
ESTIMATING LANDSCAPE PATTERN FROM SUPERVISED AND UNSUPERVISED CLASSIFICATION: STUDIES IN THE WESTERN GHATS, INDIA

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KEY WORDS: Accuracy, Classification, Ecosystems, Interpretation, Land use/Land cover, Pattern recognition, Spatial data, Sustainability

ABSTRACT

Current research suggests that metrics of landscape pattern can act as indicators of ecological processes and biodiversity maintenance. Land cover maps, created through remote sensing, enable the evaluation of such pattern. This paper compares supervised and unsupervised classification techniques for the estimation of landscape pattern, in tropical landscapes that are often inaccessible and difficult to classify. In the mountains of the Western Ghats of India, thirteen landscapes ranging from 9-54 km² were delineated for mapping. Supervised classification accuracy ranged from 70-92%. Unsupervised classification accuracy was uniformly worse, ranging from 31-75%. Misclassification errors have been previously believed not to bias metrics of landscape pattern. This paper reports a significant bias in patch and landscape metrics estimates concomitant with misclassification resulting from unsupervised classification. For all landscapes, patch size, shape and nearest neighbor distance metrics derived from unsupervised classification were significantly greater than those derived from supervised classification. Landscape metrics of mean patch size, mean patch shape, mean nearest neighbor distance and the Shannon index of landscape diversity determined from unsupervised classification were also significantly greater than those from supervised. Metrics of interspersion-juxtaposition and contagion do not however demonstrate significant differences. Possible explanations for the observed bias are discussed. Whether the bias noticed extends to other methods of unsupervised classification, requires examination. This exercise has strong implications for the development of country level methodology for monitoring biodiversity in India.

1 INTRODUCTION

The management of tropical landscapes is an increasingly pressing imperative. While the tropics are increasingly under threat due to human extraction of resources, these landscapes are also highly complex and difficult to evaluate. Due in large part to their inaccessibility, relatively little is known about these regions (Roy, 1993). Remote sensing provides an effective means of studying these parts of the world, though it is only recently that its potential for ecological studies is being utilized (Roughgarden et al., 1991). Under the auspices of "ecosystem management", land cover maps, created using remote sensors, are becoming increasingly critical inputs for biodiversity management (Naveh, 1993; Noss, 1996). Aspects of landscape structure such as shape, size and inter-patch distance for patches of various ecotope types, or land cover types, and of organization, such as the diversity and connectivity of the larger landscape in which these patches are embedded, are believed to have significant bearing on species distributions. Current research also suggests that landscape metrics, quantifying the amount and arrangement of land cover types, can act as indicators of ecological processes operating within these landscapes (Naveh, 1994; Palang, 1998). This has increased interest in quantifying landscape pattern with such metrics (Forman, 1995).

Land cover maps are commonly created from remotely sensed data through supervised or unsupervised classification techniques (Jensen, 1986). In a supervised classification, the identity and location of certain representative patches of the land cover types present in a landscape need to be identified prior to classification. Initial field input is normally required for adequate map accuracy (Lark, 1995). This can prove a limitation in relatively inaccessible tropical areas (Rey-Benayas and Pope, 1995). Unsupervised classification of satellite imagery does not require such field input. The spectral data is organized into spectral classes, typically through the use of a clustering algorithm. Post-classification, these clusters are then associated with land cover types by the analyst. This can save a great deal of effort and time. In cases where the training data is unavailable or of poor quality, unsupervised classification is preferable to supervised (Jensen, 1986).

However, unsupervised classification assumes a simple model where each spectral class directly corresponds to a single land cover type. In practice, this does not always apply (Lark, 1995). For example, a single cover type, such as a semi-

evergreen forest, may be present in two different forms, one with a more open canopy. These might be identified as two classes in an unsupervised classification, but merged in a supervised classification. The desired accuracy therefore may not be achieved with unsupervised classification.

Unsupervised classification has hitherto been mainly used for landscape mapping in the relatively homogeneous temperate forest regions (for example Belward et al., 1990; Meiger et al., 1991; Vanoverstraeten and Trefois, 1993). Nevertheless, Rey-Benayas and Pope (1995) suggest that satellite imagery can be used to provide information on landscape pattern in the tropics, obviating the need for extensive field input. It is necessary to evaluate the relative effectiveness of unsupervised classification techniques for deriving parameters of landscape pattern for more heterogeneous tropical regions, often difficult to classify.

The Western Ghats of India is considered one of the world's biodiversity "hot-spots" (Myers, 1991). Detailed classification is difficult to achieve for this hill chain due to its high topographic variability, small patch sizes, relatively large number of land cover types and complex landscape patterns - characteristics rather unfavorable for the application of remote sensing techniques (Meiger et al., 1991). Previous exercises have demonstrated a decrease in accuracy due to unsupervised classification, for this region (Nagendra and Gadgil, 1999 a, b). However, misclassification errors have been believed not to significantly bias metrics of landscape pattern (Wickham et al., 1997). This paper investigates these issues, comparing metrics of landscape pattern derived from supervised and unsupervised classification techniques for this tropical landscape.

2 METHODOLOGY

2.1 Study Area

The hill chain of the Western Ghats of India (8°–21°N, 73°–77°E) runs parallel to the western coast of India for over 1600 km. Vegetation cover in this area, mostly moist evergreen forest to begin with, has been influenced to varying extents by humans, over centuries (Pascal, 1988). The range of environmental regimes across the Western Ghats, varying in topography, soil, rainfall and temperature, make for a highly heterogeneous landscape. Over time, the extent and severity of human-affected landscape change has increased. As in several parts of the tropics, the Western Ghats landscape is now a heterogeneous, highly variegated mosaic of both natural and managed ecosystems. The region is in need of informed strategies for conservation and management (Gadgil, 1996).

Within this bio-region, thirteen landscapes ranging in area from 9-59 km² were identified. Selection of landscapes was limited by logistic constraints, and intended for incorporation into a program of biodiversity assessment. The distribution of landscapes does not therefore reflect the complete variability in environmental regimes that exists in the Western Ghats. These thirteen landscapes constitute an adequate sample group for the comparison of the utility of supervised and unsupervised classification techniques for landscape pattern assessment. Details of the geographic locations (in terms of latitude and longitude) and the area covered by each landscape can be found in Nagendra and Gadgil (1999, b).

2.2 Landscape Mapping

For these landscapes, one time imagery from the Indian Remote Sensing satellite IRS 1B LISS 2 sensor, taken between 1991-1993 depending on availability of cloud free data, was obtained. Images were selected from the dry season, mid-February to mid-June, when deciduous trees are leafless, and the contrast between evergreen and deciduous foliage is maximum (Roy, 1993). The satellite data consists of intensities at four wavelengths - 450 to 520 nm, 520 to 600 nm, 630 to 690 nm and 730 to 900 nm, with a pixel size of 36.25 m (Kasturirangan et al., 1991). This imagery was rectified to remove geometric distortions with the help of Survey of India 1:50,000 scale topographical sheets.

In conjunction with ground training information collected during the months of February-August 1995, this imagery was used to carry out supervised classification of the landscapes into land cover types. For all major land cover types, at least one or more areas of minimum four hectares in extent were used as training sites in the supervised classification. Land cover types that present in a few small patches in the landscape could not provide good training sites for the classifier, and were therefore omitted from consideration. Supervised classification was carried out by the maximum likelihood algorithm (Jensen, 1986). The Grass 4.1 image processing software was used for image processing (United States Army Corps of Engineers, 1993).

An unsupervised classification was also prepared for each landscape. The classification algorithm, specified in the Grass 4.1.5 software, uses input parameters set by the user on the initial number of clusters, the minimum allowed distance between clusters, and the correspondence between iterations which is required, in order to identify class signatures. Initial cluster means for each band are defined by giving the first cluster a value equal to the band mean minus its standard deviation, and the last cluster a value equal to the band mean plus its standard deviation. All other cluster means are equally spaced in between. The first pass through the clustering algorithm then assigns each pixel to the class to which it is closest in terms of Euclidean distance. All clusters less than the user-specified minimum distance

are then merged. New cluster means are calculated for each band as the average of intensity values in that band for all pixels present in that cluster. Pixels are then again reassigned to clusters, and this process repeated until the correspondence between iterations reaches a user-specified level.

The number of clusters was specified as the same as the number of classes in the supervised classification, for comparability. The minimum distance required between clusters was input as zero, to ensure that the final number of clusters was the same as that initially specified. The desired correspondence between iterations was specified as 98%. Once the iterations converged, class signatures (mean in four bands, and the variance-covariance matrix) were assessed. These signatures were then input into a maximum likelihood classifier, to create a map derived from unsupervised classification.

Classification accuracy was verified by field visits during the months of August and September 1997 (Nagendra and Gadgil, 1999 b). Between 70 and 120 points, randomly distributed in each landscape, were used to compare supervised and unsupervised classifications with the ground data. Each class in the unsupervised classification was assigned to a unique land cover type in order to maximize correspondence.

2.3 Comparison of Landscape Metrics

Supervised and unsupervised classification maps were used to derive estimates of patch and landscape structure, through the program FRAGSTATS 2.0 (McGarigal and Marks, 1994). This program computes several metrics of structure for each patch in the landscape, as well as for the entire landscape. A subset of these was selected, based on their relevance to species distribution (Forman 1995). Three patch metrics were identified as being concerned with different aspects of patch structure - patch size, patch shape and the nearest neighbor distance (distance from a patch to the nearest neighbor of the same type). At the landscape scale, indices of mean patch size, mean patch shape, mean nearest neighbor distance, Shannon's diversity, interspersed-juxtaposition index and contagion index, were computed. Definitions of patch and landscape metrics are provided in McGarigal and Marks (1994). They can be summarized as

Patch metrics:

- a) Patch size: Area covered by a patch, in hectares.
- b) Patch shape index: Complexity of patch shape, compared to that of a square patch of identical area. For a single patch, the shape index is 1 when square, and increases without limit as the patch becomes more irregular.
- c) Nearest neighbor distance: Edge-to-edge distance between the patch and its nearest neighbor patch of the same type.

Landscape metrics:

- a) Mean patch size: Average area covered by a patch.
- b) Mean patch shape index: Average complexity of patch shape, compared to that of a square patch of identical area.
- c) Mean nearest neighbor distance: Average edge-to-edge distance between two nearest-neighbor patches belonging to the same land cover type.
- d) Shannon diversity index: This measure of landscape diversity increases as the number of land cover types increase and/or as the proportional area distribution of these types becomes more equal.
- e) Interspersed-juxtaposition index: The degree to which patches belonging to different land cover types are interspersed. This value decreases as the distribution of adjacencies among types becomes increasingly uneven.
- f) Contagion index of pixel interspersed: The degree to which pixels belonging to different land cover types are interspersed. This value decreases as the distribution of pixel adjacencies among types becomes increasingly uneven.

For each landscape, a one-tailed Mann-Whitney U Test was used to assess whether patch characteristics estimated from the unsupervised classification differed significantly from those measured by supervised classification. A one-tailed Wilcoxon's signed-ranks test was used to assess whether landscape metrics estimated from unsupervised classification significantly differed from those estimated using supervised classification (Sokal and Rohlf, 1981).

Information on class signatures derived from supervised and unsupervised classifications was compared. For each landscape, the median of within-class variances was calculated for signatures derived using unsupervised and supervised classifications, for all four bands of imagery. This information could only be computed for twelve out of thirteen landscapes, for which class statistics were available. Values taken by the four spectral bands may be correlated to varying extents. A one-tailed Wilcoxon's signed-ranks test was therefore separately carried out for each spectral band, to assess whether within-class variance for signatures derived using unsupervised classification is significantly greater than within-class variance for signatures derived from supervised classification.

3 RESULTS AND DISCUSSION

Between five and nine land cover types were encountered in a landscape. Supervised classification accuracy ranged from 70-92%, with a mean of 84%. Unsupervised classification accuracy was uniformly worse, ranging from 31-75% with a mean of 51% (Nagendra and Gadgil, 1999 b).

Table 1 demonstrates that for all thirteen landscapes, patch metrics (patch size, shape and nearest neighbor distance) estimated using the unsupervised classification were significantly greater than those estimated from the supervised

classification ($p < 0.01$). The degree of bias in patch metrics due to unsupervised classification can be related to the Mann-Whitney index – the higher this index, the greater the bias. This bias in patch metrics estimated from unsupervised classification does not seem directly related to the degree of misclassification (difference between supervised and unsupervised classification accuracy).

	1	2	3	4	5	6	7	8	9	10	11	12	13
SIZE	41.5	84.4	51.6	35.6	39.2	69.0	61.1	45.6	51.8	43.5	66.9	45.3	54.8
SHP	40.3	82.5	50.0	34.4	37.9	62.6	59.6	44.1	50.0	42.4	65.0	43.6	55.6
NND	37.6	82.5	44.5	30.9	36.8	63.8	54.6	41.2	45.3	39.8	59.3	40.2	50.8
S-UN	27.4	32.1	29.7	46.2	15.2	34.9	30.7	41.6	52.9	9.2	50.0	39.4	32.0

Table 1. Differences between estimates of patch size (SIZE), patch shape (SHP) and nearest neighbor distance (NND) derived from supervised and unsupervised classification. In the first three rows, values represent outcomes of a one-tailed Mann-Whitney U test assessing the significance of these differences, for patch metrics denoted by row headings and landscapes denoted by column headings. The cutoff value for significance at $p=0.01$ is 2.3. Values in the fourth row (S-UN) depict the difference in percentage accuracy of supervised and unsupervised classifications, for comparison.

Landscape metrics of mean patch size, mean patch shape, mean nearest neighbor distance and Shannon landscape diversity determined from unsupervised classification were also significantly greater than those determined from the supervised classification ($p < 0.01$), based on a one-tailed Wilcoxon's signed-ranks test. However, no significant differences could be detected for indices of interspersed-juxtaposition and contagion assessed from supervised and unsupervised classifications.

Metrics of landscape structure quantify spatial as well as non-spatial pattern. The bias in the non-spatial landscape index of diversity is easily explained. The above-mentioned algorithm for unsupervised classification assigns pixels to spectral classes based on minimum Euclidean distance, and not based on a user-prescribed number of standard deviations. In supervised classification however, the spectral classes are user-defined, and may have greatly different variances. Spectral classes defined by unsupervised classification will therefore tend to have a similar variance when compared to supervised classification. As a result, spectral classes defined by unsupervised classification will also have a more even distribution of pixels. Estimates of diversity calculated from unsupervised classification will therefore tend to be higher. However, indices of interspersed-juxtaposition and contagion, both spatial metrics describing levels of patch and pixel type adjacencies, are not significantly biased by unsupervised classification. Indeed, there was no reason this might have been expected.

Unsupervised classification however creates significantly larger patches, of more irregular shapes, at greater distances from neighboring patches of the same cover type. This is an unexpected result. As space is not explicit in the clustering algorithm, it is not apparent how a bias in spatial pattern can result from unsupervised classification. Differential within-class spectral variances combined with spatial auto-correlation may provide a clue to this behavior.

In images with random noise, local variance tends to be similar to overall variance in the image. Real-life landscapes however tend to demonstrate high levels of spatial auto-correlation. Large features (patches) within the image contain clusters of pixels with very similar spectral values. The local variance tends therefore to be much lower compared to overall variance (Warner and Shank, 1997). Spectral image classification is an effort at providing spatial differentiation, to make clear this pattern of spatial heterogeneity. If spatial auto-correlation exists, the spatial characteristics of features delineated by the classifier will depend greatly on the within-class variance of class signatures. An increase in the within-class variance of spectral values should lead to the definition of larger features, i.e. greater patch size.

Information on class signatures derived from supervised and unsupervised classifications was used to compare the within-class spectral variability of classes defined by supervised and unsupervised classifications. The intent was to determine whether classes identified by unsupervised classifications had significantly greater within-class variance in spectral values, compared to classes identified by supervised classification. For twelve landscapes, the median of within-class variances was calculated for signatures derived using unsupervised and supervised classifications, for all four bands of imagery. As can be seen from Table 2, the median within-class variance for unsupervised classification was higher than for supervised in all landscapes for bands 1, 2 and 3 – with the single exception of landscape 1 (band 3). The median within-class variance in the infrared band for unsupervised classification is however higher than that for supervised in only 7 cases, and is in fact lower in 5 landscapes. A Wilcoxon's signed-ranks test declared within-class variance for signatures derived using unsupervised classification to be significantly higher than for signatures derived from supervised classification for bands 1, 2 and 3, though not for band 4 ($p < 0.01$).

The results of this statistical test, though not conclusive, indicate that unsupervised classification tends to delineate classes with higher within-class spectral variance, compared to supervised classification. Given spatial auto-correlation, a higher within-class variance can result in the inclusion of more pixels, hence larger patches, while delineating patch boundaries. Due to the nature of the shape index, by chance alone, larger patches prove more likely to have irregular shapes (McGarigal and Marks, 1994). Also, given a bounded landscape, the creation of fewer, larger patches would imply that these patches are farther apart. Thus, nearest neighbor distances would increase. The difference in within-

class spectral variances therefore provides a possible explanation for the bias in estimates of patch size, shape and nearest neighbor distance resulting from landscapes mapped by unsupervised classification.

		1	2	3	4	5	6	7	8	9	10	11	12
BAND 1	S	0.9	1.5	1.4	0.5	1.7	0.9	0.6	0.4	0.3	0.7	0.6	1.1
	U	1.5 +	2.1 +	5.6 +	1.7 +	3.2 +	1.9 +	1.7 +	2.5 +	1.6 +	3.1 +	2.2 +	2.4 +
BAND 2	S	0.7	0.8	0.9	0.5	1.2	0.9	0.6	0.3	0.3	0.9	0.5	1.0
	U	0.9 +	1.3 +	2.2 +	1.5 +	2.7 +	1.6 +	1.5 +	1.2 +	1.7 +	1.8 +	1.6 +	2.2 +
BAND 3	S	6.7	4.0	4.0	2.2	3.9	4.0	3.0	0.6	0.6	2.0	2.0	3.9
	U	5.3 -	6.1 +	9.8 +	6.3 +	8.7 +	5.9 +	4.3 +	3.6 +	9.4 +	6.9 +	8.3 +	5.8 +
BAND 4	S	3.1	8.1	5.6	2.0	4.6	15.7	6.5	13.8	7.0	6.0	7.0	8.3
	U	7.3 +	7.2 -	13.5 +	9.2 +	17.0 +	7.6 -	6.4 -	6.8 -	11.8 +	10.2 +	14.1 +	8.0 -

Table 2: For twelve landscapes, this table depicts the median of class signature variances in all four bands, for supervised and unsupervised classifications. A “+” next to the unsupervised classification value indicates that unsupervised class variance is greater than supervised; a “-” indicates the opposite.

4 CONCLUSIONS

In recent years, there has been an increasing interest in the quantification of landscape pattern, at various spatial scales (Forman, 1995). Metrics of landscape pattern are believed to have significant bearing on the distribution and maintenance of species diversity (Turner, 1989). An improved assessment of landscape pattern could not only increase our knowledge of ecology and diversity, but also improve our efforts at preservation.

Land cover maps, created through remote sensing, enable the evaluation of such pattern. The study of landscape and patch structure has however been mainly carried out in the temperate regions of the world (see for example, Baskent and Jordan, 1995; Palang et al., 1998). Large parts of the tropics remain unstudied (Roy, 1993; Rey-Benayas and Pope, 1995). This paper attempts to compare the behavior of supervised and unsupervised classification techniques for landscape pattern assessment.

Unsupervised classification provides a means of mapping where ground information is often difficult to obtain, though it can result in increased misclassification (Nagendra and Gadgil, 1999 b). Misclassification is known to influence the estimation of landscape pattern, but has been previously believed not to bias landscape metrics significantly (Wickham et al., 1997). This paper however reports a significant positive bias in estimates of patch size, patch shape, nearest neighbor distance and landscape diversity, due to misclassification by a technique of unsupervised classification. Indices of interspersed-juxtaposition and contagion do not demonstrate this bias.

Further investigations are required to study the effect of within-class variance on patch statistics for unsupervised classification. Simulated data with known levels of spatial auto-correlation and spectral variance, may be used for this purpose. Whether the bias observed in landscape pattern metrics is specific to the algorithm of unsupervised classification used here, or applies also to other algorithms of unsupervised classification, requires exploration. Investigations along these lines are underway.

Assessing the distribution of the diversity of life forms on the earth and the efficacy of measures for their conservation is a major scientific challenge. The Global Biodiversity Assessment (Heywood, 1995) recommends remote sensing for country studies to identify components necessary for biodiversity conservation and maintenance. In India, as elsewhere, there is increasing interest in the estimation of landscape metrics for this purpose (Roy, 1999). It is essential to take cognizance of the possible effects that classification methods may have on these estimates. This exercise has strong implications for the development of country level methodology for monitoring biodiversity in India.

ACKNOWLEDGEMENTS

I thank U. Ghate, V.V. Sivan and K.A. Subramaniam for assistance with landscape classification, and M. Gadgil and N.V. Joshi for helpful discussions. This research was financially supported by the Ministry of Environment and Forests and the Department of Space, Government of India. I thank the organizers of the XIXth ISPRS Congress for providing travel and financial assistance, thereby enabling this paper to be presented at the Congress.

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