AWMSI value. It rapidly decreases to the maximum membership class value, which is indicated by the straight line in the graphs, at around the 0.2-0.3 α-cut. AWMSI remains fairly constant until around the 0.7 α-cut, and then increases rapidly again to a large value at the 0.95 α-cut (Figure 6 A). The 0.5 α-cut (also referred to as the crossover α-cut) is coincident with the wide minimum of the curve.

By comparison, the values for the fuzzy inundated savannah class decrease with increasing values of α-cut (Figure 6 B). The decline is discontinuous, and the crossover (0.5) α-cut is approximately equal to the maximum membership class value shown as the straight line.

Total core area index (TCAI)

TCAI for the forest class shows the inverse of the AWMSI (Figure 7 A). A wide maximum occurs from about α-cut 0.25-0.65, which is approximately equal to the maximum membership class value. TCAI values for inundated savannah increase continuously. The intersection of the curve and the line of maximum membership class is very close to the crossover α-cut of the class.

Largest patch index (LPI)

The graphs for LPI show somewhat different patterns to those metrics describing patch characteristics. Broadly, the LPI (Figure 8) shows values increasing with increasing α-cut. The forest cover class shows a small initial drop in the 1986 values shown, but the rise is continuous in other years analysed. In all years there is a step coincident with the maximum membership class value. The curves for the inundated savannah class shows an initial drop for 3 of the 19 α-cut values, but then a continuous and smooth increase (Figure 8 B).

Mean patch size (MPS)

In the case of MPS and the next two metrics graphs for all three years are shown because different characteristics are illustrated in each year. MPS for the forest class in 1985 and 1989, dry seasons (Figure 9 A and C) show steep sided peaks in the plots both reaching maxima at α-cuts less than the crossover value, and only in 1985 is the maximum coincident with the maximum membership class value; in 1989

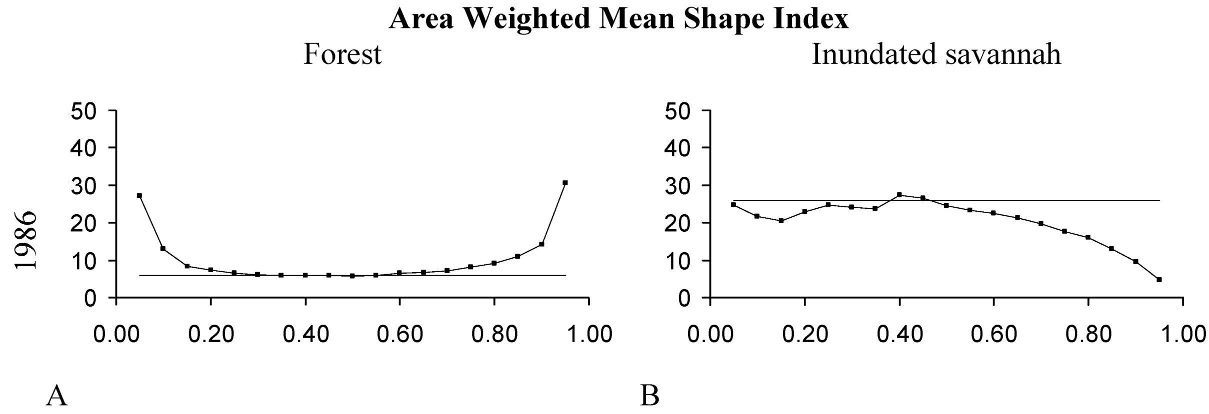

Figure 6. Plots of Area Weighted Mean Shape Index for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. For comparison, the straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership class realisation of the landscape.

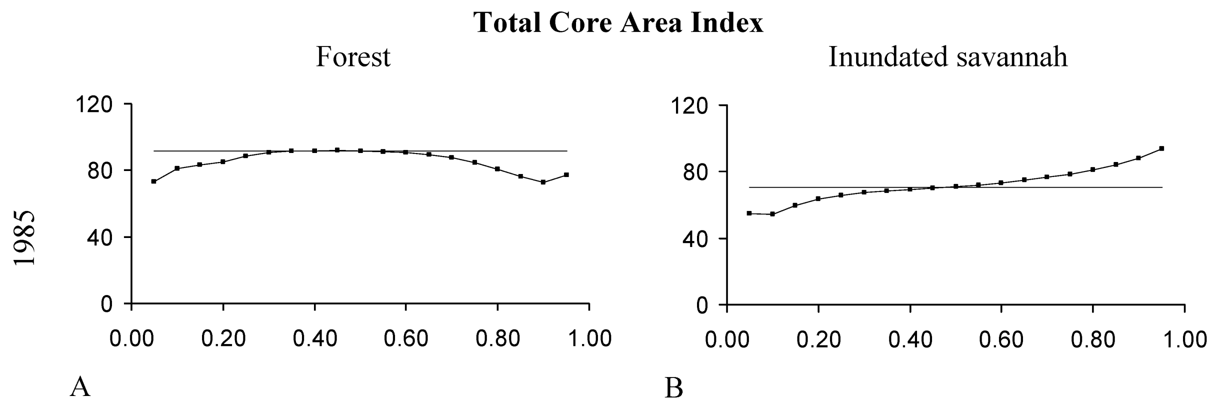

Figure 7. Plots of Total Core Area Index for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. The straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership class realisation of the landscape.

the curve twice crosses the line of the maximum membership class value. The 1986 wet season profile has a maximum which is less peaked, and is coincident with the maximum membership class value, but is associated with an α-cut much less than the crossover value. In the inundated savannah class, the MPS values show a very different pattern which is stepped like the profile for the Largest Patch Index for the forest class.

Mean shape index (MSI)

MSI for forest class has a more variable relationship to the maximum membership class value (Figure 10). The MSI of the inundated savannah class displays the inverse form to the Mean Patch Size. The maximum MSI is very close to both the maximum membership class value and the crossover α-cut. The irregularities of the curves for the forest class are particularly interesting with the curves having two minima and a central maximum in the 1985 and 1989 curves, but a single pronounced minimum in the 1986 curve. The MSI curve also crosses the maximum membership class line at values much less than the crossover α-cut.

Nearest neighbour standard deviation (NNSD)

NNSD (Figure 11) shows a more complex profile with increasing α − cut values than the other metrics. All profiles are characterised by multiple peaks frequently with very steep sides, and numerous

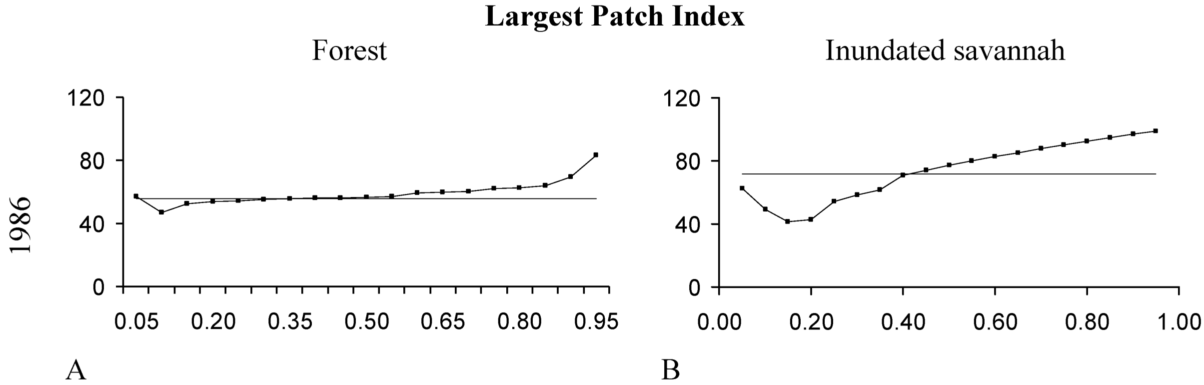

Figure 8. Plots of Largest Patch Index for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. The straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership realisation of the landscape.

crossings of the maximum membership class line ranging from 2 in Figure 11 B to 5 in Figure 11 F. This result is perhaps the most unexpected of those presented here, because change of the metric with α-cut in both land covers is very variable with no clear pattern, and within one land cover type there is no consistent pattern in the graph.

Discussion and conclusion

The central idea in landscape ecology is that the spatial arrangement of landscape phenomena is a key determinant of ecological process and landscape health. Landscape ecology often proceeds by trying to find a significant correlation between some selected landscape metrics and an ecological variable, such as the presence or absence of a particular organism. This raises two main problems: deciding what to map (is the scientist's perception of the land cover and habitats relevant to the organism being studied?), and how to map it (is a landscape really a set of unambiguously defined, homogenous, crisp edged objects?). In this paper we attempt to determine the extent to which a subset of landscape metrics is influenced by the way that the landscape is characterised, and hence, the extent that any correlation between landscape structure and ecology is more than simply an artefact of the data. That is not to say that the fuzzy mapping with α − cuts characterises the landscape more *accurately* than the Boolean maximum membership, but rather it is based on a different conceptualisation of the landscape which *may* be more valid. The analysis is still the product of the method employed and subject to measurement and classification errors.

In the results presented here the values of many of the landscape metrics for the maximum membership classification are broadly representative of the set of values which can be derived from many of the α − cuts at the same date. Thus, to an extent, the classic metrics derived for the Boolean model of the landscape provide a representative estimate of those values. However, for other metrics, the maximum membership value is *not* representative, and no single α − cut corresponds to the maximum membership class value. In a number of cases, the range of values varies greatly between years for the same cover type.

In some cases the α − cut value for the metric at the crossover (membership 0.5) is approximately equal to the maximum membership value (Figure 6A, Figure 7A-B 8A, 9D-F, 11A-B, 11D, 10C, 10E-F), but in other cases the maximum membership value is at less than the crossover value (Figure 8B, Figure 9A-B, 10A-B). In some cases the maximum of the curve is approximately coincident with the 0.5 membership, but the value of the metric at that point is much larger than the maximum membership value (Figure 9C, Figure 11C-D). In some cases, the value is equal to the maximum membership value at more than one α − cut (Figure 6B, Figure 9C-F, 10A-E, 11A-F). In some of those cases the gradient on the line is steep and relatively constant (Figure 8B). In short, the only generalisation that can be made is that in many cases the maximum membership class value is less than or equal to the crossover value. However, there is no predictable relationship between the α − cut profile and the maximum membership class values. In the only measure of metric dispersion, the nearest neighbour standard deviation, the relationship

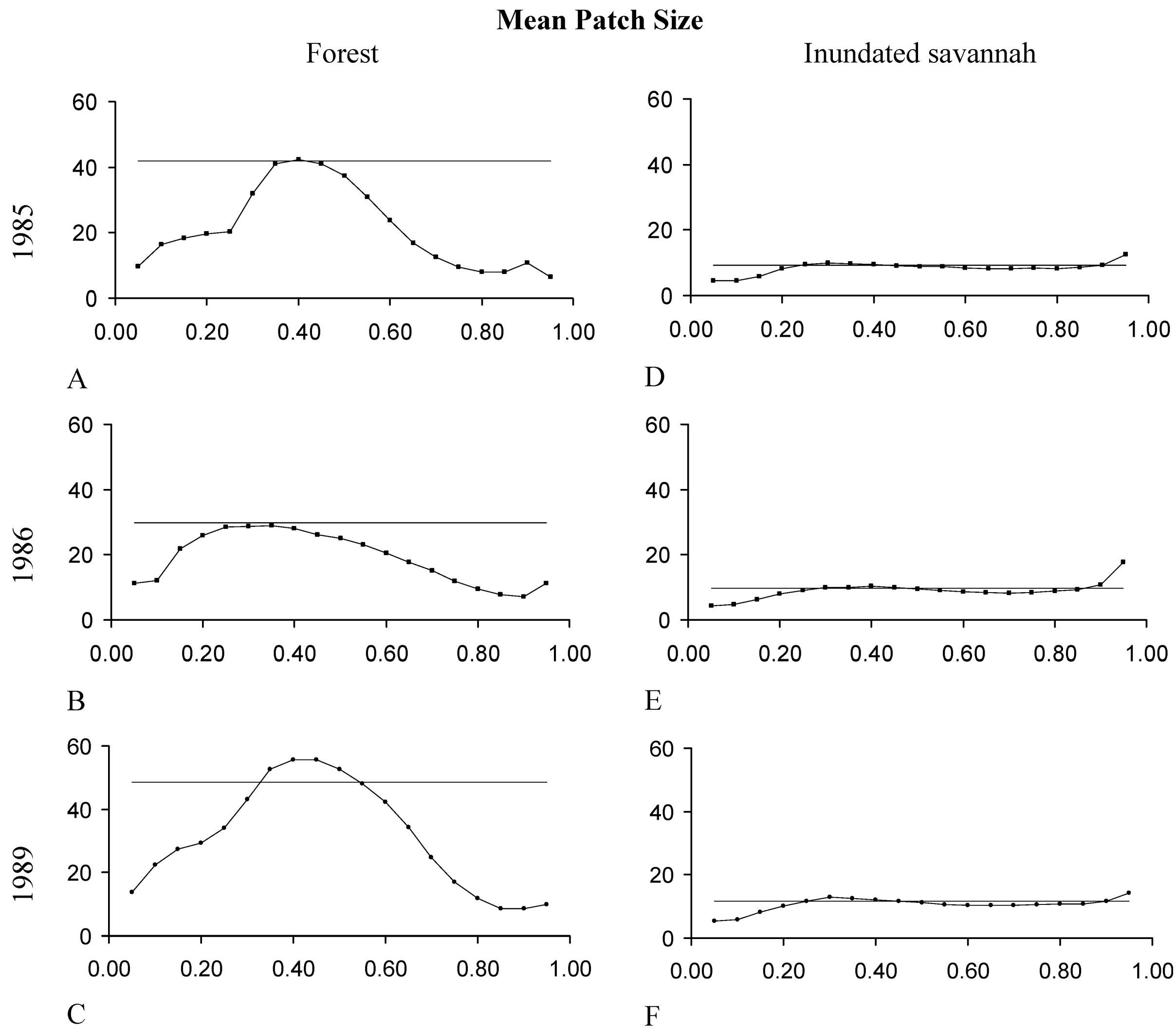

Figure 9. Plots of Mean Patch Size for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. The straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership class realisation of the landscape.

is very variable, and shows no consistency between dates (Figure 11).

When landscape metrics are analysed using a fuzzy approach, which explicitly explores the spatial structure of a 2D ecotone, they are found to behave variably. In the majority of cases the values for the landscape metrics for the Boolean landscape can be considered representative of the landscape, but some cases they are not. The two land cover classes (from an analysis which yields only 4 classes) discussed in this paper necessarily give a limited view of the problem. More typically land cover classifications derive more classes (often many more), and as the number of classes increases the difference between the α-cut values and the maximum membership class value will diverge because the maximum membership class rule becomes increasingly arbitrary.

In this paper we have studied a single landscape. It is a relatively simple landscape with two major land cover types forest and savannah. In the case of the forest, the ecotone is relatively narrow with respect to the size of the land cover mapping units. The ecotones between the inundated savannah and other classes (especially dry savannah) is wide with respect to the size of the mapping units. The relationship between the forest class α-cuts profiles and the maxi-

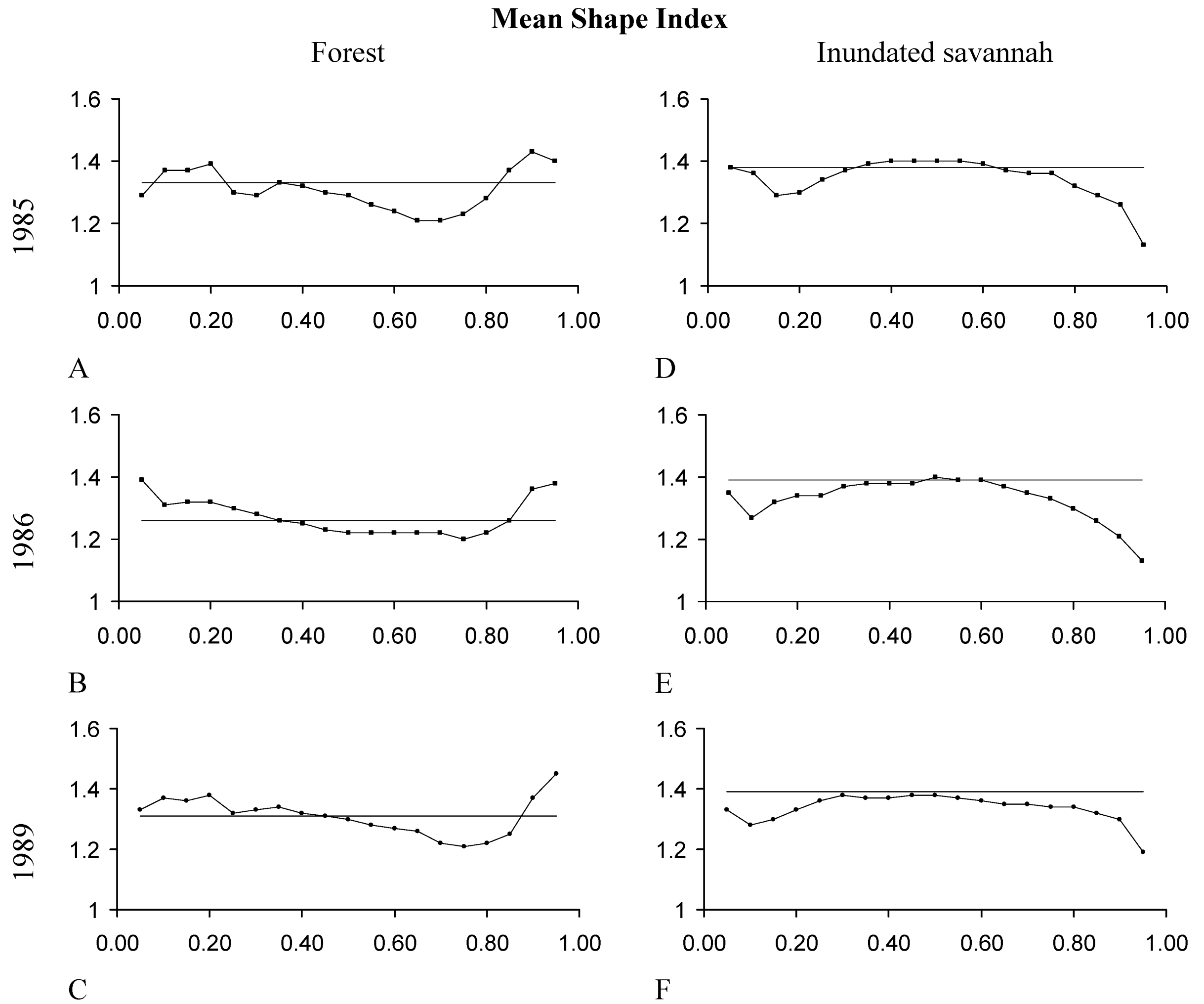

Figure 10. Plots of Mean Shape Index for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. The straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership class realisation of the landscape.

mum membership class value is perhaps slightly more predictable (the maximum membership class value is more representative) than for the savannah classes (compare Figure 9A-C and 10A-C with 9D-F and 10D-F).

For both the forest and savannah classes the α-cut values are observed to diverge from maximum membership class values. In a managed or agricultural landscape where the landscape units of analysis can be demonstrated, or expected, to have sharp, narrow boundaries, landscape metrics will give a reliable measure of landscape pattern. In semi-natural and natural landscapes, however, where ecotones may occupy a large part of the area, the classic Boolean mapping and resulting landscape metrics are more problematic.

If we study the influence of the landscape on flora or fauna, neither the Boolean landscape nor any single α−cut need characterise the environment correctly for all species. Rather, it is suggested that the α−cut approach demonstrated here should be employed in future research in quantitative landscape ecology, and the response of flora and fauna to landscape metrics should be tested against all α−cut values. If only a portion of the range of possible α−cuts are to be tested, then work should concentrate on the lower range of values; the most ecologically specific of species may only be interested in a habitat with

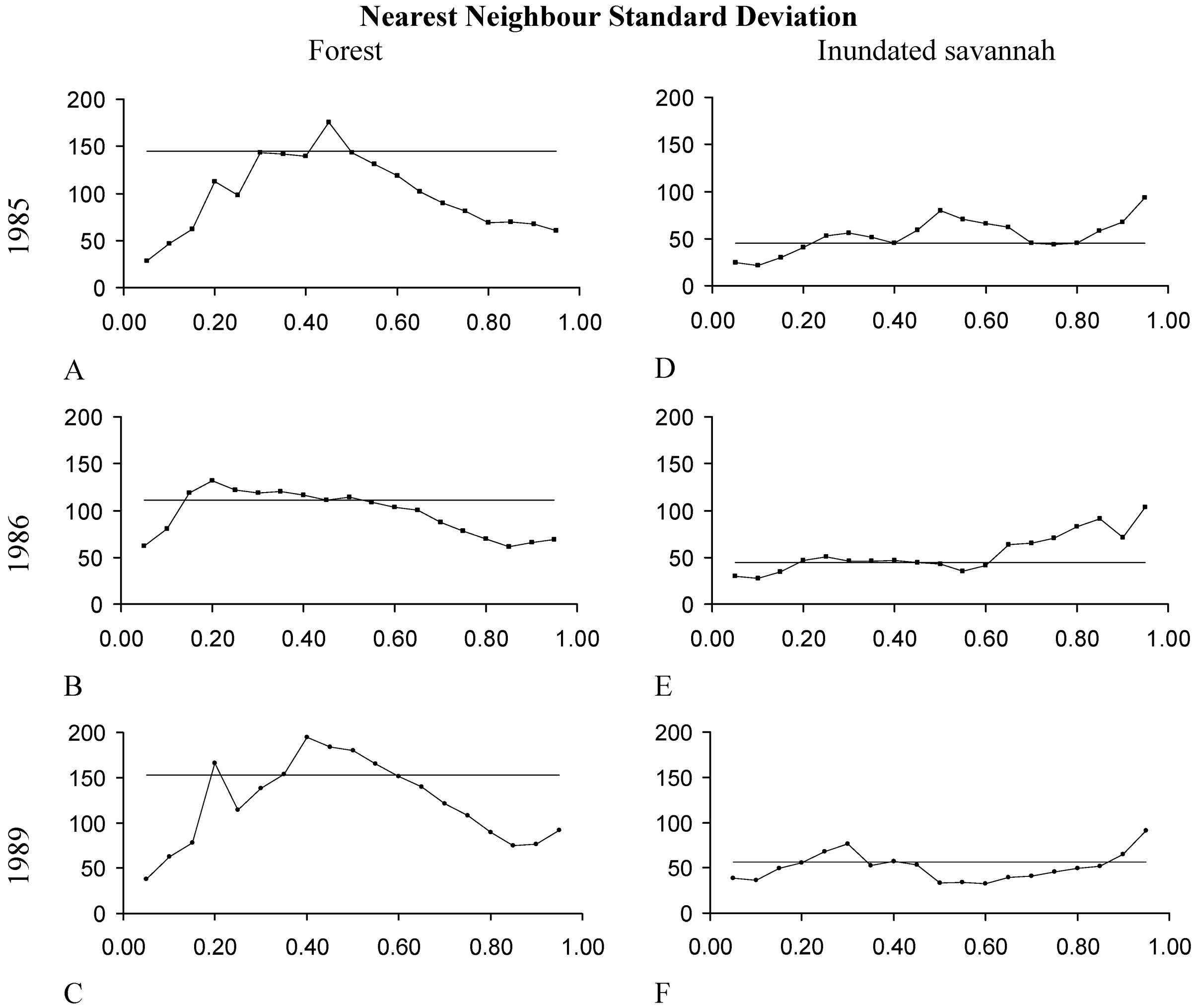

Figure 11. Plots of Nearest Neighbour Standard Deviation for forest and inundated savannah for the three study years against the alpha-cut value of the fuzzy memberships. The straight, horizontal line in each plot is the metric's value for the maximum fuzzy membership class realisation of the landscape.

very large memberships, but many species may be able to exploit a habitat which is only just suitable (has small membership). Therefore research might focus on memberships in the range 0.2-0.6, for example.

Scale is a well-known issue with respect to landscape metrics (Wu et al. 2002), and the interaction of scale and ecotone should be a subject for future study. We believe that the ecotone is, however, scale independent. If the scale of measurement in the satellite image or in fieldwork changes, and there is no change in the conceptualisation of the landscape, the ecotone issue remains. There may be a scale when the ecotone is reliably smaller than the spatial unit of measurement (pixel), and when that happens there may be little point in exploring fuzzy memberships and $\alpha-$cuts, but if ecotones could be thought to characterise the landscape then the usefulness of the whole analysis might be questioned.

A further concern, however, is the meaning of the fuzzy membership values, and so the representativeness of the $\alpha-$cuts. Fuzzy set theory and fuzzy classification as they have been applied to landscape interpretation and land cover classification from satellite imagery, is grounded on the idea that the membership values relate to the degree of similarity of a location to a prototypical concept of a land cover class. Although this is supported where it has been tested (Fisher and Pathirana 1990; Foody 1992; Foody 1996; Zhang and Foody 1998), the statistical relationship is never definite, and different methods of extracting fuzzy values will yield different fuzzy membership values (Bastin 1997). Therefore, although this article has demonstrated cause for concern over using Boolean divisions of natural landscapes, alternative methods grounded in fuzzy set theory can only be considered indicative.

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