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DISCRIMINATION OF TROPICAL FOREST COVER TYPES USING LANDSAT MSS DATA

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ABSTRACT

In this study, an attempt has been made to discriminate various tropical forest cover types using Landsat MSS data in two areas of north-eastern India. A pairwise divergence analysis indicated the spectral separability of two forest density classes and grasslands, however, grasslands, shifting cultivation and sparsely vegetated areas could not be reliably separated. Two edaphic forest-types formed distinct separable classes. The classification analysis indicated that forest and non-forest could be mapped effectively, 65% to 80% accuracy, using Landsat MSS data. The classification accuracy modestly improved in the areas of homogeneous cover types by applying a 3x3 contextual filter to the classified image.

I. INTRODUCTION

The use of digital analysis of Landsat MSS data for the mapping of forest cover types has been extensively investigated for temperate areas (Aldrich, 1979, Heller and Ulliman, 1983). However, the experience gained in the application of Landsat MSS data to temperate forests are not directly applicable to humid tropical forests due to the following reasons:-

- 1- Temperate forests are mostly simple structured communities, containing a few species with a dominant crown cover, whereas, the majority of the tropical forests are structurally complex communities, with a rich array of species distributed in multiple-storeys.
- 2- Temperate forests tend to occur in homogeneous stands with strong ecological site preferences, whereas, the tropical mixed forests are heterogeneous in nature and the strong ecological site preferences are not so

frequently observed.

3- In temperate areas cultural practices are relatively uniform, whereas, in the tropical areas the cultural practices are many and varied.

Therefore, only limited forest typological classification may be possible with the help of remotely sensed data. Because of the diversity and intermixing of cover-types use of Landsat MSS data may often result in insufficiently high classification accuracies being achieved. A major limitation arises when classification of tropical forest cover classes from Landsat data is insufficient to accurately separate categories that may require quite different management policies (Cochrane, 1983).

In this study an attempt has been made to evaluate the utility of digital Landsat MSS data for discrimination of various land cover types in tropical forest environment of north-eastern India.

II. THE STUDY AREA AND DATA DESCRIPTION

A. THE STUDY AREA

Two 256x256 pixel areas, located in the north-eastern part of India, were chosen for investigation (Figure 1, Area 1 and 2). The north-eastern region of India comprises 6.66% of national geographic area with only 3.89% of the population. The north-eastern region is now the region with the richest reserves of forest wealth in India. It has luxuriant forest growth with major species such as Shorea, Dipterocarps, Bauhinia, Terminalia besides tropical pines, oaks and bamboos.

Among the most important causes of the deforestation in the tropical world is shifting cultivation (Lanly, 1983), which demands a perpetual supply of uncultivated land, and north-eastern India is no exception to this. The exact area presently under shifting

cultivation is not known, mainly, because of the absence of land records, the lack of resource surveys and continuous clearing of new forest areas. It is estimated that out of total area of about 2.7 million hectares affected by shifting cultivation 16.8% area is cultivated at one point of time.

Shifting cultivation, locally called jhuming, is a method of cyclic cultivation in which an area of forest is cleared, the debris is burnt and the land is cultivated for a few years. The same patch of the land is cultivated after a lapse of number of years termed as 'shifting cultivation cycle'. In the process of 'jhuming' the character of the vegetation undergoes a drastic change due to onset of xerophytic conditions. The regression proceeds apace and the forests of high trees are replaced by inferior species, bamboos and that ~~order~~ ending up with barren slopes. The mapping and assessment of the forest degradation problem caused by jhuming is a sine qua non for adopting a suitable land management strategy in the region.

Area-1, is situated in the Manipur state, the terrain is extremely rugged and mixed broadleaved forests are heavily affected by jhuming. Dense subtropical evergreen forests occur on high hills and moist deciduous forests are distributed in the valleys and on low hills. Many of the steep slopes are densely forested and are inaccessible, whereas, the majority of the forests occupying moderately steep to gentle slopes have been extensively modified by slash and burn agriculture. All stages of succession from the natural unmanaged forest through secondary forests, grasslands, barren areas, abandoned jhum patches to current jhum fields are present.

Area-2, is located within the state of Assam. This is a lowland area with subdued relief. The forests can be classified into Tropical Semievergreen Forest and Secondary Moist Bamboo Brakes. The top canopy is characterised by the species which are leafless for a short period. The middle and lower storeys are more or less evergreen throughout the year.

B. LAND COVER CLASSIFICATION

Land cover rather than land use formed the basis of classification. Stand density and stand height were considered to be the most important parameters for mapping purposes. The definition of cover classes is given below:-

AREA-1.

1. Forest: Land covered by trees, minimum area two hectares.
- 1.A. Closed Forest: Canopy closure >50%.

- 1.B. Open Forest: Canopy closure 20-50%.
2. Grassland: Land covered by grasses and herbaceous plants, maximum height two meters.
3. Bare Soil: Land surfaces are devoid of vegetative cover or support very little vegetation <20%.
4. Jhum: Area which is under active jhum, freshly burned or abandoned land but regenerated crop is not more than three years old.
5. Regrowth: Abandoned jhum land with more than three years of regenerated crop.
6. Shadow: Shadow is not a valid ground cover but steep topography on the forested area produces dark pixel values.
7. Cloud: A small patch of the cloud was visible on the images.

AREA-2.

1. Closed Forest: Mixed broadleaved forests, canopy closure >50%.
2. Open Forest: Canopy closure 20-50%.
3. Dense Mixed Bamboo: Broadleaved species mixed with bamboo. Canopy closure >50%.
4. Scrub: Vegetation type the main woody elements of which are shrubs of more than 50 cms. and less than 7 meters height.
5. Mixed Agriculture: Forest trees interspersed with agriculture fields.
6. Shadow: As defined for area-1.
7. Cloud: As defined for area-1.

C. PREPARATION OF REFERENCE DATA SET

For Area-1, forest-types map at 1:50,000 scale was used for the collection of data from representative field areas. A stratified random sampling was conducted. A 3x3 pixel window was selected as strata and 30 sample points within each of the categories were located using random spatial coordinates. These points were carefully located on enlargements of Landsat MSS imagery with the help of topographic maps. Later on, with the help of a cursor controlled by a bitpad, line and pixel numbers of these points in the images were determined and a file containing the coordinates of the sample points was created in the computer to be used for subsequent training and testing purposes. For Area-2, a map of forest-types prepared at a scale of 1:63,360 was used for generating the training and testing sites. Due to some practical constraints it was not possible to do field sampling in this area.

D. LANDSAT DATA

The Landsat MSS data used in this analysis was from Landsat-2 for path 145, row 042, on the 6-Dec.-1981, received at N.R.S.A. India.

III. METHODOLOGY AND TECHNIQUES

A. Digital Image Processing

All the image processing and analysis was performed on Department of Geography, University of Reading, U.K., microcomputer based interactive image processing system with indigenously developed software. This is complete a stand alone system based on a Cromemco Model 3 computer, S-100 bus micro-computer with a Z-80 microprocessor, CP/M operating system. A more complete description of the hardware configuration and software system is given in Harrison and Singh, (1984). Image data, specially MSS band-4, showed prominent banding at six line interval. The mean values recorded by each of the six detectors were calculated and then weighting was applied in order to equalise these means thus destriping the images. Then detection of bit slips and data drops was carried out by using following algorithm:-

$$S = \text{DATA}(I+1, K) - \text{DATA}(I, K)$$

where, DATA(I, K) is the pixel value at the K-th pixel of the I-th scan line. The value of $S > 20$ was considered as bit slips or data drops. The detected values were manipulated by replacing these values by average of the corresponding values in the preceding and succeeding lines.

B. PAIRWISE DIVERGENCE ANALYSIS

In order to evaluate the potential of Landsat MSS data for land cover discrimination a pairwise transformed analysis was conducted. The pairwise divergence is a measure of the difficulty of discriminating between two classes on the basis of their mean vectors and covariance matrices (Swain and Davis, 1978, Singh, 1984).

For this analysis, a number of training sites corresponding to areas of high spectral homogeneity for the dominant cover types were selected. Means, Covariance and correlation matrices were calculated for each of the training sites. The sample statistics was pooled for each class and then the pairwise transformed divergence measure for the four features was calculated to determine the interclass separability of the different cover types.

A plot of grey levels of different cover types against MSS bands for the two areas are given in the figures 2 and 3 and the pairwise transformed divergence matrices are given in the tables 1 and 3. For the first area, this measure indicated the spectral separability of two forest density classes, grassland and area without an effective

vegetative cover. However, the following pairs of cover classes could not apparently be reliably separated using Landsat MSS data. Namely.

Bare Soil and Jhum
Grassland and Jhum
Jhum and Regrowth
Open Forest and Regrowth

In order to test the optimal discriminatory potential of Landsat MSS data only one representative training set for each cover types was used in the analysis. The result in table 2 indicates that grassland and Jhum areas are still confused and open forest and 7 years old regrowth, which was confirmed from historical Landsat MSS data and maps, are more or less inseparable.

In the second area, the spectral separability for open forest, forest trees interspersed with agriculture and scrub was found to be unreliable.

C. CLASSIFICATION ANALYSIS

C.I. Supervised Classification

A supervised multispectral image classification procedure based on the minimum distance to mean algorithm was used in the study. In this classifier, the Euclidean distance is computed for each pixel vector from the class means and the pixel is assigned to the class with the nearer mean (Swain and Davis, 1978). Due to its computational efficiency it was thought to be the most suitable for implementing on the microcomputer system.

In the classificatory procedure, for Area-1, regrowth and open forest and for Area-2, open forest and forests interspersed with agriculture fields were grouped together because they were spectrally very similar and did not form a distinctive separate physiognomic unit. Cloud and shadow were not considered in the further analysis, although they formed a distinct spectral classes.

C.II. Reclassification

Once the classification was performed the classified images were reclassified using a 3x3 pixel window central pixel being assigned to the majority class of the surrounding pixels in the window. This potentially has the benefit of improving classification accuracies by removal of isolated inliers within homogeneous areas (Justice and Townshend, 1982). The same test sites were used for accuracy assessment purposes for the classified and reclassified images.

C.III. Accuracy Assessment

Analysis of accuracy was conducted using the confusion matrix in tables 4-7 which summarises the result of the classification.

IV. RESULT AND DISCUSSION

The analysis of Landsat MSS data conducted here offers some interesting results regarding tropical forest cover mapping. In the studies concerned with the temperate forests it has been shown that the differences in crown canopy closure cause significant differences in spectral response on Landsat MSS data (Heller, 1975, Hoffer and Staff, 1975b, Strahler et al., 1978, Williams and Haver, 1976). As the canopy becomes more open there is an increase in reflectance measured by Landsat. Williams and Haver (1976) pointed out that the increase in reflectance was most apparent in the near infrared bands. In tropical forest environment, it was found that the opening of forest canopy does induce increased reflectance in visible bands but this is followed by decrease in reflectance in the near IR bands. Even two edaphic forest-types (closed forest and dense mixed bamboo forest) were found to be distinguishable due to their distinct spectral response in IR bands. However some important physiognomic units such as scrub and open forest, grassland and jhum could not be reliably separated.

The quantitative evaluation of classificatory performance indicated more or less similar results as obtained by the various workers in temperate forests. The level-1 classification i.e. forest and non-forest appeared to be reasonably accurate but further breakdown of the classes did not yield satisfactory classification accuracy. Contextual considerations modestly improved the classification in areas of homogeneous cover types but the result was not encouraging for the areas of heterogeneous cover types. The result is summarised below:-

	AREA-1	AREA-2
CLASSIFICATION:	5 Classes =50.76%	5 Classes =42.39%
	2 Classes =79.71%	2 Classes =64.60%
RECLASSIFICATION:	5 Classes =50.20%	5 Classes =46.10%
	2 Classes =76.98%	2 Classes =68.08%

There are number of factors which could have affected the classificatory performance, such as:-

1. In wildland areas the cover types of interest are often not spectrally homogeneous, use of supervised techniques does not yield acceptable accuracy or reliability (Heller and Ulliman, 1983).
2. Variations in slope and aspect of the terrain causes distinct differences in reflectance measured by the satellite even though there were only minimal differences in the type and conditions of the forest cover (Hoffer and Staff, 1975a).
3. In areas affected by shifting cultivation complexity of cover types arises mainly from the variable mixture of various elements on the ground such as soil, grass, regrowth, scattered trees within the limits of resolution. The field sizes are quite small and occur in irregular shape.
4. With the present resolution of Landsat MSS, location of random test sites will remain difficult in areas with a high degree of mixture and may possibly lead to a spurious increase in error of misclassification (Justice and Townshend, 1982).
5. In mountainous terrain, shadow is one of the major source of misclassification, which was not pursued in this study, as in Area-1 roughly 15% of the pixels were affected by shadow.

V. CONCLUSION

The main discrimination that can be made with high degree of accuracy on Landsat is limited to forest versus non-forest. This capability itself is very useful to forest planners concerned with the large area inventories in regions with a large inaccessible forests.

The coarse resolution of Landsat MSS system has its limitations. In fact, MSS samples the spectral distribution of a green vegetation in a quite limited way (Landgrebe, 1983). It is expected that analysis based on Thematic Mapper data will provide greater accuracy. Substantial improvements over MSS imagery are expected from Landsat-D's Thematic Mapper as a result of spectral resolution alone. Coupled with increased radiometric resolution, increased spatial resolution and additional bands, the state-of-the-art of satellite remote sensing of vegetated surfaces should be advanced dramatically (Tucker, 1978).

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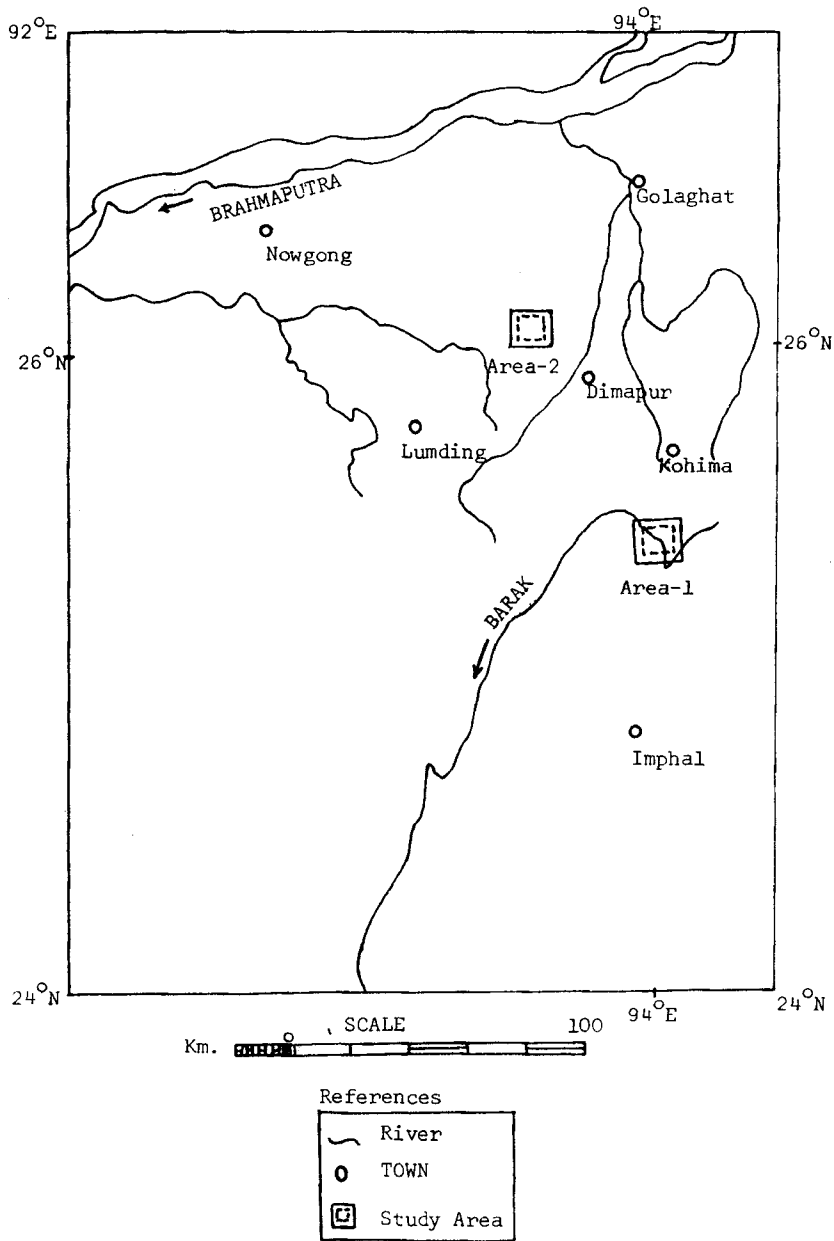


Figure 1. Location Of The Study Areas.

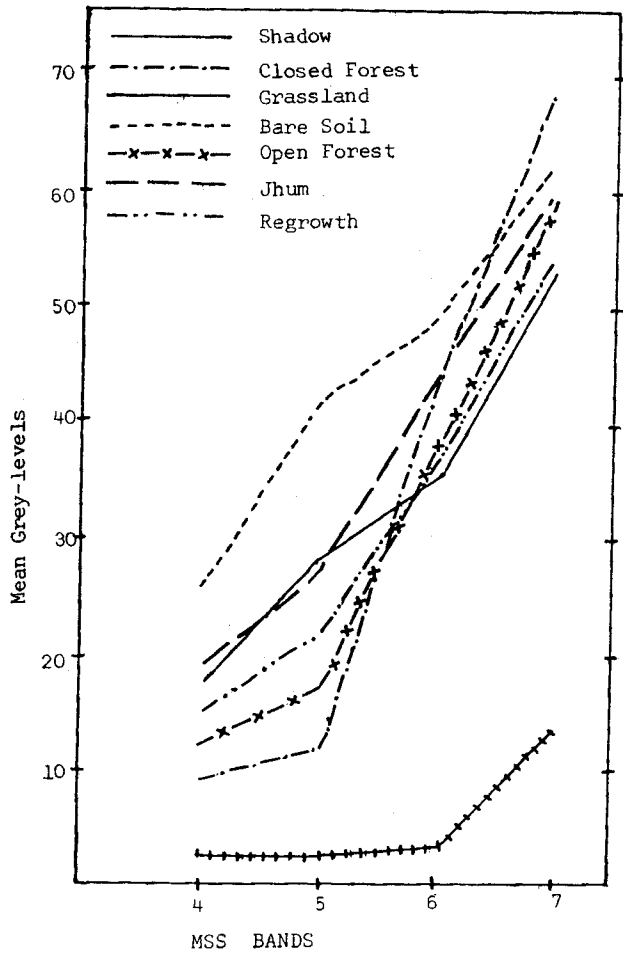


Figure 2. Mean Spectral Response Of Cover Classes in Area-1.

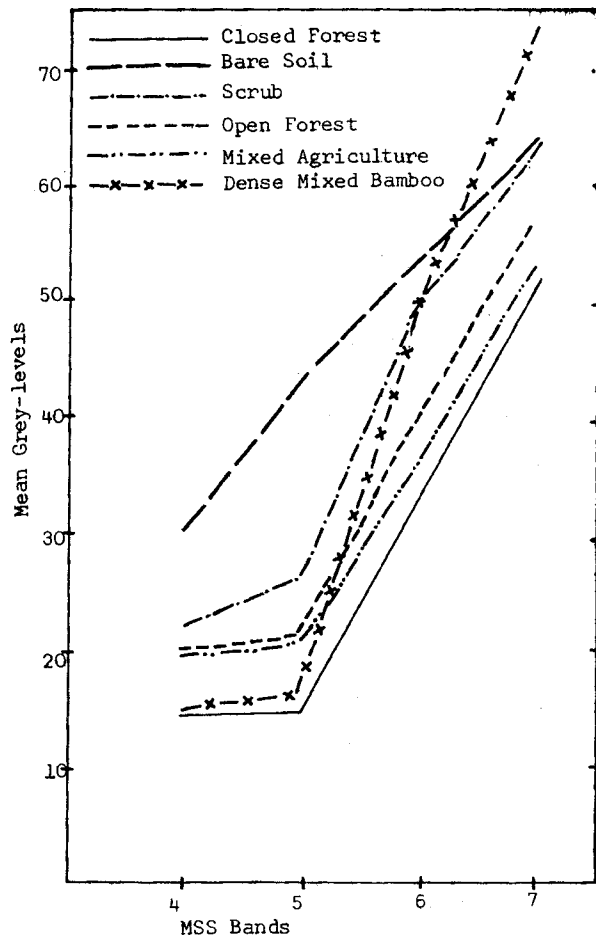


Figure 3. Mean Spectral Response Of Cover Classes in Area-2.

Table 1. Transformed Pairwise Divergence Matrix For Area-1.

Class ^a	1	2	3	4	5	6	7	8
1	0							
2	2000	0						
3	2000	2000	0					
4	2000	2000	1514	0				
5	2000	2000	1256	472	0			
6	2000	1996	1545	665	369	0		
7	2000	1990	1998	1746	1516	991	0	
8	2000	2000	2000	2000	2000	2000	2000	0

a 1-Cloud,2-Shadow,3-Bare Soil,4-Grassland,5-Jhum,6-Regrowth,7-Open Forest, 8-Closed Forest.

Table 2. Transformed Pairwise Divergence Matrix For Area-1 (One Training Set).

Class ^a	1	2	3	4	5	6	7	8
1	0							
2	2000	0						
3	2000	2000	0					
4	2000	2000	1931	0				
5	2000	2000	1860	717	0			
6	2000	2000	2000	1858	1970	0		
7	2000	2000	2000	1925	1968	1447	0	
8	2000	2000	2000	2000	2000	1999	1958	0

a Same as in Table 1.

Table 3. Transformed Pairwise Divergence Matrix For Area-2.

Class ^a	1	2	3	4	5	6	7	8
1	0							
2	1998	0						
3	2000	2000	0					
4	2000	2000	2000	0				
5	2000	1962	2000	1508	0			
6	2000	1989	2000	1515	269	0		
7	2000	1977	2000	1955	932	744	0	
8	2000	2000	2000	1729	1786	1774	1836	0

a 1-Cloud,2-Bare Soil, 3-Shadow,4-Closed Forest,5-Mixed Agriculture, 6- Open Forest,7-Scrub,8-Dense Mixed Bamboo Forest.

Table 4. Classification Performance in Area-1 by Applying the Supervised Classification

Landsat Class Ground Class	Bare Soil	Grassland	Jhum	Open Forest	Closed Forest
Bare Soil	73.52	11.76	8.82	5.88	0.00
Grassland	42.59	14.81	20.37	20.37	1.85
Jhum	8.19	21.31	21.31	27.86	21.31
Open Forest	3.63	3.63	10.90	80.00	1.81
Closed Forest	2.46	2.46	1.23	29.62	64.19

Average performance by class: 5 classes=50.76%, 2 classes: Forest=88.97%, Non Forest=70.46%.

Table 5. Classification Performance in Area-1 by Applying the Reclassification

Landsat Class Ground Class	Bare Soil	Grassland	Jhum	Open Forest	Closed Forest
Bare Soil	73.52	5.88	8.82	11.76	0.00
Grassland	44.44	9.25	9.25	35.18	1.85
Jhum	4.91	21.31	11.47	40.98	21.31
Open Forest	0.00	0.00	3.63	96.36	0.00
Closed Forest	3.70	1.23	0.00	34.56	60.49

Average performance by class: 5 classes=50.21%, 2 classes: Forest=95.58%, Non Forest=58.38%.

Table 6. Classification Performance in Area-2 by Applying the Supervised Classification

Landsat Class Ground Class	Bare Soil	Scrub	Open Forest	Closed Forest	Dense Mixed Bamboo
Bare Soil	11.76	61.76	26.47	0.00	0.00
Scrub	4.80	44.80	30.80	19.60	0.00
Open Forest	5.33	45.33	26.66	22.66	0.00
Closed Forest	2.50	8.75	23.00	65.75	0.00
Dense Mixed Bamboo	0.75	18.75	5.50	12.00	63.00

Average performance by class: 5 classes=42.39%, 2 classes: Forest=76.87%, Non Forest=52.46%.

Table 7. Classification Performance in Area-2 by Applying the Reclassification

Landsat Class Ground Class	Bare Soil	Scrub	Open Forest	Closed Forest	Dense Mixed Bamboo
Bare Soil	5.88	64.70	29.41	0.00	0.00
Scrub	0.80	56.40	27.60	15.20	0.00
Open Forest	3.11	58.66	18.22	20.00	0.00
Closed Forest	0.50	6.00	11.00	82.50	0.00
Dense Mixed Bamboo	0.00	16.75	2.50	13.25	67.50

Average performance by class: 5 classes=46.1%, 2 classes: Forest=77.36%, Non Forest=58.80%.

AUTHOR BIOGRAPHICAL DATA

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