The use of GIS and remote sensing techniques to classify the Sundarbans Mangrove vegetation

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Abstract: Deforestation has been a very critical environmental problem during the past few decades. Monitoring the forest land use conditions and their changes are essential to the management of this global environmental problem. Remote sensing can provide an effective tool for monitoring land use and environmental changes on regional as well as global scale. This has focused attention on developing more effective and efficient techniques for the management and survey of land use and forest areas. This study was designed to assess the feasibility of utilizing Landsat TM image in classifying the vegetation in the Sundarbans reserve mangrove forest. Vegetation classification was performed using satellite image taken in 1996 and supported by 2001 image. An IDRISI image processing system was used to analyse the satellite data. The images were registered and spectral signatures of each point on band 2, 3, and 4 were directly compared with the false colour composite image (FCC). Correlation analysis was used to evaluate the similarity of two spectral signatures. A false colour composite image of bands 2, 4 and 3 (Red-Green-Blue) was used in visual interpretation and unsupervised classification. The study classified the mangrove vegetation in nine categories in the Sundarbans reserve mangrove forest with an accuracy of 78.32 and 81.62 per cent in unsupervised and supervised classification respectively. Thus it appeared that the GIS and remote sensing are effective techniques for classifying the mangrove vegetation.

Key words: mangrove, remote sensing, land use, classification, Sundarbans

Introduction

The coastal zone and mangrove contains diverse and unique resources as well as ecosystems that are important for biological and economic productivity, functioning also as an ecotone, a transitional protective area between the land and the sea (Clark, 1983). Mangrove stabilizes the coastal shoreline, render protection to land mass from tidal surges, cyclonic storms and high winds. Mangrove forest and swamps are inhabited by innumerable taxa of flora and fauna, micro and macro illustrating the high productivity of the vibrating ecosystem which is exposed in high and low tides twice in 24 hours (Ali, 1998).

The Sundarbans is composed of naturally grown halophytic plants, commonly referred as mangroves. Its tidal forest is divided into low mangrove forests, tree mangrove forests, salt water *Heritiera* (Sundri) forests, and freshwater *Heritiera* forests. On the other hand, based on productivity of the forests, foresters have classified the Sundarbans into three major zones, each of which coincides with a varying range of salinity (Fig.1).

The importance of mangroves as coastal resources is well established. Mangrove forests are used throughout the tropics as fishing areas, wildlife reserves, for recreation, human habitation and aquaculture. Mangrove vegetation itself is harvested directly as feed supplement and for timber products (Long and Skewes, 1996; Wafar *et al*. 1997; Wong and Tam, 1995). Mangroves are also important nursery areas for the juveniles of many commercial fish and crustacean species (Robertson and Duke 1987; Wong and Tam, 1995) and play important roles in coastal protection and water quality (Kapetsky, 1985). This importance is reflected in the economic value of mangroves which lies in the range of US $ 100-277,000 /km^2 depending on use (Stevenson, 1997). To study mangrove and other land uses effectively, and to monitor changes over time, accurate, rapid and cost-effective mapping techniques are required. The use of remotely sensed data offers many advantages in this respect and has been used to monitor deforestation and aquaculture activity, in environmental sensitivity analysis and for resource inventory mapping purposes (Green *et al*. 1996).

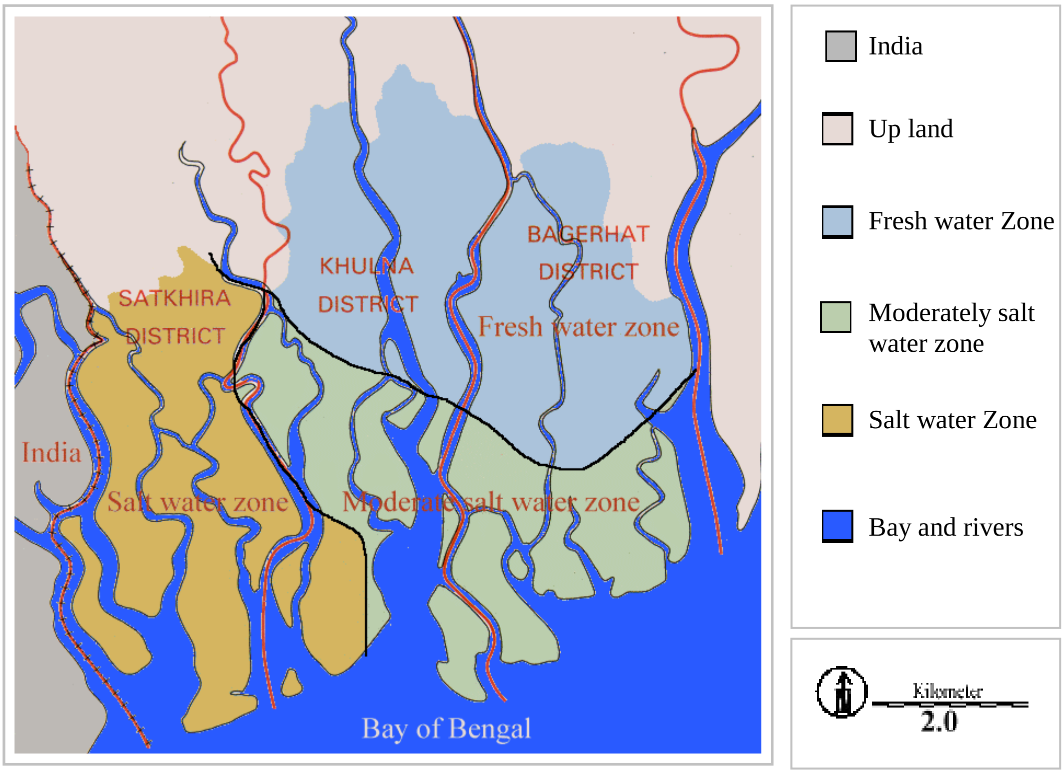

Figure 1. Illustrates the three salinity dominated zones in the Sundarbans mangrove forest

However, the accuracy of the final map is affected by the ability of the classification procedure to discriminate between various vegetation types. The ability to do this is partly a function of the sensor's resolution, and partly a function of the image processing method or classification procedure adopted. For example, when mapping real habitats it has been shown that the overall accuracy of habitat maps and user's accuracy of individual classes is dependent upon the particular classification procedure adopted (Green *et al*. 1998). Not only satellite and airborne systems available to the users of remote sensing but there are also many different image-processing techniques. The present study has, therefore, been taken to classify the mangrove vegetation of the

Sundarbans using GIS and remote sensing techniques.

Materials and Methods

For the image classification, supplementary data were collected from the field visit in an extensive data collection programme using hand held Garmin GPS II. The data were collected from various institutions and organisations in Bangladesh and UK, which were supported by the literatures. Mangrove Inventory map was collected and used to verify the result. Image processing technique followed in this study has been shown in Fig. 2.

Image Enhancements

Landsat TM images path 137 and 138 and row 44 of February, 1996 were provided by NPA a satellite Imaging Groups in London. These images represented dry season vegetation growth when the majority of the rivers were dry due to Farrakka barrage in the up stream and less water flow through the rivers particularly Gorai river which was fully dry means no water flow in the lower part of the area through this river. Moreover, tidal water intrusion in to the land and the salinity of the water was higher compared to the pre Farrakka barrage which has changed the forest vegetation and forest community characteristically than the before situation.

The images were subjected to preliminary digital enhancements in order to enable their interpretation. A false colour composite using Landsat TM bands 2, 4 and 3 (RGB) was found to give a clear visual discrimination of the mangrove and non-mangrove boundary (Gray, 1990; Trolier and Philipson, 1986). An associated contrast stretch of 5% was also applied to give a better visual representation (Fig. 3).

Masking

The mangrove areas were separated from the other inland vegetation and water bodies prior to image classification. Because, young mangrove trees gave the same reflectance as palm trees farther inland and apparent scattered mangroves were observed far away from the mangroves mixed with inland trees (Aschbacher *et al*.1995; Chuvieco and Congalton, 1988; Green *at al*. 1998; Yusof, 1998). Moreover, irrigated boro rice and marshland in the mangrove also gave the same reflectance, which was difficult to separate. Furthermore, the image was taken during the time of an intermediate stage of shrimp culture and agricultural crops. Ponds were drying or had been left with little water, which gave a similar reflectance to irrigated rice. Not only that, bare-land also gave a similar reflectance to the cities. To overcome these problems, mangroves were separated from other areas using masks, which were developed using on screen digitising facilities in IDRISI. The vector files were then rasterized and applied as masks to the colour composite image using OVERLAY module in IDRISI.

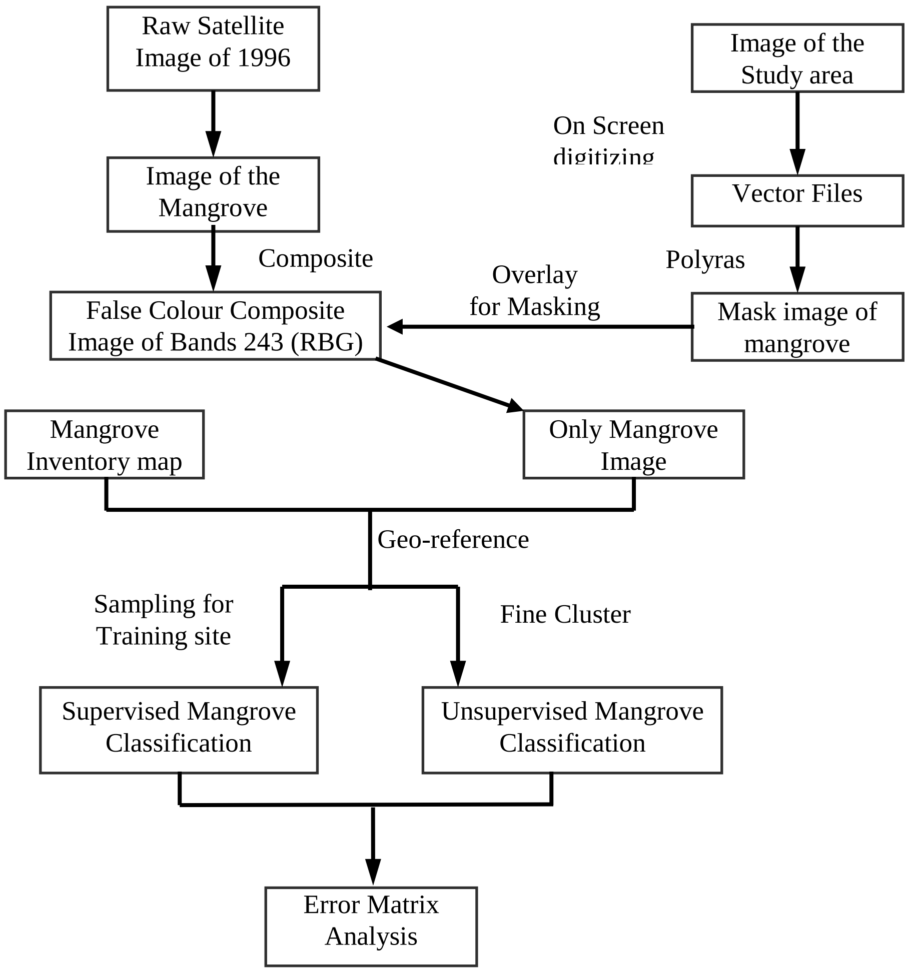

Figure 2. Schematic diagram of image processing techniques used in the study

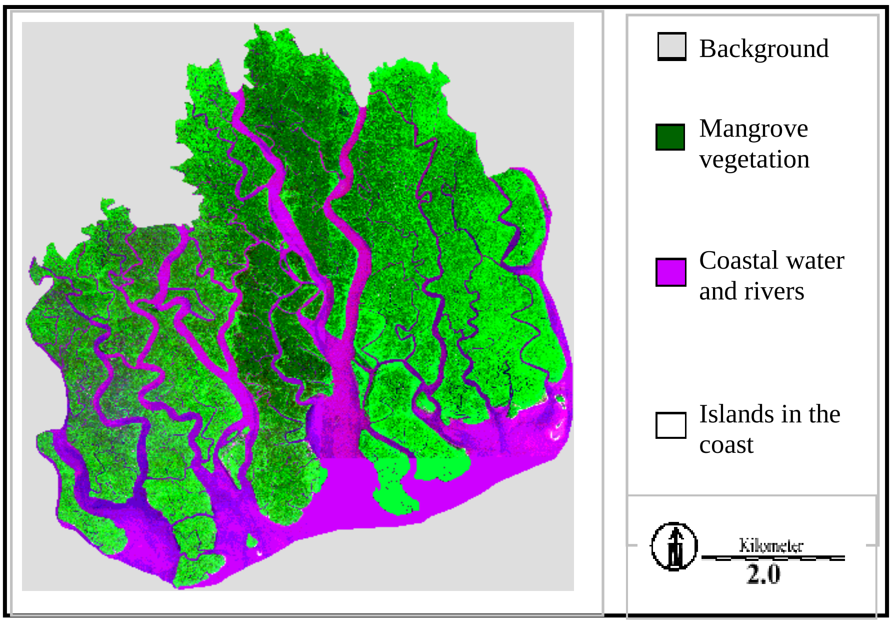

Figure 3. A false colour composite image of Landsat TM bands 2, 4 and 3.

Table 1. Groups formed by the fine cluster analysis with 30 clusters.

Name of the tree species	Reflectance of the clusters
Sundri (*Heritiera fomes)*	3
Sundri - Gewa *(Heritiera fomes* and *Excoecaria agallocha)*	2, 7
Gewa *(Excoecaria agallocha)*	8
Gewa - others *(Excoecaria agallocha)*	5
Goran *(Ceriops decandra)*	16
Goran- others *(Ceriops decandra)*	11, 12, 15
Kewra *(Sonneratia apelata)*	7
Grassland/ Bare land/ Beaches	14, 17, 21, 27
Water	4, 9, 13, 14, 17, 18, 19, 20, 21, 22, 24, 25, 26, 27

Unsupervised Mangrove Classification

The logic by which unsupervised classification works is known as cluster analysis in IDRISI. Cluster module groups together features with similar reflectance patterns. The module was used to produce an unsupervised classification from the colour composite image which provided the number of spectral classes in the raw data. This was done in several steps. Cluster was used with 30 fine clusters of user define classes in the final image. The module then classifies the image into discrete categories. Following the cluster, a 3 x 3 mode FILTER was carried out to eliminate small clusters with less than 3 pixels. The clusters were then identified and further reclassified into nine forest cover classes based on the mangrove forest inventory map (Chaffy, 1985), supplemented by the colour composite Landsat TM image and field visit data. Table 1 shows the groupings of forest categories from the cluster analysis.

Selecting Training Sites

In supervised image classification, training sites are those areas which the analyst identifies that exemplify each land-cover type in the image to be classified. These sites are used to "train" the software classifier to recognise each cover type so that all pixels in the image may be assigned to their appropriate cover classes (Eastman, 1997). The success of supervised land use classification depends on how well the training sites are picked up. The reference data aided in the analysis and interpretation of remotely sensed data, i.e., it established a link between variation on the ground and variation in the image. This link was pertinent for assigning image spectral classes to land cover classes in the image classification process. Training sites are also important in assessing the accuracy of the classified image.

Supervised Mangrove Classification

Supervised Classification is a technique for the computer-assisted interpretation of remotely sensed imagery. The operator trains the computer to look for surface features with similar reflectances to a set of known interpretation within the image. These areas are known as training sites. For the spectral supervised classification, signatures for groups were developed based on the three bands of raw

Landsat TM data, mangrove inventory map and GPS reading.

Supervised classification begins with digitizing of polygons thought to be representative of the intended spectral or textural classes. Digitizing was conducted, using the on screen digitizing facilities and windowing and vector drawing features in IDRISI. Each polygon was assigned a group number. The MAKESIG module was then used to process the polygons into spectral signatures representative of the intended classes. The SIGCOMP module was then used to evaluate the quality of the signatures, and allows the user to compare the signatures for each of the bands of raw data as line graphs. The greater the degree of spectral separation between each signature, the better the final classified image is expected. The SCATTER module was also used to evaluate the quality of the signatures in the raw data and MINDIST module was used to process the raw data for supervised mangrove classification.

Error Matrix Generation

An error matrix is a square array of numbers set out in rows and columns which expresses the number of sample units (i.e., pixels, clusters of pixels, or polygons) assigned to a particular category relative to the actual category as verified by some reference data. The columns usually represent the reference data while the rows indicate the classification generated from remotely sensed data. In other words, an error matrix is a comparison between sampled areas on the map generated from the remotely sensed data and those same areas as determined by some reference data (Table 2). The reference data are typically ground visits or large-scale photographs. The data are then used as a reference map against the classified image in error matrix to calculate the accuracy. An assumption was made here is that all differences between the remotely sensed image classification and the reference data are due to classification or delineation error. However, there are many other sources of confusion between the remotely sensed image classification and the reference data that must also be considered.

Resampling of Images

When comparing two or more images, spatial registration is a crucial step for the purpose of accuracy assessment. This is because the process of looking at the image to be classified and the reference image is typically done by examining the differences in the values of corresponding cells in the multiple images. This process will only make sense provided that the corresponding pixels of each image actually describe the same location on the ground.

Table 2. A typical Error Matrix generation table (modified after Congalton *et al*. 1998).

		REFERENCE DATA			
CLASSIFIED MAP	Class 1	Class 2	Class 3	Class 4	Row MARGINALS
Class 1	✔	O			RT
Class 2	C	✔	C	C	RT
Class 3		O	✔		RT
Class 4		O		✔	RT
COLUMN MARGINALS	CT	CT	CT	CT	Σ

RT, CT Sum of Row or Column Entries
Σ Number of Total Sampled Observations
✔ Total Diagonals Entries = Correctly Classified Units
C, O Number of Row Commission and Number of Column Omission Errors

Results

Results of the Unsupervised Mangrove Classification

Unsupervised classification through the CLUSTER module was conducted on the raw data of mangroves. The number of clusters to be used was specified as thirty. The classification for the mangrove produced adequate results for the purposes of the study. Most of the cases, the spectral categories as defined by the CLUSTER module corresponded to the information classes. Kappa Index of Agreement (KIA) for the mangrove-unsupervised classification was 0.605 and over all accuracy was 78.32%, which was judged good for a large mangrove vegetation classification. In unsupervised classification, the water separated better than other categories. However, few misclassifications were observed with the tree species of Gewa and others, which were followed by Gewa, whereas, grassland/bare land category produced large errors in unsupervised mangrove classification. The result of the mangroves-unsupervised classification is shown in Figure 4**.**

The error matrix module generated the KIA, which is particularly important as it is used to determine the degree of agreement between the two images. Kappa ranges in value from -1 to +1. A value of +1 indicates that the two images are in perfect agreement (no change occurred), whereas, if the two images are completely different from one another, then the Kappa value is -1. If all the changes that occurred could be accounted for by chance, then Kappa is 0.

Results of the Supervised Mangrove Classification

The SAMPLE module for the accuracy assessment selected two hundred and seventy two sampling points over the mangroves forest inventory map. The accuracy assessment of supervised mangrove classification indicated that the methodology produced very good results, with overall percentage correct pixels of 81.62% and KIA of 0.65, which is slightly better than the unsupervised classification.

The methodology produced the best results for the water classes, followed by Sundri and Sundri-

Gewa tree species. On the other hand, the poorest results were obtained for the Gewa-others, Goran and grassland/bare-land classes. This error could be related to the reference map, since the difference of seasons and the environmental conditions between the Landsat data and the mangrove inventory map. There was 11 year gap between the Landsat image acquisition and the mangrove inventory map preparation, which could be crucial. Discrimination between the grassland and other vegetation was good. Supervised classification of the Sundarbans mangroves vegetation final image is shown in Figure 5.

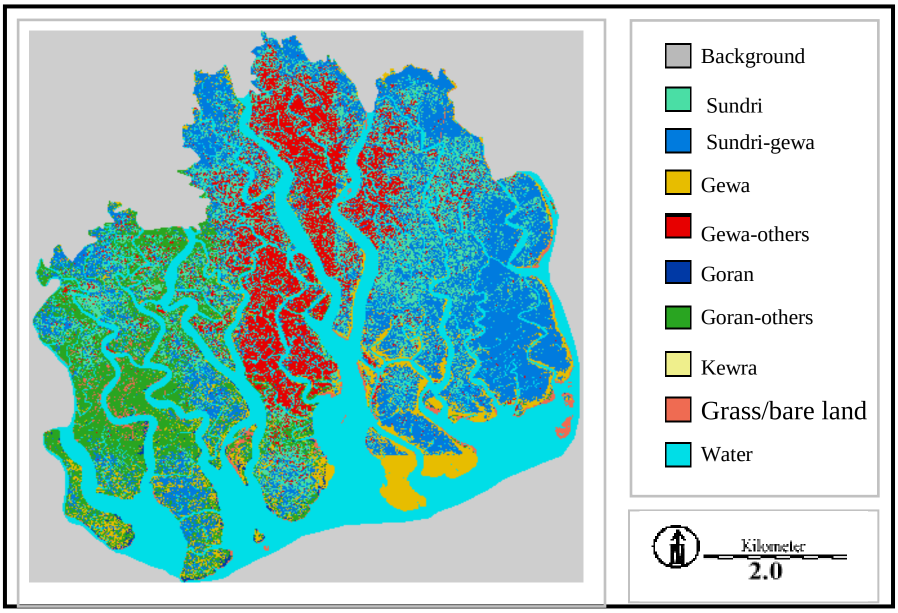

Figure 4. The result of unsupervised mangrove classification.

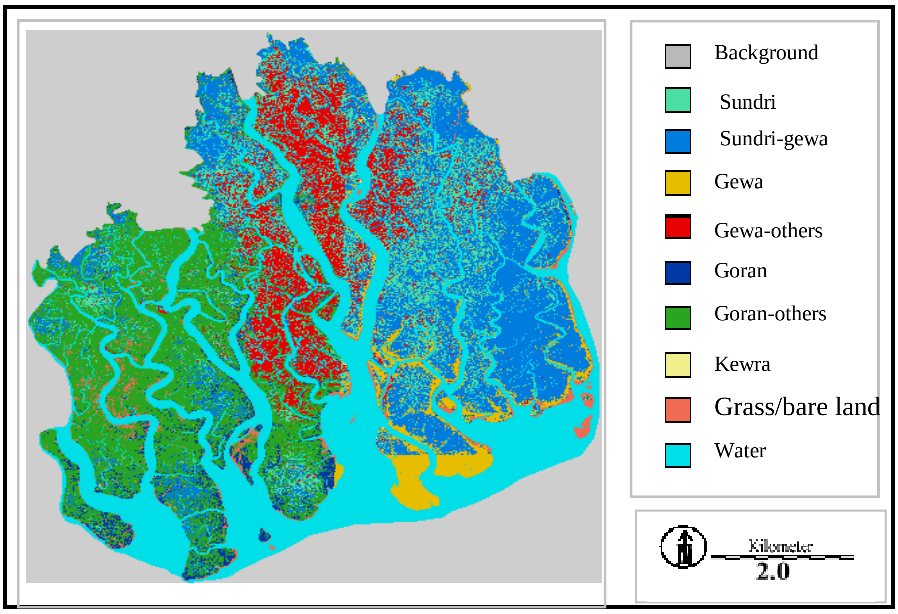

Figure 5. Supervised classification of the Sundarbans mangroves vegetation

4. Discussion

The results of the mangrove unsupervised and supervised classification showed that the satellite image can be a valuable tool to classify and update the forest vegetation maps and to locate and inventory the forest for formulating policies, plans and programmes for sustainable development and management of the forest. However, the advantages and limitations of the techniques also need to be fully understood.

There is 11 years gap between the TM image acquisition (1996) and the preparation of mangrove inventory map (1985), which means, the changed could happen in these areas especially due to erosion and accretion because of the dynamic nature of the rivers and regeneration of mangrove forests. In addition, cyclones have caused some damage in the forest since 1996.

Tidal height at the time of imaging can affect the mapping accuracy of the mangrove forest as well as in lands. Mangroves, which are located in the flat, shallow inter-tidal zone, have a spatial extent and spectral features that are highly vulnerable to fluctuation in tidal height. A high tide caused muddy ground and even some of the shorter mangroves to be totally submerged, whereas, a low tide exposed them and the muddy ground. In the former case, the disappearance of bare land drastically reduced the confusion of mangroves with mud flats, and to lesser degree, with bare land. Although the area classified as mangroves is reduced, the mapping accuracy is higher due to decreased confusion. On the other hand, the mapped mangroves may have a broader spatial limit at a low tide; such an expanded extent being a consequence of larger errors of commission. The Landsat TM data used in the eastern part of the image were recorded at just after 9:42 AM, 9 February 1996, about 1 hour before the (10:49) low tide in the upper portion of the mangroves and about 3 hours before the (13:10) high tide in the lower portion of the mangroves according to the tidal chart. The situation was very similar on 16 February 1996, when the western part of the image was recorded. Thus, the confusion of mangroves with mud flats and wetlands occurs on a wide scale. A similar situation encountered by Gao (1998).

There are about 20 major mangrove species growing in the Sundarbans mangrove forest. However, mixed stands of *Heritiera fomes* and *Excoecaria agallocha* are the major forest types and constitute over 70% of the forests. In this study, 7 forest types and grass or bare land and water bodies were discerned with a classification accuracy of 81.62%. In a similar study using Landsat TM sense, Chaudhury (1990) mentioned that it would not be possible to perfectly classify mixed forests, like the Sundarbans.

Generally the accuracy of the image classification depends on the purpose of the project and extent of the area. For example, in a simple classification scheme the required level of detail may be only to distinguish residential areas from commercial areas. For this type of classification, accuracy could be less than a forest classification. Cihlar *et al.* (1997) achieved an overall accuracy of 66.6% and khat value of 0.56 in a land cover classification of the Boreas region of 9,850 km^2 area from Landsat TM data which is lower than the present study.

One advantage of visual processing is that it is much more accessible than computer automated processing. Good results have been obtained by visual analysis of Thematic Mapper images for hydrological inventory including water bodies and wetlands (Trolier and Philipson, 1986). Computer processing of the imagery in contrast to visual analysis provides for more efficient use of time and for more comprehensive analysis.

Brisco and Brown (1995), Congalton *et al.* (1998), Kapetsky (1987 and 1989), and others have shown that digital processing of satellite imagery, combined with field visits and aerial photography as ancillary data, can accurately produce both detailed and broad GIS coverage of vegetation / land cover type.

Image registration differences occurred while scanning the forest inventory map of 1:50,000 scale to 1:2000,000 to put into error matrix. This was revealed following visual inspection of the colour composite image and the inventory maps. Other problems were that the size class (i.e., diameter of the trees, shape and size of the water bodies) can change between the time of the inventory map production and remotely sensed data acquisition, especially in a fast growing area such as the Sundarbans mangrove forest. Moreover, inconsistencies in human interpretation, especially for heterogeneous areas, can be a very difficult factor to control. Measures of variation in interpretation need to be further developed that can test the validity of class boundaries while at the same time provide for allowable variances in the accuracy assessment (Congalton and Green, 1993; Lunetta *et al*. 1991).

Conclusion

The study classified the mangrove vegetation in nine categories in the Sundarbans reserve mangrove forest with an accuracy of 78.32 and 81.62 per cent in unsupervised and supervised classification respectively. Apart from vegetation classification, satellite imagery can be used to inventory the crop yield, condition of agricultural crops and monitoring fisheries resources, aquaculture and small water bodies. Thus, used in the combination with other information in a GIS, satellite data can be a tool for sustainable mangrove forest management as well as for development which can be replicate in other fields as well.

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