Ordinal-Level Classification of Sub-Pixel Tropical Forest Cover

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Abstract
Remotely sensed data have considerable potential for mapping and monitoring tropical forests. For the production of regional scale maps which may be up-dated periodically, relatively coarse spatial resolution remotely sensed data, such as those from the NOAA AVHRR, are an appropriate source of data for such mapping applications. These maps, however, typically depict land cover at the nominal level only and may be unsuitable for the estimation of forest extent and dynamics. In this paper, results of an investigation into the estimation of sub-pixel forest cover and classification at the ordinal level are presented. Based on an analysis of Landsat MSS data that had been degraded spatially to a 1.2-km resolution, a strong correlation, r = 0.94, was observed between predicted and actual sub-pixel forest cover. These estimates of sub-pixel forest cover may be used to produce an ordinal-level classification of forest cover. Using a classification accuracy assessment procedure that accounts for the higher information content of ordinal level data over nominal level data, the degree of agreement between predicted and actual class for a four-class classification of tropical forest cover was estimated to be 75.2 percent.

Introduction
Tropical forests have recently become a focus of significant attention. These forests cover some 7 percent of the Earth's land surface yet contain nearly two thirds of the global standing biomass and are the world's largest bank of species diversity (Whitmore, 1990). Our knowledge of tropical forests, however, is limited. We do not, for instance, know accurately basic properties of these forests, such as their areal extent and dynamics. Global estimates of tropical forest coverage and dynamics, for instance, vary considerably (Sader *et al.*, 1990; Townshend *et al.*, 1991). Information on these latter issues is, however, required for a number of applications. Tropical forests, for instance, play a major role in global biogeochemical cycles. A major current concern is the role of tropical forests as both source and sink of atmospheric carbon (Enting and Mansbridge, 1991; Houghton, 1991) and the anthropogenic modifications on the magnitude of the carbon flux between the tropical forests and the atmosphere. It has been inferred, for example, that a significant proportion of the enhanced carbon loading of the atmosphere can be attributed to tropical deforestation. The accuracy of predictions of future atmospheric carbon loadings and, hence, resultant climatic changes are therefore dependent partly on the quality of information on tropical forest coverage. More accurate information on the extent of tropical forests and other terrestrial ecosystems would therefore facilitate the refinement of global carbon models which currently mis-estimate significantly atmospheric carbon loadings (Tans *et al.*, 1990).

A range of remotely sensed data sets have been used to classify tropical forests (Green and Sussman, 1990; Sader *et al.*, 1990; Malingreau, 1991). In terms of data availability and coverage, data from the NOAA AVHRR are particularly appropriate for the mapping and monitoring of tropical forests at the regional to global scale. This system allows the collection of data at a high temporal frequency, approximately every twelve hours, and, consequently, cloud free regional views may be acquired through the use of data acquired over several days.

NOAA AVHRR data have, unfortunately, a relatively coarse spatial resolution, 1.1 km at best. As a consequence, the proportion of mixed to homogeneous pixels may be high (Campbell, 1987). In such circumstances misclassification may be likely and an estimate of the extent of tropical forest cover in a region derived from the number of pixels allocated to the forest class by an image classification may be erroneous. Recent studies have found that estimates derived from classifications of remotely sensed data with spatial resolutions of or near that of the NOAA AVHRR may be inaccurate (Cross *et al.*, 1991; Foody *et al.*, 1991). While the observed pattern of misclassification can be used to reduce error in the calculation of the areal extent of a class within a region (Prisley and Smith, 1987; Conese and Maselli, 1992; Czaplewski, 1992), the utility of such procedures may vary with the proportion of pixel area that must comprise a class for it to be allocated to that class. Furthermore, the "hard" allocation of a classification may result in a poor representation of the forest distribution, with large root-mean-square (RMS) errors. The classification also typically presents the data at the nominal level (e.g., forest, agriculture, and urban), the lowest form of data measurement in which the classes differ only in kind, not by degree (Norcliffe, 1982). To reduce the problems of utilizing coarse spatial resolution imagery, spectral mixture modeling approaches may be used to estimate sub-pixel forest cover accurately. The results of such an analysis could be an image depicting the extent of class cover on a per-pixel basis (Drake and White, 1991), or an ordinal-level classification (e.g., large, intermediate, and small forest cover) may be produced. The latter represents a higher level of data measurement than the nominal level, with classes differing by degree and which may be placed in rank order (Norcliffe, 1982).

This paper presents results of a pilot study to classify

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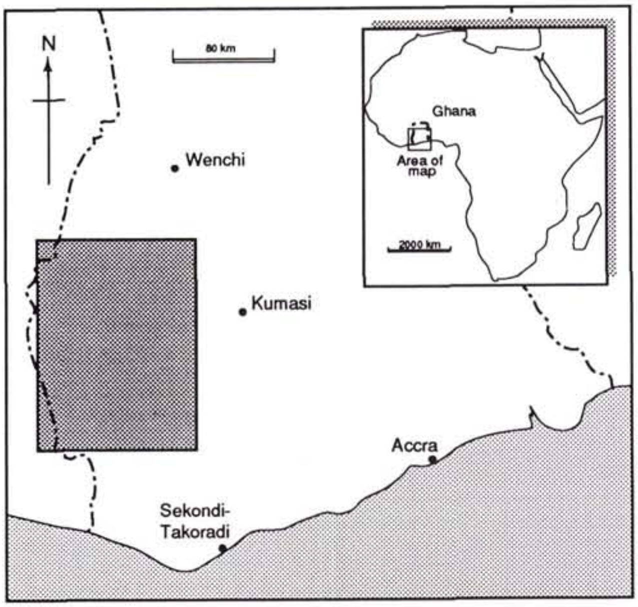

Figure 1. Approximate test site location, shaded box, in Ghana, West Africa.

tropical forest cover at the ordinal level, performed as part of a preliminary investigation into the classification of tropical forests throughout South America and West Africa for regional carbon modeling (Curran *et al.*, 1992). Attention is focused on the accuracy with which sub-pixel forest cover may be estimated and on the accuracy assessment of an ordinal-level classification of forest coverage. The latter involved the evaluation of classification accuracy or agreement with a technique designed to utilize the information content of ordinal-level data more fully than conventional classification accuracy assessment techniques. While ordinal-level classifications of a variety of phenomena have been performed with remotely sensed data (e.g., Curran and Williamson, 1987), the accuracy of these classifications has generally been assessed with techniques designed for application to a conventional, nominal level, image classification. The latter techniques make no allowance for the variation in the size of the error that is associated with a misclassification, which at the ordinal level is dependent on the characteristics of the classes and the distance between the actual and predicted class of membership; a misclassification of a case of large forest cover to the intermediate cover class is, for example, less erroneous than its allocation to the small cover class.

Data and Methods

The investigation focused on tropical forest reserves in Ghana, West Africa (Figure 1). Within this region moist evergreen and moist semi-deciduous forest predominate (Hall and Swaine, 1981; Whitmore, 1990). These forests are bordered typically by savanna, much of which is used for agroforestry and agriculture. The boundary between the forest and savanna is abrupt and may be sharpened by fire within the savanna (Hall and Swaine, 1981). The abruptness of the forest boundary was evident in the remotely sensed data used in this investigation which was a relatively fine spatial resolution (79 m), near-infrared (0.8-1.1 μm waveband) Landsat MSS Image (Figure 2). Data acquired in this waveband only were used to minimize the effects of atmospheric attenuation and because forest/non-forest contrast is high in the near-infrared as the forest may act as a "trap" for such radiation (Malingreau *et al.*, 1989). The Landsat MSS image was resampled to 57-m pixel size with cubic convolution resampling, and was degraded to simulate imagery with a spatial resolution of 1.2 km, approximately that of NOAA AVHRR data, using a filtering approach similar to that described by Justice *et al.* (1989) which provides a set of co-registered imagery that may be considered identical in all aspects except spatial resolution. For each pixel in the simulated coarse spatial resolution image, the proportion which was forest covered was derived from a forest/non-forest classification of the original, undegraded spatially, Landsat MSS image. The use of a classification of fine spatial resolution data to evaluate the performance of classifications of coarse spatial resolution data has been used in other studies (e.g., Iverson *et al.*, 1989; Spanner *et al.*, 1989) and this approach was necessary given the lack of accurate ground data. For the purpose of this paper the forest cover estimates derived from the original Landsat MSS data in this way will be referred to as the "actual" cover although they are themselves only an approximation. These were then used to assess the accuracy of the estimates of sub-pixel forest cover in the simulated coarse spatial resolution image (Figure 3).

The sub-pixel forest cover prediction was achieved by deriving a regression relationship between the strength of forest class membership, as indicated by the fuzzy membership function associated with forest and the proportion of forest cover within the pixel, determined from the Landsat MSS classiffication. The fuzzy membership functions were generated from a supervised version of the fuzzy *c*-means algorithm presented by Bezdek *et al.* (1984). This is based on a fuzzy *c*-means partition,

$$M = \{U{:}u_{ik} \in [0,1];\ \sum_{k=1}^{n} u_{ik} > 0,\ i = 1, \ldots, c;$$
$$\sum_{i=1}^{c} u_{ik} = 1,\ k = 1, \ldots, n\}$$

where U is a fuzzy c-partition of n observations and c fuzzy groups, and u_{ik} is an element of U and represents the membership of an observation x_k to the i^{th} class, where x_k is a vector the length of which is the number of attributes used.

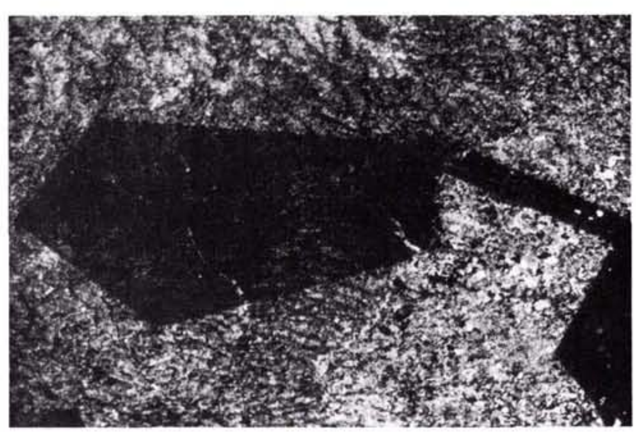

Figure 2. Landsat MSS image (0.8- to 1.1-μm waveband) of part of the test site acquired in November 1973. The tropical forest reserves (dark tone) may be readily distinguished from the surrounding land.

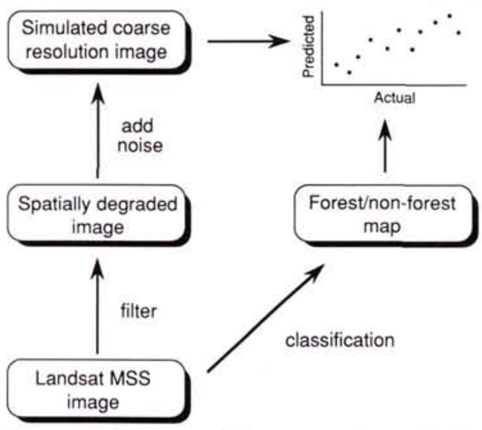

Figure 3. Summary of the approach used. The Landsat MSS image (Figure 2) was degraded spatially to a 1.2-km spatial resolution by a filtering approach which maintains the noise and other properties of the data. The proportion of forest cover in pixels within the simulated coarse spatial resolution image was then predicted, based on a regression relationship between the fuzzy membership function associated with forest and the proportion of forest cover derived from a sample of pixels. The accuracy of this prediction was then assessed relative to the proportion of forest cover in the area corresponding to each pixel in the simulated coarse spatial resolution image, derived from a forest/non-forest classification of the original, undegraded spatially, Landsat MSS image.

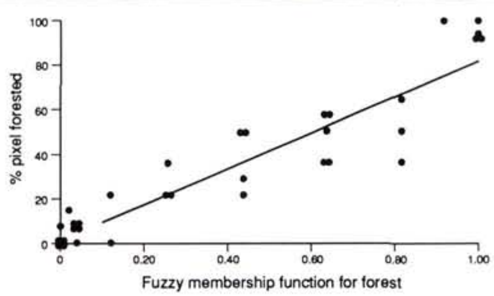

Figure 4. Regression relationship between the percentage of pixel area forested (y) and the fuzzy membership function associated with forest (x). The regression equation was $y = 1.37 + 80.3x$.

The optimal fuzzy c-partition is identified through the minimization of the generalized least-squared errors functional J_m,

$$J_m(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m (d_{ik})^2$$

where V is a c by p matrix whose elements, v_{ik}, represent the mean of the k^{th} of p attributes in the i^{th} class, m is a weighting parameter, $1<m<\infty$, and d_{ik} is a measure of dissimilarity based on the distance between an observation and a class centroid which can be determined from

$$(d_{ik})^2 = (x_k - v_i)^{\mathrm{T}}\mathbf{A}(x_k - v_i)$$

in which $\mathbf{A}$ is a weight matrix which determines the norm to be used (Bezdek, 1981; Bezdek *et al.*, 1984). In this paper the Mahalanobis norm was used, and attention was focused on the fuzzy membership functions, u_{ik}, output with $m = 2.0$. The latter variable is positively related to the degree of "fuzziness," and a conventional hard classification may be obtained with $m = 1.0$. The fuzzy membership functions derived in the analysis lie on a scale between 0 and 1 and sum to 1 for each case. They are to some extent, therefore, similar to *a posteriori* probabilities of class membership and their magnitude will be related to the proportion of a particular class within a pixel (Fisher and Pathirana, 1990; Foody, 1992a).

In total, 89 pixels were sampled from the simulated coarse spatial resolution image. The DN of 12 pixels located at each end of the forest cover continuum was used to derive the end member spectra for the calculation of the fuzzy membership functions. Of the remaining 65 pixels, 33 were used to derive the regression relationship and the other 32 were used to provide an independent testing set to assess the accuracy of the analysis. The sub-pixel forest cover was, however, estimated for all 89 pixels from the regression relationship. Each pixel was then allocated to one of four ordinal level classes of forest cover; large (>80 percent), intermediate (20 to 80 percent), small (2 to 19 percent), and very small (less than 2 percent) forest cover. The accuracy of this classification, which may be inflated due to the inclusion of training data, was assessed using the τ coefficient presented by Jolayemi (1990). For a c by c contingency table, this may be calculated from

$$\tau = \sqrt{\frac{\chi^2}{(c-1)N}}$$

where χ^2 is the Pearson chi-squared statistic and N is the number of cases. The τ statistic, $-1<\tau<1$, provides a measure of agreement between the actual and predicted class allocations (Jolayemi, 1990). This measure of classification quality was used in preference to other measures such as Cohen's Kappa coefficient (Congalton, 1991) which were designed for application to nominal level classes and would therefore not utilize fully the information content of an ordinal level classification.

Results and Discussion

With the 12 pixels sampled from each end of the forest cover continuum used to define the end member spectra, the regression relationship between the fuzzy membership function associated with forest and the percentage pixel forest cover was derived for 33 pixels. A strong positive relationship was obtained (Figure 4), with $R^2 = 0.87$, significant at the 99 percent level of confidence. This regression relationship was then used to predict the amount of sub-pixel forest cover in all 89 pixels sampled from the simulated coarse spatial resolution image. The accuracy of prediction based on this regression relationship was assessed using the 32 independent testing pixels. A strong and significant correlation between predicted and actual sub-pixel forest cover was obtained (Figure 5); the correlation coefficient, $r = 0.94$, was significant at the 99 percent level of confidence. Moreover, for the 32 independent testing pixels, the observed RMS error was 13.95 percent pixel cover, substantially less than that which would have been derived from a conventional image

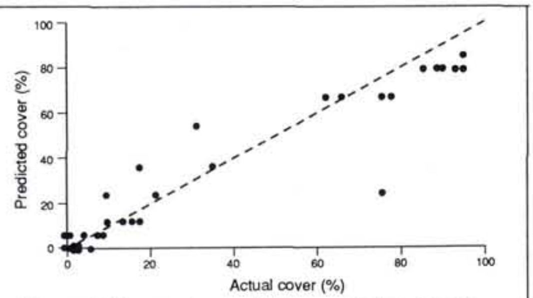

Figure 5. Comparison of the predicted forest cover in the simulated coarse spatial resolution imagery and actual percentage of pixel area forested derived from the Landsat MSS image classification. The dashed line illustrates the 1:1 relationship.

Actual \ Predicted	L	I	S	VS	Σ
Large (L)	18	6	0	0	24
Intermediate (I)	0	21	0	0	21
Small (S)	0	3	15	4	22
Very Small (VS)	0	0	6	16	22
Σ	18	30	21	20	89

Frequency of correct allocation :
observed = 70
expected by chance = 22.05
(derived from row and column marginals)

$$\text{Percentage correct allocation} = \frac{70}{89} \times 100 = 78.65\%$$

$$\text{Kappa} = \frac{70 - 22.05}{89 - 22.05} \times 100 = 71.62\%$$

$$\tau = \sqrt{\frac{151.011}{3\,(89)}} \times 100 = 75.2\%$$

Figure 6. Contingency table of actual against predicted forest cover for the assessment of classification accuracy and the three classification accuracy statements. For clarity the main diagonal, which illustrates agreement, is highlighted.

classification, 23.26 percent pixel cover. Similar results were also obtained for data at different simulated spatial resolutions and for an analysis using NOAA AVHRR data (Curran and Foody, 1993).

Each of the 89 pixels was then allocated to one of the four classes of forest cover, and a contingency table of predicted against actual forest cover, derived from the Landsat MSS classification, was constructed (Figure 6). Although the data set was limited, especially in terms of sample size, the quality of the classification was then assessed. For illustrative purposes, three measures of classification accuracy are presented in Figure 6, each expressed as a percentage. These measures were the percentage correct allocation (Hord and Brooner, 1976), Cohen's Kappa coefficient (Rosenfield and Fitzpatrick-Lins, 1986; Congalton, 1991), and τ (Jolayemi, 1990). The latter two measures, unlike the percentage correct allocation, incorporate information contained in the off-diagonal elements of the matrix and compensate to some extent for the effect of chance agreement (Foody, 1992b) and so are more useful, but of a lower magnitude than the percentage correct allocation. Note also, however, that the τ coefficient is slightly larger than the Kappa coefficient.

With an ordinal-level classification, the significance of a misclassification may vary considerably. Thus, for example, the incorrect allocation of a case of large forest cover to the intermediate cover class would be less erroneous than its allocation to the small forest cover class. In this study, all the misclassifications observed were between "neighboring" classes and so the full range of error magnitudes were not covered. Had any of the misclassifications shown in Figure 6 been more extreme, the differences between the estimated measures of classification accuracy may have been more marked and in some instances τ may be the only measure sensitive to the distribution of error magnitude (Foody, 1992b). For ordinal level classifications, such as here, τ would therefore appear to be the most appropriate of the measures for evaluating classification accuracy.

Summary and Conclusions

In mapping tropical forests from remotely sensed data, use has frequently been made of relatively coarse spatial resolution imagery. While forest mapping has been achieved with some success from such imagery, the spatial resolution of the data may limit the accuracy of estimates of the extent of the forest at large and small scales (Cross *et al.*, 1991; Foody *et al.*, 1991). Furthermore, only nominal level maps, which show typically the presence of the most likely land-cover class only, are presented. By deriving sub-pixel estimates of forest extent and mapping the forest distribution at the ordinal level, more information may be conveyed on forest distribution. While the forest reserves at the site may not be representative of tropical forests in general, three main conclusions may be drawn from this investigation for the forests in the test site:

- Sub-pixel forest coverage can be estimated accurately from remotely sensed data with a coarse spatial resolution.
- The sub-pixel forest cover estimates derived can be classified at an ordinal level, which may be mapped to show a generalized view of the spatial distribution of forest cover.
- To utilize the additional information content of an ordinal classification relative to a nominal classification, the assessment of classification accuracy with the τ coefficient is recommended because it will account for the distribution of error in the classification contingency table in a more meaningful manner than measures such as Cohen's Kappa coefficient.

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