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Selection of scale for Everglades landscape models

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Abstract

This article addresses the problem of determining the optimal "Model Grain" or spatial resolution (scale) for landscape modeling in the Everglades. Selecting an appropriate scale for landscape modeling is a critical task that is necessary before using spatial data for model development. How the landscape is viewed in a simulation model is dependent on the scale (cell size) in which it is created. Given that different processes usually have different rates of fluctuations (frequencies), the question of selection of an appropriate modeling scale is a difficult one and most relevant to developing spatial ecosystem models.

The question of choosing the appropriate scale for modeling is addressed using the landscape indices (*e.g.*, cover fraction, diversity index, fractal dimension, and transition probabilities) recently developed for quantifying overall characteristics of spatial patterns. A vegetation map of an Everglades impoundment area developed from SPOT satellite data was used in the analyses. The data from this original 20 × 20 m data set was spatially aggregated to a 40 × 40 m resolution and incremented by 40 meters on up to 1000 × 1000 m (*i.e.*, 40, 80, 120, 160 ... 1000) scale. The primary focus was on the loss of information and the variation of spatial indices as a function of broadening "Model Grain" or scale.

Cover fraction and diversity indices with broadening scale indicate important features, such as tree islands and brush mixture communities in the landscape, nearly disappear at or beyond the 700 m scale. The fractal analyses indicate that the area perimeter relationship changes quite rapidly after about 100 m scale. These results and others reported in the paper should be useful for setting appropriate objectives and expectations for Everglades landscape models built to varying spatial scales.

1. Introduction

Disturbances such as fire, drought, and man-made water delivery mechanisms with their associated water quality implications, are processes that have altered the landscape structure within the Everglades. Management decisions have often had unclear long-term ramifications for Everglades landscapes, ecosystems and species. Deterministic landscape simulation models are now being developed that may enable the prediction of future landscape structure under a variety of management scenarios (Costanza *et al.* 1992; Fitz *et al.* 1993). Such models could be used to predict what the effects of external human activities might be, and to analyze how the Everglades landscape structure may fluctuate over time.

Ecologists have only recently recognized and studied the importance of spatial patterns and scale that characterize heterogeneity in landscapes (Risser *et al.* 1984; Meettemeyer and Box 1987; Urban *et al.* 1987; Turner *et al.* 1989a, 1989b; Turner 1990; King 1987; Cullinan and Thomas 1992; Holling 1992). In landscape ecology, scale generally refers to both grain and extent of an observation set (Turner and Gardner 1991; Milne 1992). Grain is the minimum spatial resolution of the data whereas the extent describes the areal breadth of a study (Milne 1991). We define scale as is commonly done in ecology (*e.g.*, fine or small scale refers to minute resolution, and broad or large scale refers to coarse resolution) rather than use the cartographic interpretation (*e.g.*, large scale refers to small resolution) (Turner and Gardner 1991). This study investigates procedures for determining the optimal "Model Grain" or spatial resolution (scale) for landscape model development.

Selecting the appropriate scales for landscape modeling is a critical task that is necessary before using spatial data for model development. How the landscape is viewed in a simulation model is dependent on the scale (cell size) in which it is created. From a computational point of view, a modeler may prefer to choose a broader scale (model grain size approaches the extent). However, more often than not, models valid at finer scales may not be scaled-up to broader scale without significant modifications. In addition, the broader model scale selected for economic reasons may lead to information losses that may have serious implications to the accurary and realism of the model.

Ecosystem simulation models typically require the inclusion of processes that cover many disciplines including hydrology, water quality and ecology. They are complex because they simulate individual processes as well as the interactions and the feedbacks amongst them. Given that different processes usually have different rates of fluctuations (frequencies), the question of selection of an appropriate modeling scale is a difficult one and most relevant to developing spatial ecosystem models. This paper will show that selecting a model scale *a priori*, based solely on economics and without a thorough analysis, can potentially bias model results and significantly reduce model realism.

The question of choosing the appropriate scale for modeling is addressed using the landscape indices recently developed for quantifying overall characteristics of spatial patterns (O'Neill *et al.* 1988; Turner *et al.* 1989a; Turner 1990). Although these indices are getting wide recognition and are being used extensively for characterizing landscape patterns, their links to ecological processes are not explicit and, as a consequence, a better approach may be needed to address the scale question. However, these indices should be useful for initial screening purposes. The primary focus of this study will be on the loss of information and the variation of spatial indices as a function of model scale (grain size).

2. Methods

Many indices have been used in the literature to characterize landscape patterns. These include the information of theoretic measures (Shannon & Weaver 1949) and their variations (O'Neil *et al.* 1988; Turner 1990; Turner *et al.* 1989a; Li & Reynolds 1993) and the fractal dimension of patch characteristics (Mandelbrot 1977; Lovejoy 1982; Burrough 1986; Milne 1991; Turner *et al.* 1989b; De Cola 1989). Most of these indices compute an overall measure to describe a particular pattern or characteristic (*e.g.*, predictability, Turner *et al.* 1989b) of a landscape. It should be noted that some indices are interdependent and therefore may be redundant. Information theoretic indices have been criticized (Pielou 1975) in the past because of their sensitivity to varying the number of cover types in a given landscape. In this study however, the number of cover types remained the same as indices varied as a function of broadening scale. The indices chosen for this investigation of model scale are described below.

2.1. Cover fraction

A vegetation mosaic consists of a finite number of cover types each encompassing a fractional portion at a given scale. As the model scale becomes coarser certain cover types may disappear and others may dominate the landscape. This results in a fractional change in areal extent for cover types compared to the original observation set. In the case of spatial landscape models, the magnitude of this fractional change may significantly alter model predictions. For example, simulation results for hydrologic processes such as evapotranspiration and vegetation roughness could change with increasing grain because evapotranspiration volume computed for a dominant vegetation cover type at a broad scale may be very different from that calculated using a finer resolution which included many cover types. Thus, broadening the scale and the resulting loss of information may produce different simulation modeling results for ecological processes. However the importance of this difference is dependent on the objectives of the modeling exercise.

2.2. Diversity index

An index which attempts to combine both the number of species (richness) and the abundance of species (evenness) is species diversity (Ludwig and Reynolds 1988). In this study, the overall measure of diversity of landscape pattern is investigated using the diversity index which is based on information theory (Shannon and Weaver 1949):

$$H = \Sigma \; p_k \; \log p_k \qquad (1)$$

where p_k is the fraction of cover type k and the summation is over all cover types present at a particular model scale. For a specified number of species, the above diversity index H is highest when the community is even (equal proportions of each species). One of the major difficulties in using any diversity index is the interpretation of its meaning. Different combinations of richness and evenness for a community can produce the same magnitude for diversity. In addition, different forms and units of diversity indices can make comparisons difficult. In this study the Shannon-Weaver diversity index was utilized to measure and compare species richness and evenness as a function of increasing model scale.

2.3. Fractal dimension (FD)

Understanding how landscape patterns relate to the processes that generate them is of fundamental importance in landscape ecology (Krummel *et al.* 1987). It is hoped that as the science of landscape modeling progresses, models can accurately simulate land cover patterns resulting from management actions. Depending on the ultimate objectives of landscape modeling, patch characteristics will influence the selection of the appropriate model scale to varying degrees. Because patch characteristics can influence such parameters as nearest neighbor probabilities, they may also be important in stochastic transition models.

The *FD*, an indice which describes the changing complexity of patches in the landscape, is investigated using Mandelbrot's (1977) fractal analysis of area (A) and perimeter (P) relationship (Gardner *et al.* 1987; Krummel *et al.* 1987; Barnsley 1988; Feder 1988; Milne 1988, 1992; Turner and Ruscher 1988; De Cola 1989; Pastor and Broschart 1990). Estimation of *FD* is achieved by regressing log (P/4) on log √A and calculating *FD* as given by the following formula.

$$P/4 = (\sqrt{A})^{FD} \qquad (2)$$

For smooth shapes such as a square $FD = 1$, whereas for more complex shapes *FD* approaches the value 2.

The observation that *FD* is constant (or self similar) over many scales may suggest that a single, scalable process is dominant; the observation that *FD* changes with scale may indicate the dominance of different processes (Burrough 1984). This 'self similarity rule' has proved to be a very useful tool in describing many kinds of complex boundaries (Burrough 1981, 1983; Lovejoy 1982; Bradbury *et al.* 1984; Milne 1988). If a landscape is self-similar with respect to its pattern, it may be possible to develop a coarser scale model if one assumes that the processes that formed the landscape are also self-similar. However, this self similarity may be structured and have levels of variability clustered at particular scales. Mandelbrot (1977) and Burrough (1981) consider that it is quite acceptable to have a series of zones of distinct fractal dimensions connected by transition zones. Rather than calculating only the fractal dimension within an interval of scales, it is perhaps more interesting to look for those scales of observation where the fractal dimension is changing. At those critical scales, the constraints of the environment that act upon the characteristics under study are also changing (Frontier 1987). Identifying such scales could be of enormous practical value in adjusting sampling and modeling schemes (Krummel *et al.* 1987).

2.4. Transition probabilities

The diversity of a landscape should include both composition and configuration (Li and Reynolds 1993). Composition is accounted for by the number of patch types and their relative fractions. Configuration refers to the spatial patterns of patches in the landscape. Clumpiness or the fragmentation

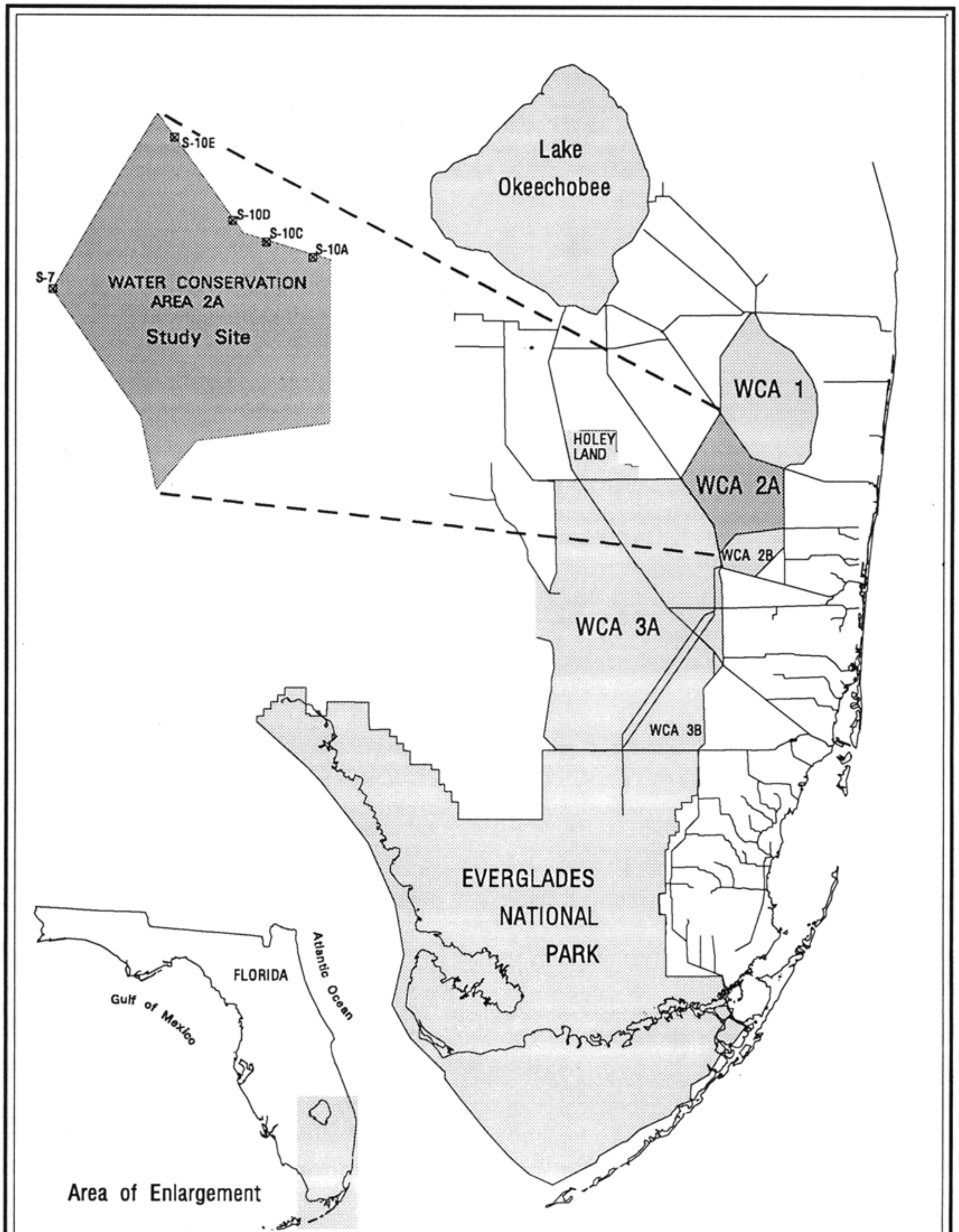

Fig. 1. Location of Water Conservation Area (WCA) 2A in the Everglades region. Note that S-10 stands for structure 10. All structures shown are inflow structures.

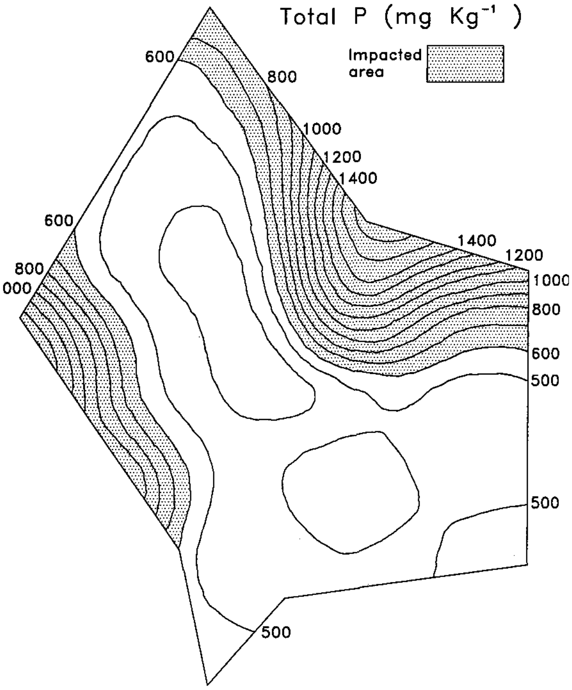

Fig. 2. Location of impacted and unimpacted areas based on total phosphorus concentrations in the top ten cm of soil. Areas greater than 600 mg kg^{-1} were considered impacted and areas 600 mg kg^{-1} or less were unimpacted.

of patches in a landscape can be characterized by the contagion index (O'Neill *et al.* 1988; Turner 1990; Li and Reynolds 1993). Rather than using overall indices such as contagion or predictability (Turner *et al.* 1989b), the state transition probabilities, which are the basis for such indices, are used for scale analysis in this study. The transition probability, P_{ij} is defined as the proportion of cells of type i that are adjacent to cells of type j in a given direction (horizontal or vertical).

Although such transition probabilities are not directly used in mechanistic or deterministic type landscape simulation models, they are the basis for transition models (Turner 1987). Transition probabilities at a particular scale can also be used as indices to verify spatial patterns of simulations made by a landscape model developed for that scale.

2.5. Data

Rutchey and Vilchek (1994) classified an August 10, 1991 SPOT scene of Everglades Water Conservation Area 2A (WCA2A) (Figure 1) into twelve wetland classes using ERDAS software (Atlanta, GA). The remotely sensed data were rectified to a Universal Transverse Mercator (UTM) map projection having 20 × 20 m pixels. The thematic accuracy of the 1991 SPOT wetland classification map was documented by analyzing 241 stratified random ground reference locations surveyed using GPS instruments. The overall map accuracy was 81%.

DeBusk *et al.* (1994) conducted research in WCA2A in 1990 to determine the spatial distribution of selected nutrients in the soil. Final results from geostatistical analyses produced isarithmic ("contoured") maps for selected parameters. Results showed that total phosphorus concentrations in the 0-10 cm soil depth were significantly different for the sawgrass, mixed sawgrass-cattal and cattail marshes. Data from this study also indicated that the distribution of cattails in WCA2A coincides closely with soil P enrichment. These areas have also seen a significant impact over the past thirty years in the conversion of several thousand hectares of sawgrass to cattail (Davis 1991, Rutchey and Vilcheck, Jensen *et al.* 1995). This has been due to surface water runoff from adjacent agricultural land. In order to investigate if there were differences in the spatial arrangement of vegetation cover types in these areas, the WCA2A 20 × 20 m raster vegetation data set produced by Rutchey and Vilchek (1994) was divided into "impacted" and "unimpacted" areas based on total P concentrations in the top ten cm of soil (Figure 2). Areas greater than 600 mg kg^{-1} were considered impacted and areas 600 mg kg^{-1} or less were unimpacted. Thus, three data sets were now available for analysis: whole, impacted and unimpacted.

Each of the three original 20 × 20 m data sets were spatially aggregated, using the ERDAS command AGGIE, to a 40 × 40 m pixel resolution and incremented by 40 meters on up to 1000 × 1000 m (*i.e.*, 40, 80, 120, 160 ... 1000) pixel resolution. The AGGIE algorithm is an aggregation resampling process which takes an original image and

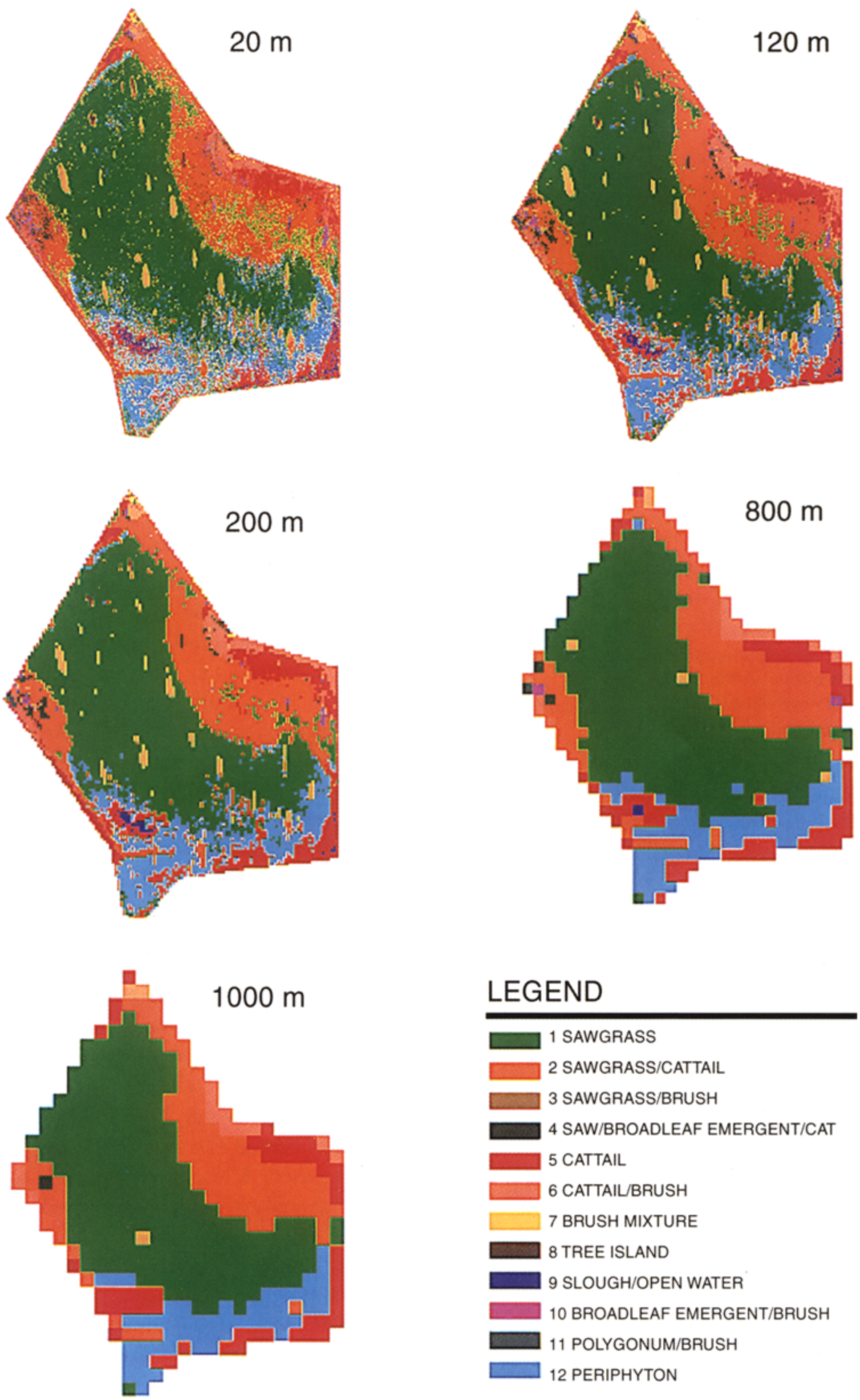

Fig. 3. Changes in the vegetation patterns of WCA2A resulting from broadening spatial resolution.

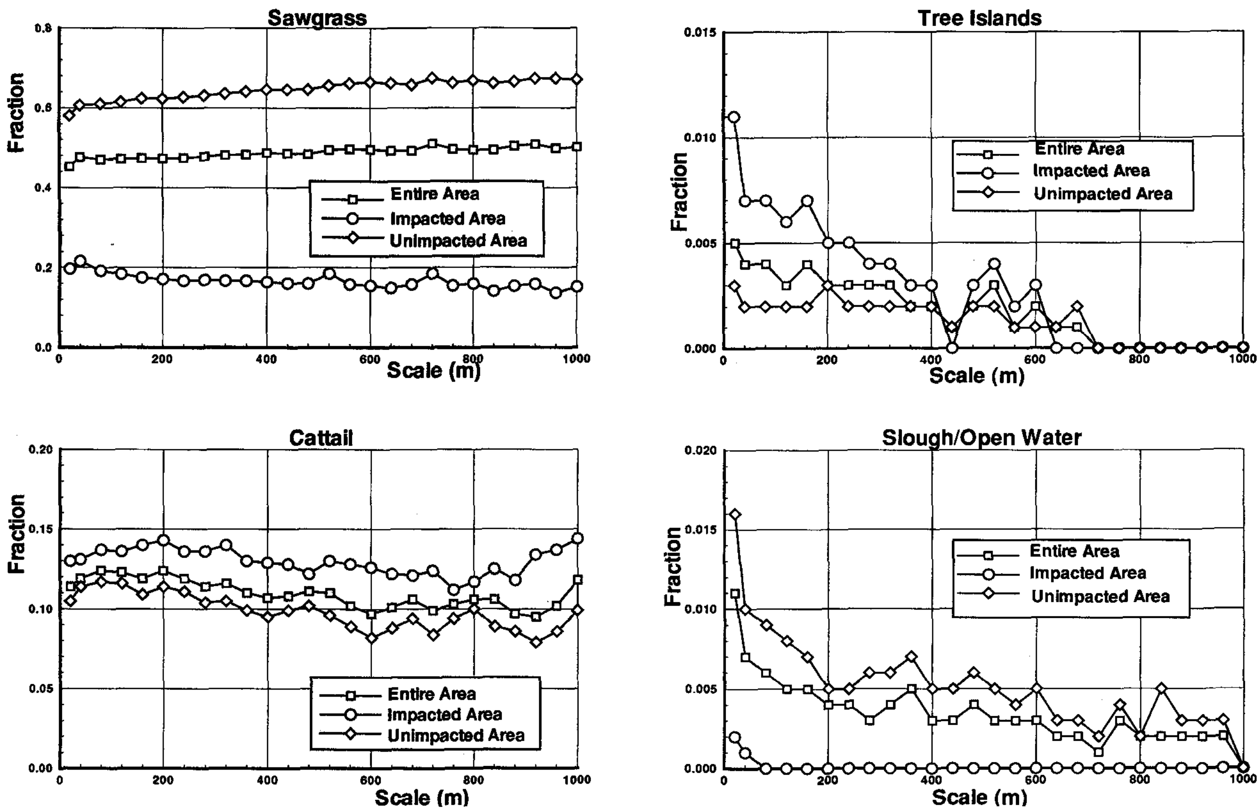

Fig. 4. Variation of cover fraction as a function of scale for the cover types sawgrass, cattail, tree islands and slough/open water. Results are shown for three landscape regions: (a) entire area; (b) impacted area; and (c) unimpacted area.

divides it into windows (boxes), according to a size that you specify. The cell size increases by an integer factor. If a 2 × 2 window is used, and the original cell size is 20 meters, then the output cell size will be 40 meters. Windows or boxes will always start at the origin of the original image. The output class value of a window of pixels uses the majority rule. Thus, twenty-six data sets, each with a different pixel resolution, were produced for each of the whole, impacted and unimpacted regions. The ERDAS command DATATAB was used to produce an ASCII file, in tabular format for each of the data sets.

The primary tool used for analyzing the landscape pattern at various scales was the Spatial Analysis Program, SPAN developed by Turner (1990). SPAN is a grid-cell based analysis program developed to quantify landscape patterns and their changes in an ecologically meaningful manner. The output from the SPAN program was analyzed by using the commercially available Statistical Analysis System (SAS 1990).

Although it is desirable to have the same number of rasters as one increases the scale, it was not attempted here. The underlying assumption was that the number of rasters was large enough to produce reliable estimates of the indices. For a given scale, maximum possible number of rasters was used to obtain the best estimates of the indices.

Results and discussion

Figure 3 graphically illustrates the changes in the vegetation patterns of WCA2A resulting from broadening the spatial resolution. While the general shape of the impacted area remained the same up to a scale of 1000 m, the finer scale features of the landscape pattern were lost beyond a scale of about 200 m. The tree islands and brush mixture communities nearly disappeared from the landscape pattern at the 800 m scale. At the 1000

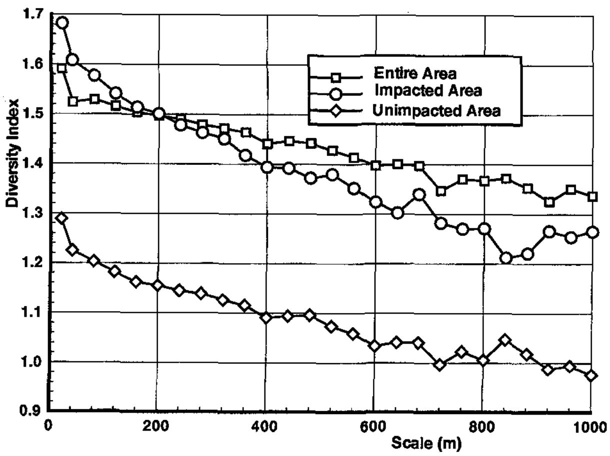

Fig. 5. Variation of shannon-Weaver diversity index as a function of increasing scale for: (a) entire area; (b) impacted area; and (c) unimpacted area.

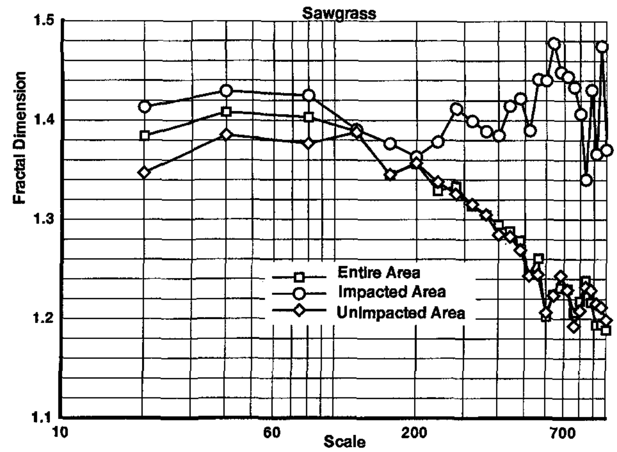

Fig. 6. Variation of Fractal Dimension computed from Area-Perimeter relationships of sawgrass patches generated by increasing scale in each of the following landscapes: (a) entire area; (b) impacted area; and (c) unimpacted area.

m scale only a few cover types dominated the landscape namely sawgrass, cattail and periphyton.

Fractional variation as a function of broadening scale is shown in Figure 4 for sawgrass, cattail, tree islands, and slough/open water for the whole, impacted, and unimpacted regions. The fractional magnitude of change for each region for sawgrass and cattail was small. Consequently, at a coarser scale, a grid based spatial model may be able to simulate such hydrologic processes as evapotranspiration for these cover types. It should be noted that cover fraction values changed drastically from one region to another. For example, sawgrass proportion in the impacted area was about one third the corresponding fraction of the unimpacted area. As expected, the cattail fraction in the impacted area was thirty percent larger when compared to the unimpacted area.

The cover fraction for tree islands and slough/open water areas decreased rapidly with broadening scale. Tree islands and brush mixture communities practically disappeared at about 700 m scale. Slough/open water coverage declined continuously with increasing scale. The formation of tree islands and their current health status in the Everglades has and is a direct consequence of hydrological conditions. Prolonged hydroperiod has been shown to change the species composition of forested tree islands by increasing mortality of hardwood species (Craighead 1971; Gunderson *et al.* 1988; Worth 1988). Dineen (1972, 1974) concluded that the loss of trees and woody vegetation on tree islands was the result of prolonged high water stages. Davis *et al.* (1994) showed a community shift from wet prairie and slough to sawgrass during 15–21 years of recent management practices. Anthropogenic changes in hydrology and fire regimes were given as plausible hypotheses to explain the plant community shift from wet prairie/slough to sawgrass. By broadening the model scale, some of these observations for community change could be lost in a landscape model.

The diversity index for a given region decreased almost linearly with broadening scale due to the dominance of certain cover types (Figure 5). At the 20 m scale, which was the grain size of the original data set, the diversity index for the impacted area was about 1.7 which was 25% less than its potential maximum value ($\log_e 12 = 2.48$). The diversity index of the unimpacted region was about 25 percent smaller than the impacted area. The diversity index of the entire landscape decreased at a lower rate than the impacted and unimpacted regions. If spatial indices are to be used for comparing simulations of a landscape model, a relevant question is: Should one compare the diversity index of a model simulation of vegetation patterns generated at a broad scale with one generated at a fine scale? Models developed at

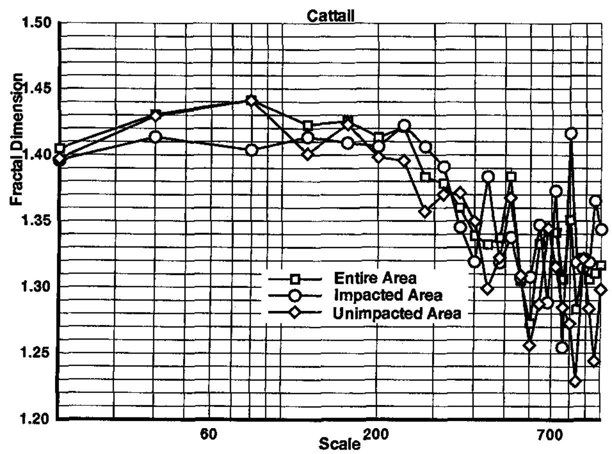

Fig. 7. Variation of Fractal Dimension computed from Area-Perimeter relationships of cattail patches generated by increasing scale in each of the following landscapes: (a) entire area; (b) impacted area; and (c) unimpacted area.

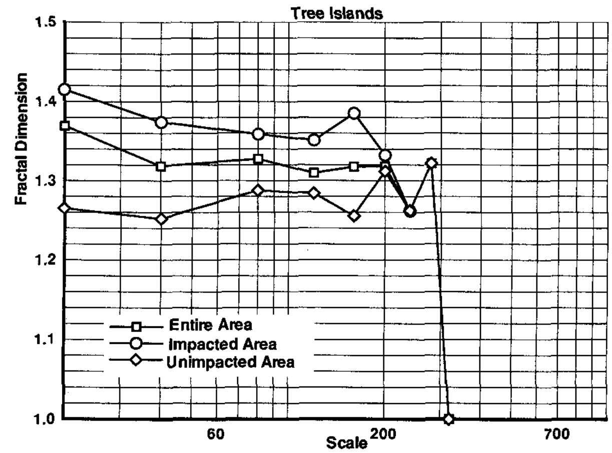

Fig. 8. Variation of Fractal Dimension computed from Area-Perimeter relationships of tree island patches generated by increasing scale in each of the following landscapes: (a) entire area; (b) impacted area; and (c) unimpacted area.

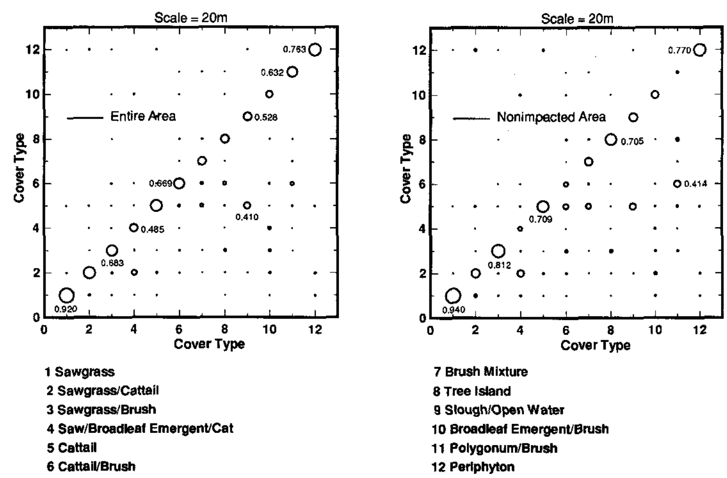

Fig. 9. Nearest neighbor transition probabilities of the WCA2A vegetation map at 20 m scale for (a) entire area; (b) impacted area; and (c) unimpacted area.

broader scales may not necessarily simulate spatial patterns that have the diversity characteristics of finer scales.

The fractal analysis results for cover types sawgrass, cattail, and tree islands are shown in figures 6 through 8. The fractal dimension (*FD*) for patches in the original observation set (20 m scale) for these cover types was approximately 1.3–1.4. As shown in figures 6 and 7, the fractal dimension for saw grass and cattail remained relatively constant at around 1.4 for finer scales and decreased rapidly for scales coarser than 100 m. Sawgrass was the exception in the impacted area. Its fractal dimension did not decline, became more variable, and increased slightly. For tree islands (Figure 8) the values of *FD* remain relatively constant up to about 200 m scale. As discussed earlier, the tree islands disappear at broader scales.

A constant fractal dimension (*i.e.*, the "self similarity rule") was valid only within a limited scale range of approximately 20–100 m. With broadening scale, the A-P relationship changed producing different patterns or patches in the landscape. If one were to accept the hypothesis that the patch

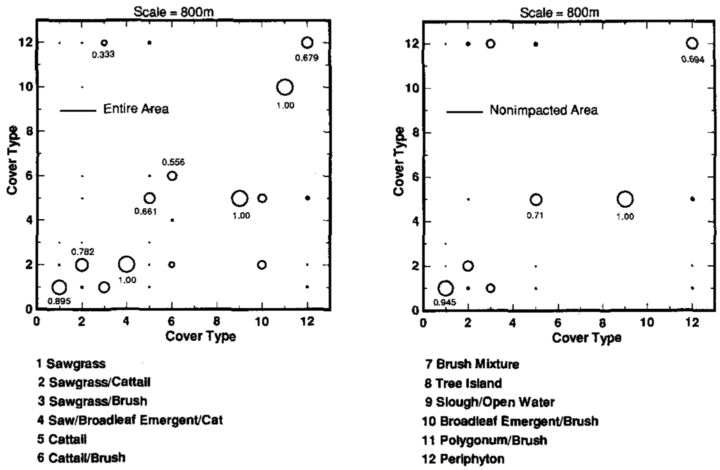

Fig. 10. Nearest neighbor transition probabilities of the WCA2A vegetation map at 800 m scale for (a) entire area; (b) impacted area; and (c) unimpacted area.

characteristics such as lengths of edges are important for spatial modeling of a landscape, this analysis indicates that the appropriate scale for an Everglades landscape model may not exceed 100 m. Modeling at such fine scales may be cost prohibitive and even impossible due to lack of data. The goals of a landscape model may be such that the use of such a fine scale is unnecessary, and the modelers should clearly state such goals a priori, to limit and set expectations of modeling.

Figures 9 and 10 show the horizontal transition probabilities for two scales: 20 m (finer resolution) and 800 m (coarser resolution) scale. The size of each circle inside the figures was proportional to the nearest neighbor transition probability. Corresponding cover types are indicated on the two axes. The larger diagonal values for the 20 m scale indicated clumpiness of the landscapes. In the entire area, the relatively large off-diagonal term 0.410 (Figure 9) indicates a transition to cover type 5 (cattail) from cover type 9 (slough/open water). This observation supports other research which suggests that cattail under high nutrient conditions and prolonged hydroperiod will invade and dominate deeper open water slough areas of the Everglades (Urban *et al.* 1993; Davis 1989).

Clearly, the transition probabilities at 800 m scale show no resemblance to those at 20 m scale. Some probabilities are at their limit of 1. Consequently, the configuration of patches in the landscape is very different from that of the 20 m scale. It is obvious that the transition models developed for these two scales will simulate very different spatial patterns. Care must be exercised in selecting the appropriate scale to compute transition probabilities. These transition probabilities can be useful for verifying the simulations of a process based spatial model for landscape.

4. Conclusions

The selection of scale for landscape modeling projects can be a difficult decision. To our knowledge there is no formula or elegant theoretical approach for selecting an appropriate spatial scale. Since such models can include processes with very different spatial/time scales, the selection of an appropriate scale for all processes is a significant landscape modeling topic. As a preliminary analysis, the investigation of variation of a selected set of indices and the fractal dimension of the area-perimeter relationship of individual patches as a function of scale are proposed as selection tools. These "tools" included cover fraction, diversity index, fractal dimension and transition probabilities because they can be used to focus on information loss and the lack of self similarity as a function of scale. It should be noted that a process based theoretical approach is probably more appropriate for selection of scale for landscape models. However, in the absence of such an elegant theoretical approach, the use of spatial and fractal dimension indices can be useful for initial screening.

The application of the proposed methods to the SPOT image of Everglades Water Conservation Area 2A found that features such as tree islands in the landscape nearly disappear at or beyond about 700 m scale. Slough/open water areas decreased continuously with increasing scale. A landscape model must address issues of spatial scale, especially if its function is to simulate diverse vegetation patterns resulting from changing hydrological conditions.

The fractal analyses indicate that the fractal dimension of the Area-Perimeter relationship decreased quite rapidly after about 100 m scale indicating that this may be the upper limit for ensuring appropriate patch characteristics in an Everglades landscape model. Recognizing that a model at this scale for the entire Everglades may be cost prohibitive, the appropriate scale for a landscape model may be influenced by other considerations such as the intended use of such a model.

A comparison of the nearest neighbor transition probabilities at two extreme scales indicated that they can be very different. This is an important issue for stochastic transition models. It can also be important if transition probabilities, or other indices derived from them, are used to compare simulations of landscape patterns generated from models.

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