Sensitivity of Selected Landscape Pattern Metrics to Land-Cover Misclassification and Differences in Land-Cover Composition

James D. Wickham, Robert V. O'Neill, Kurt H. Riitters, Timothy G. Wade, and K. Bruce Jones

Abstract

Calculation of landscape metrics from land-cover data is becoming increasingly common. Some studies have shown that these measurements are sensitive to differences in land-cover composition, but none are known to have tested also their sensitivity to land-cover misclassification. An error simulation model was written to test the sensitivity of selected landscape pattern metrics to misclassification, and regression analysis was used to determine if these metrics were significantly related to differences in land-cover composition. Comparison of sensitivity and regression results suggests that differences in land-cover composition need to be about 5 percent greater than the misclassification rate to be confident that differences in landscape metrics are not due to misclassification.

Introduction

Analysis of landscape pattern makes use of measurements of the connectedness (e.g., contagion, percolation), diversity (e.g., Shannon diversity, dominance), shape complexity (e.g., fractal dimension), and size of land-cover patches to study ecological condition at local to regional scales (Turner and Gardner, 1991). These metrics (O'Neill *et al.*, 1988) have been used to assess landscape condition (Krummel *et al.*, 1987; Graham *et al.*, 1991; Wickham and Norton, 1994), infer ecological process from pattern (Turner, 1989; Milne, 1992), and show how landscape configuration can impose constraints on biological populations (Browder *et al.*, 1989; Hoover and Parker, 1991; Flather *et al.*, 1992; Pearson, 1993). From a regional perspective, land-cover patterns may be considered as either forcing or constraint functions for sub-regional dynamics, or as integral parts of strictly regional models (Allen and Starr, 1982; O'Neill *et al.*, 1994). Information about land-cover patterns has proven useful for both local and regional assessments of ecological condition (Vos and Opdam, 1993; Meyer and Turner, 1994).

Measurements of landscape pattern are commonly made from land cover (e.g., Krummel *et al.*, 1987; Turner, 1987; Turner, 1990a; Turner, 1990b; O'Neill *et al.*, 1988; Graham *et al.*, 1991; Olsen *et al.*, 1993; Wickham and Norton, 1994; Wickham and Riitters, 1995; Wickham *et al.*, in press; Riitters *et al.*, 1995). However, measurement of landscape pattern from land-cover maps has been undertaken without investigation of the sensitivity of these measurements to classification error (Hess, 1994). The objectives of this paper are two-fold: (1) to determine the sensitivity of landscape metrics to land-cover misclassification, and (2) to determine the sensitivity of landscape metrics to differences in landscape condition. These objectives are necessarily connected. Ideally, landscape pattern metrics would be insensitive to misclassification but sensitive to differences in land cover.

Land-cover data, mapped from Landsat TM for the Chesapeake Bay Regional Watershed, were used for this study. The data were divided into 57 eight-digit U.S. Geological Survey (USGS) hydrologic units or watersheds. Sensitivity to misclassification is tested using a simulation model based on a published land-cover error matrix (Green *et al.*, 1993). Sensitivity to differences in landscape condition is tested by comparison to the amount of human land use in the watershed. Landscape condition is measured as the ratio of anthropogenic land use to total area (U) (O'Neill *et al.*, 1988). Low values reflect that a watershed is primarily forested, while high values reflect dominance by human land uses. The use of U as a measure of landscape condition is based on observations in ecology and biogeography that the Chesapeake Bay Regional Watershed was almost entirely forested prior to conversion to human land use (Whittaker, 1975).

Landscape Pattern Metrics

Three landscape pattern metrics were chosen for analysis: average patch compaction (APC), contagion (C), and fractal dimension (F). APC, C, and F were selected because they were found to represent orthogonal axes among 55 landscape pattern metrics tested in a factor analysis (Riitters *et al.*, 1995). Therefore, these metrics represent independent information about landscape pattern. The formulas for calculating these metrics are listed in Appendix A.

Average patch compaction, APC, is the ratio of patch area to the size (area) of the smallest square that will contain that patch. The ratios are averaged over all patches in a landscape. APC has a value of 0 for linear patches and a value of 1 for perfectly square patches (Riitters *et al.*, 1995).

Contagion, C, measures the degree to which the landscape is composed of a few large or several small patches. Contagion ranges between 0 and 1. High values of contagion indicate that the landscape is clumped into a few, large patches.

Fractal dimension, F, is commonly calculated as twice

J.D. Wickham and K.H. Riitters are with the Tennessee Valley Authority, Norris, TN 37828.

R.V. O'Neill is with the Oak Ridge National Laboratory, Oak Ridge, TN 37831.

T.G. Wade is with the Desert Research Institute, Reno, NV 89506.

K.B. Jones is with the Environmental Protection Agency, Las Vegas, NV 89193.

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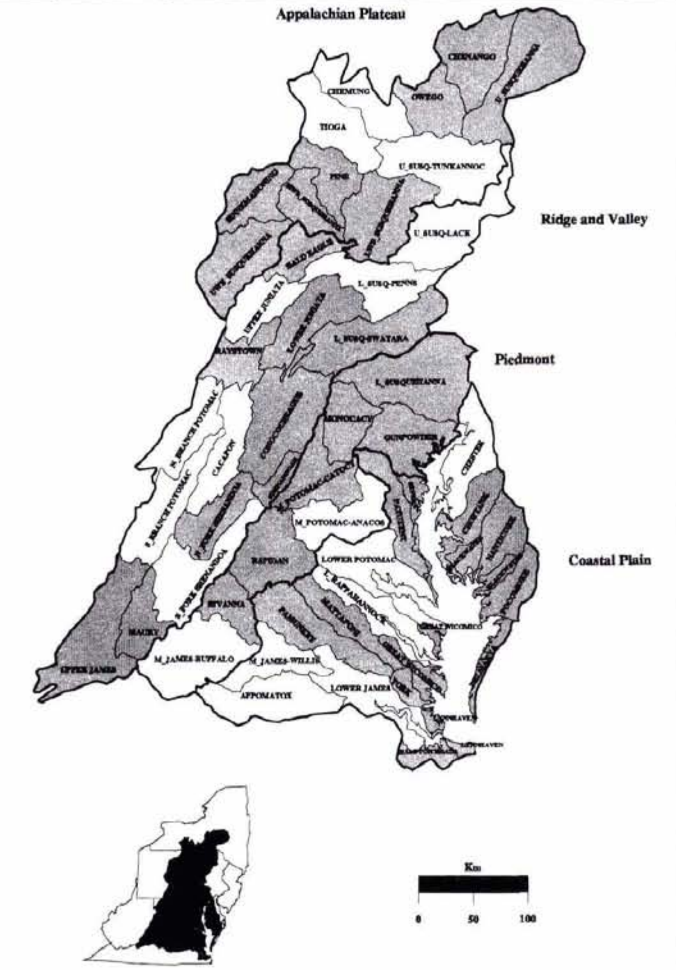

Figure 1. Map of Chesapeake Bay Regional Watershed. Smaller 8-digit USGS watersheds shown in white and gray. Gray shaded watersheds were used in error simulation modeling. Bold lines mark the boundaries between the four physiographic provinces. The first 16 characters are used to identify the USGS watershed name, except where appropriate (e.g., uwb_susquehanna = upper west branch, susquehanna).

the slope of a log-log regression of perimeter versus area (Lovejoy, 1982). Fractal dimension ranges between 1.0 and 2.0, with higher values indicating more complex shapes.

A fourth metric, index of landscape pattern (I_{LP}), was calculated as the sum of *APC*, *C*, and *F* minus 1 (1 was subtracted from *F* so that its range was also 0 to 1). I_{LP} combines the information contained in *APC*, *C*, and *F* into a single metric. Calculation of I_{LP} simply as the addition of *APC*, *C*, and *F* is appropriate because these metrics are orthogonal.

Methods

The Landsat TM-based land-cover data used in this study were mapped by the U.S. Environmental Protection Agency (USEPA) for the Environmental Monitoring and Assessment Program (EMAP). An unsupervised-supervised classification algorithm was used for mapping. Unsupervised methods were used to identify spectral clusters, which in turn were used as training sets to drive a supervised classification of six categories: high intensity developed, low-intensity developed, woody, herbaceous, exposed land, and water. These classes were effectively urban, suburban/residential, forest, agriculture, beaches and extractive operations (mining), and water, respectively.

A simulation model was used to test the sensitivity of landscape pattern metrics to misclassification. The simulation model randomly introduced error into the Chesapeake Bay land-cover map. The simulation was run 100 times on each watershed, providing a different spatial distribution of error at each iteration. The landscape metrics were then calculated at each iteration of the simulation for each watershed. The simulation model was run on 39 of the 57 USGS watersheds in the study area (Figure 1), representing all four physiographic provinces: Coastal Plain, Piedmont, Ridge-and-Valley, and Appalachian Plateau (Hunt, 1967).

The simulation model was used to test two components of error in landscape metrics as a result of misclassification. The first was the difference between original and simulated mean values for each metric. This difference is the bias in the estimate of a landscape metric as a result of misclassification. Second, the confidence interval around the simulated mean gives a rigorous estimate of the potential variability in a given landscape pattern metric due to misclassification. The confidence interval around the simulation mean is given by

$$\mu_a = \bar{X} \pm tS_{\bar{x}} \qquad (1)$$

where μ_a is the population mean at confidence level *a*, $\bar{X}$ is the sample mean, $S_{\bar{x}}$ is the standard error of the mean, *t* is a value from the Student's *t* table for a given level of *a*, and *n* is sample size. For this study *a* was 0.05, *n* was 100, and *t* was 1.98.

Regression was used to test the sensitivity of the landscape pattern metrics (*APC*, *F*, *C*, I_{LP}) to differences in land-cover composition (*U*), using the original (not simulated) values for each watershed. By comparing the solution of the regression equation to the mean difference between the simulated and original value for each landscape pattern metric, it is possible to evaluate both the sensitivity to misclassification and differences in land-cover composition.

Prior to the regression analyses, the data (*U*, *APC*, *F*, *C*, and I_{LP}) were inspected for normality. All data were normally distributed except *F* and *U*, which showed a slight skewness. Each regression model was inspected for heteroscedasticity. None was found.

Error Simulation Model

The error simulation model, written using the Arc/Info GRID module (ESRI, 1994), was based on (1) misclassification calculated from an error matrix, and (2) spatial autocorrelation in land-cover classification error (Congalton, 1988). The error matrix (Story and Congalton, 1986) is the standard medium for reporting land-cover classification accuracy (Congalton and Green, 1993). An error matrix is constructed as a square contingency table where the columns represent reference data and rows represent classified data.

An error matrix from Green *et al.* (1993) was used to establish the per-class accuracies for the simulation model (Table 1). This error matrix was chosen because (1) it was constructed from Landsat TM-derived land-cover data for a similar environment (New Jersey); (2) had a nearly identical legend; (3) had high accuracy rates; and (4) the conditional probabilities of correct classification, omission, and commission were determined by dividing the actual pixel counts by the corresponding row totals. This method of conditional probability determination assumes that a stratified random sample, where the stratification was based on the classification results, was used to construct the error matrix (Green *et al.*, 1993). This approach is commonly used to conduct accuracy assessments.

Some changes in the Green *et al.* (1993) error matrix were required before it could be used with the Chesapeake Bay data. The classification error reported by Green *et al.* (1993) for their built-up class was used for our urban and residential classes. However, we assumed that the confusion between urban and forest reported by the authors was largely between residential and forest, not urban and forest, because residential areas contain lawns, parks, and perhaps small woodlots which are more likely to have a spectral signature similar to that of forest than to more densely urbanized areas. For our urban class, we assumed that confusion was with barren and residential. For our residential class, we assumed that confusion was with forest, agriculture, and urban.

To incorporate spatial autocorrelation into the simulation model, the accuracy of edge pixels was reduced five percentage points from that reported by Green *et al.* (1993) for the corresponding class. Likewise, the accuracy of interior pixels was increased by five percentage points for interior pixels. While previous studies have found that classification error tends to be higher at the edge between two land-cover types than in the interior of a single land-cover patch (Congalton, 1988), we found no information on the actual difference in misclassification rate between edge and interior pixels. We assumed an overall 10 percent difference in misclassification rate between edge and interior pixels. This modification yields edge and interior error matrices that can be weighted and combined into a matrix that incorporates spatially autocorrelated classification error. An example is shown for one iteration of the simulation model for the Choptank Watershed (Tables 2a, 2b, and 2c).

The eight nearest neighbors to each pixel were searched to define an edge. Any pixel surrounded by identical land cover was treated as being interior. When the simulation identified error on an edge, the most frequent value of the eight nearest neighbors was used as the correct land-cover type.

The overall estimate of error (1 minus the percent correctly classified; see Table 2c) varied slightly as a result of the composition of the watershed. Watersheds dominated by

TABLE 1. ERROR MATRIX FOR TM CLASSIFICATION OF NEW JERSEY. COLUMNS REPRESENT REFERENCE DATA AND ROWS REPRESENT CLASSIFIED DATA. CELL VALUES ARE ROW ADJUSTED PROBABILITIES. REPRODUCED WITH PERMISSION FROM GREEN ET AL. (1993)

	Forest	Non-Forest	Built-Up	Barren	Water	Cloud
Forest	0.88	0.08	0.04	0.00	0.00	0.00
Non-Forest	0.09	0.81	0.10	0.00	0.00	0.00
Built-Up	0.16	0.06	0.78	0.00	0.00	0.00
Barren	0.00	0.00	0.00	1.00	0.00	0.00
Water	0.00	0.00	0.00	0.00	1.00	0.00
Cloud	0.00	0.00	0.00	0.00	0.00	1.00

TABLE 2. INTERIOR (A), EDGE (B), AND COMPOSITE (C) ERROR MATRICES FOR CHOPTANK WATERSHED IN CHESAPEAKE BAY. COLUMNS REPRESENT REFERENCE DATA AND ROWS REPRESENT CLASSIFIED DATA. NUMBERS IN PARENTHESES ARE PIXEL COUNTS. MATRIX POSITIONS WHERE PIXEL COUNTS ARE LESS THAN 0.1 PERCENT (0.001) ARE TREATED AS ZERO (0).

Chesapeake Bay, Choptank 8-Digit USGS Watershed

A: Error Matrix, Interior Pixels

	Woody	Herbaceous	Urban	Residential	Water	Exposed Land
Woody (684900)	0.931 (637609)	0.050 (33946)		0.019 (13345)		
Herbaceous (1814609)	0.069 (126070)	0.861 (1562753)		0.069 (125786)		
Urban (2066)			0.832 (1718)	0.049 (101)		0.120 (247)
Residential (37117)	0.093 (3452)	0.054 (1987)	0.021 (778)	0.833 (30900)		
Water (317577)					1.000 (317577)	
Exposed Land (642)			0.040 (26)			0.960 (616)

B: Error Matrix, Edge Pixels

	Woody	Herbaceous	Urban	Residential	Water	Exposed Land
Woody (291116)	0.831 (242012)	0.159 (46326)	0.0 (31)	0.003 (795)	0.007 (1948)	0.0 (4)
Herbaceous (354960)	0.192 (68359)	0.761 (270069)	0.002 (766)	0.007 (2485)	0.037 (12981)	0.001 (300)
Urban (7658)	0.006 (50)	0.081 (620)	0.730 (5587)	0.098 (747)	0.085 (654)	
Residential (18948)	0.076 (1448)	0.131 (2479)	0.047 (892)	0.723 (13705)	0.021 (403)	0.001 (21)
Water (75316)	0.009 (681)	0.037 (2789)	0.002 (170)	0.001 (77)	0.950 (71539)	0.001 (60)
Exposed Land (2017)	0.002 (4)	0.042 (85)		0.003 (6)	0.058 (118)	0.910 (1804)

Chesapeake Bay, Choptank 8-Digit USGS Watershed

C: Error Matrix, Composite (Interior and Edge)

	Woody	Herbaceous	Urban	Residential	Water	Exposed Land
Woody (976016)	0.901 (879621)	0.082 (80272)	0.0 (31)	0.014 (14140)	0.002 (1948)	0.0 (4)
Herbaceous (2169569)	0.090 (194429)	0.845 (1832822)	0.0 (766)	0.059 (128271)	0.006 (12981)	0.0 (300)
Urban (9724)	0.005 (50)	0.064 (620)	0.751 (7305)	0.087 (848)	0.067 (654)	0.025 (247)
Residential (56065)	0.087 (4900)	0.080 (4466)	0.030 (1670)	0.796 (44605)	0.007 (403)	0.0 (21)
Water (392893)	0.002 (681)	0.007 (2789)	0.001 (170)	0.0 (77)	0.990 (389116)	0.0 (60)
Exposed Land (2659)	0.001 (4)	0.032 (85)	0.010 (26)	0.002 (6)	0.044 (118)	0.910 (2420)

forest had slightly higher overall accuracies because of a higher per-class accuracy for forest. The overall estimate of error ranged from 0.085 to 0.158 across the 39 watersheds on which the simulation model was run. The average error rate across the 39 watersheds was 0.122.

Results

Sensitivity of Landscape Pattern Metrics to Land-Cover Misclassification

Because *APC*, *F*, and *C* all have ranges between either 0 and 1 or 1 and 2, the magnitude of bias in these measurements is directly comparable to the misclassification rate. The bias in landscape metrics as a result of misclassification was equal to or less than the misclassification rate (Table 3). The mean bias estimates, averaged over all watersheds, were 0.022, 0.074, 0.122, and 0.070 for *APC*, *F*, *C*, and I_{LP}, respectively. Only the bias in contagion approximated the misclassification rate. Differences greater than these values would indicate that the difference is not simply due to land-cover misclassification. Also, the direction of the bias for each estimate was consistent — misclassification always resulted in lower values for *APC*, *C*, and I_{LP}, and higher values for *F*.

The confidence intervals about the simulated means show the sensitivity due to differences in the spatial distribution of misclassification. The confidence intervals are two or more orders of magnitude smaller than the bias (Table 4). Variability in the spatial distribution of misclassification does not appear to affect the estimates of landscape pattern metrics.

TABLE 3. SUMMARY STATISTICS OF BIAS ESTIMATES DUE TO LAND-COVER MISCLASSIFICATION.

Landscape Metric	Direction	Mean	Minimum	Maximum
Average Patch Compaction	decrease	0.021557	0.000980	0.051696
Fractal Dimension	increase	0.074297	0.017696	0.111183
Contagion	decrease	0.122129	0.075568	0.155760
Landscape Pattern Index	decrease	0.069620	0.008498	0.115556

TABLE 4. SUMMARY STATISTICS OF ERROR VARIANCE DUE TO LAND-COVER MISCLASSIFICATION.

Metric	Mean	Minimum	Maximum
Average Patch Compaction	0.000669	0.000289	0.001533
Fractal Dimension	0.000708	0.000317	0.001410
Contagion	0.000091	0.000020	0.000535
Landscape Pattern Index	0.001114	0.000432	0.002265

Sensitivity of Landscape Pattern Metrics to Land-Cover Composition

U ranged from 0.071 (dominated by forest) to 0.685 (dominated by human land uses) across the watersheds. I_{LP} showed a negative relationship with *U* (R^2 = 0.496) (Figure 2). The regression model (Table 5) shows that a 10 percent difference in *U* between watersheds results in a change of 0.042 in I_{LP}. Therefore, the proportion of anthropogenic land use must

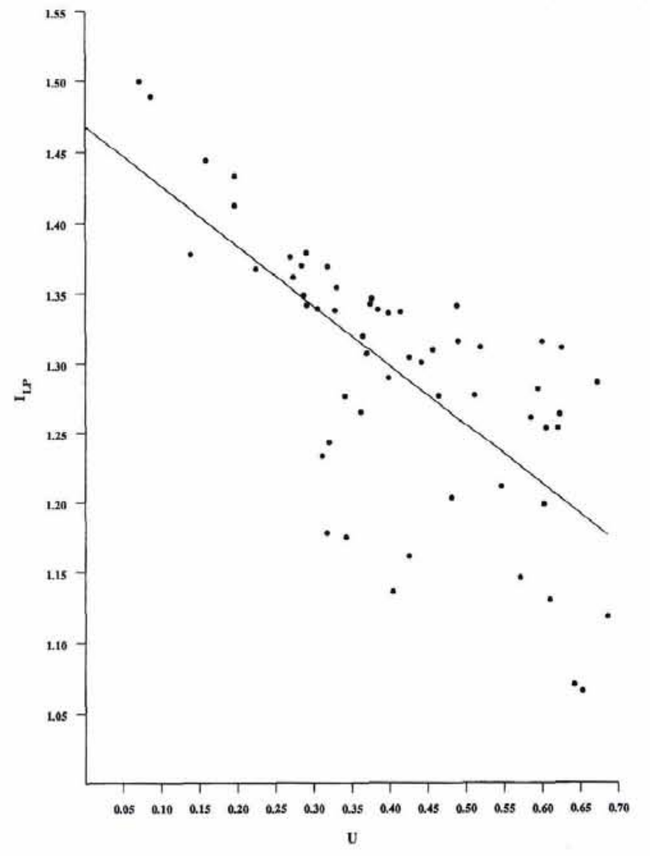

Figure 2. Landscape pattern index versus *U*. Regression line from Table 5 shown.

TABLE 5. REGRESSION RESULTS FOR LANDSCAPE PATTERN INDEX (I_{LP}) VERSUS U.

Dependent Variable: Landscape pattern index (I_{LP})					
Source	DF	Sum of Squares	Mean Square	F Value	$Pr>F$
U	1	0.24527	0.24527	54.17	0.0001
Error	55	0.24901	0.00453		
Corrected Total	56	0.49428			
$R^2 = 0.496$					
Model: $I_{LP} = 1.468 - 0.425\ (U)$					

change by about 17 percent for two values of I_{LP} to be different by more than the mean bias due to misclassification.

Contagion also showed a negative relationship with U ($R^2 = 0.499$), but regression models of *APC* versus U and F versus U were not significant. However, the signs of the relationships (negative for F versus U and positive for *APC* versus U) were consistent with observations that humans create compact patches with simple perimeters (Krummel *et al.*, 1987; Riitters *et al.*, 1995). In addition, the *APC* versus U regression model was significant with the removal of one outlier (Delmarva watershed). Others have shown that fractal dimension is sensitive to the amount of human land use in the landscape (Krummel *et al.*, 1987; Rex and Malanson, 1990; Wickham and Norton, 1994).

Summary and Conclusion

Based on the data and methods described herein, bias in landscape metrics does not appear to be amplified by land-cover misclassification. A misclassification rate of about 12 percent produced mean bias estimates that were about half the misclassification rate, except for contagion. The bias in contagion was about equal to the misclassification rate. The bias for all landscape metrics tested had a consistent direction, either being higher or lower than the original value for each watershed. The variability in the spatial distribution of misclassification had almost no effect on the landscape metrics.

A synthetic measure of landscape pattern (I_{LP}) was significantly related to the amount of human impact (U) in the landscape. Comparing bias due to misclassification with the regression model indicated that a difference in land-cover composition of at least 17 percent was needed to distinguish between two values of I_{LP} and be certain the difference was not due to misclassification. Based on these data, differences in land-cover composition need to be slightly larger (17 percent) than the misclassification rate (12 percent) in order to be confident that differences in landscape metrics are not due to misclassification.

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Appendix A
Formulas for Calculating Landscape Metrics

Landscape Contagion

$$C = 1 - \frac{\sum_{i=1}^{t} \sum_{j=1}^{t} (v_{ij} \ln (v_{ij}))}{2 \ln (t)}$$

where t is the number of different land-cover types and v_{ij} is the proportion of pixel edges joining cover types i and j.

Average Patch Compaction

$$APC = \frac{1}{p} \sum_{i=1}^{p} 16 \frac{A_i}{OE_i^2}$$

where p is the number of patches, A is the number of cells (i.e., area) in patch i, and OE is the number of outside edges enclosing the patch.

Patch Fractal Dimension

$$F = 2\beta_1$$

where β_1 is the estimated slope from the regression of $\ln(OE)$ on $\ln(A)$. OE and A are the same as described for average patch compaction. Only patches that are greater than three pixels are included.

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