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Remote sensing for developing an operational monitoring scheme for the Sundarban Reserved Forest, Bangladesh

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Abstract

Sundarban Reserved Forest in Bangladesh is playing a significant role in local and national economy and is providing protection to the coastline as well as to the indigenous people. During the past decades and also in recent time this forest was heavily disturbed by human intervention in many aspects. As a consequence the resources of the forest are fragmenting, shrinking and declining, which in turn leads to an increasing failure of satisfying increasing demands both at local and national levels. Therefore accurate and continuously updated spatial information is needed for optimising forest management and environmental planning on both levels to support the fulfilment of urgent needs of sustainability of the development of the forest ecosystems. Considering the specific topography and the poor accessibility of the forest versus the task of collecting information, remote sensing is an attractive, if not the only means of obtaining sound full-coverage spatial information on forest cover of Sundarban. This research investigated the identification of the operational tools for mapping and monitoring the forest as well as on the examination of the reliability of the application of multitemporal satellite remote sensing data for building spatial databases on forest cover in Sundarban. Medium resolution geometrically and radiometrically corrected Landsat ETM data of November 2000 and Landsat TM data of January 1989 were used for the study. Based on the existing management plan of the forest as well as the spectral properties of Landsat ETM imagery a level III classification system was developed. This classification strategy was tested by applying several methods to achieve the classification result with the highest accuracy and thus to build the most reliable methodology for mapping forest cover in Sundarban. Forest cover change was assessed during an eleven years period using postclassification approach. Significant changes have been observed due to illegal removal of trees from the forest although a governmental moratorium on banning timber extraction exists since 1989. In order to track the changes and trends continuous monitoring is necessary for assessing spatial parameters of forest ecology and forest resources periodically and for planning decisions at local and national level. This research has developed an operational monitoring scheme by means of multitemporal satellite imagery analysis, which will allow concerned authorities to set up sustainable and appropriate monitoring of the Sundarban Reserved Forest.

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List of Acronyms

ACF	Assistant Conservation of Forest
BTM	Bangladesh Transverse Mercator
C-CAP	Coastal Watch Change Analysis Project, USA
CF	Conservator of Forest
dbh	diameter at breast height
DCF	Deputy Conservator of Forest
DN	Digital Number
DOS	Dark Object Subtraction
EMR	Electro Magnetic Radiation
ESCAP	Economic and Social Commission for Asia and the Pacific
ETM	Enhanced Thematic Mapper
ERS	Earth Resource satellite
FRMP	Forest Resources Management Project
GIS	Geographical Information System
GPS	Global positioning system
GDP	Gross National Product
GLCF	Global Land Cover Facility
IHS	Intensity Hue Saturation
LUCC	Land Use Cover Classes
MS	Multi Spectral
MIR	Medium Infrared
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
ODA	Overseas Development Authority
Pan	Panchromatic
PCA	Principal Component Analysis
RGB	Red Green Blue
RIMS	Resource Information Management System
SRF	Sundarban Reserved Forest
SWIR	Short Wave Infrared
TIR	Thermal Infrared
TM	Thematic Mapper
UTM	Universal Transverse Mercator
USGS	United States Geographical Survey
VIS	Visible

Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Necessary contacts to the officials and private individuals and use of image processing facilities have been done as mentioned in this dissertation and with the agreement of the supervisors.

(Mariam Akhter)
Dresden, Germany
July, 2006

Dedicated to the departed soul
of my Father

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Chapter 1

Remote sensing for forest information

1.1 Background

Forests globally provide economically important and often irreplaceable products and services to humans and affect climate by acting as sources and sinks of heat trapping carbon dioxide. The forest actively contributes to the world's environmental stability such as preventing soil degradation and erosion, protecting watersheds or stabilizing mountainous areas. Forests serve as natural habitats to almost two third of all Earth's species, therefore acting as a stronghold to safeguard biodiversity. Forest also plays a cultural role in almost all societies, as mythical sceneries or historical backgrounds and as living habitats for about 60 million people worldwide. Despite the importance of forests, many reports around the world continue to indicate huge forest losses (FAO 1997).

Mangrove forests are one of the most important coastal ecosystems in the world in terms of primary production and coastal environment protection. Mangroves are evergreen forests between the land and the sea occupying tracts along sheltered coasts, estuaries and deltas where they are influenced by tides, salinity and rainfall. Mangrove forest is found in the tropical and sub tropical region. They are possibly the simplest and best defined ecosystem among tropical forests (UNESCO 1981). These forests provide a complex and dynamic environment for a diverse marine, terrestrial flora and fauna and enhance water quality by trapping nutrients and heavy metals (Clark 1998, De Lacerda 1998, Tam and Wong 1999). They also support coastal and offshore fisheries by providing breeding grounds for many fish species. However, all over the world mangrove ecosystems are threatened with destruction through various forms of human pressure, in particular extraction, pollution and reclamation (Farnsworth and Ellison 1997). Also the species richness of mangroves in many geographical areas is decreasing over time (Hamilton and Snedaker 1984). The mangrove areas worldwide have dropped below 15 million hectares by the end of 2000 down from an estimated 19.8 million hectares in 1980 (FAO 2003a). Yet, the unique coastal tropical forests are among the most threatened habitats in the world due to global warming and a rising sea level. They may be disappearing more quickly than inland tropical rainforests, and so far, with little public notice (UNDP 2002, SFR 2001).

The world's largest natural mangrove forest the Sundarban situated in Bangladesh along the Bay of Bengal covering an area of 601,700 hectare. This mangrove forest is declared as Reserve Forest[1] in 1875. Three wildlife sanctuaries, which are about 32,400 hectares area of the Sundarban have been acknowledged as World Heritage Site in 1999. This forest represents 4.07% of total landmass of the country and is managed by the Bangladesh Forest Department. Sundarban, unlike mangroves in many other countries in Asia, Africa and Latin America, supports a very rich and diverse flora and fauna. It plays an important role in the local and national economy. The forestry sector contributes about 5% of the total Gross Domestic Product (GDP) of Bangladesh (Forest Department web page) and the Sundarban alone is contributing 68% of it (McCarthy 2000). Also a quite large population depends directly or indirectly on the Sundarban. Ecologically this forest is particularly important for the region and acting as a barrier of cyclones and tidal surges. It is providing safeguard against coastal erosion and is also acting as a huge sink of carbon and other pollutants from air and water. Further more it is an attracting place for eco-tourism by the national and international tourists.

1.2 Need for monitoring the Sundarban Reserve Forest

Monitoring in the context of this research is understood as the repeated measurement of forest for the purpose of detecting qualitative and quantitative changes in the forest cover. Monitoring the forest over time in order to determine trends is essential in resource management because it provides essential information to decide whether the forest cover is stable, increasing, or decreasing as the result of management actions (Friederici 2003). Thus monitoring explores the status of the forest estate at regular intervals.

The SRF has become increasingly threatened due to human intervention and also natural hazards in the last decades. Due to excessive exploitation of the natural forests, the Bangladesh Government imposed a moratorium on timber felling in 1989 (excluding diseased *Heritiara fomes* and *Excocaria agallocha*). In spite of the existence of the moratorium there is huge illegal timber extraction taking place regularly. The extent of the Sundarban forest has not changed much but it is losing growing stock even though several forest policies, laws and management plans have been enacted to protect the forest (Iftekhar and Islam 2004).

[1] Any land declared as forest under the purview of Forest Act by government or the competent authority of a country where every thing is strictly prohibited unless or otherwise permitted.

SRF was for the first time inventoried in 1933 by Curtis and thus in 1959 by Forestal, in 1983 by Overseas Development Authority (ODA) and in 1996 by Forest Resources Management Project (FRMP). Figure 1.1 indicates the declination in the growing stock (volume) of tree resources in SRF during last four decades.

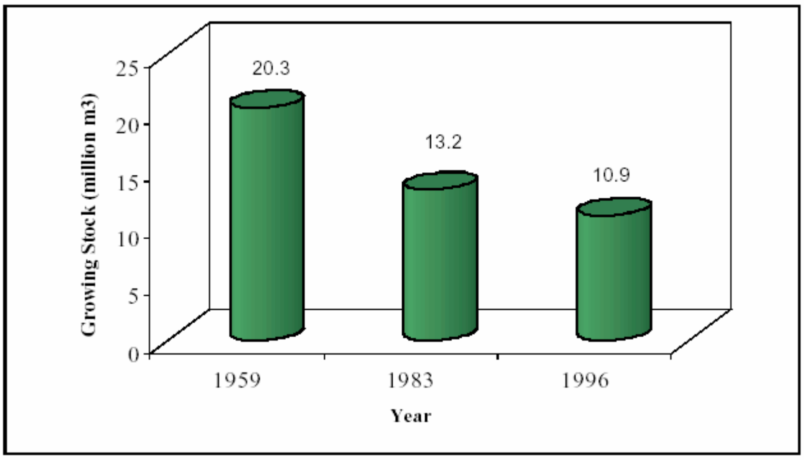


Figure 1.1: Growing stock in Sundarban Reserved Forest (FAO 1999)

There are many problems exist in the SRF. As Bangladesh is a densely populated country, overexploitation of forest resources to meet the growing requirement of the people is one of the main problems also in the SRF. This has resulted in depletion of economically valuable species, growing stock and productivity of the forest. Other problems in this forest are geomorphological changes, increased salinity, inadequate regeneration, top dying of *Heritiera fomes*, expanded shrimp farming in the surrounding of the forest etc. These problems frequently shift the SRF towards a state of unsustainability.

Due to the current trends in terms of population growth, demand of the forest resources and the impact of human activities on forest change, monitoring of the forest resources is essential in providing data for making policy decisions and generating management plans for sustainable development. The tsunami has provided an opportunity to illustrate that healthy mangroves serve as a natural barrier against natural or man made disasters such as protecting infrastructure and saving lives. Sustainable development of the forest depends on the availability of accurate, timely and easy accessible spatial information on forest resources in order to trace the reasons of deforestation and forest losses for which there is an urgent need to develop operational monitoring of the remaining forests at a regular interval (FAO

1999). The most important difficulties in updating maps of the topography and the forest cover of SRF are:

- Inaccessibility of most of the areas due to presence of innumerable rivers, creeks and water-bodies
- Presence of anthropophagous tigers in the forest and occasional presence of crocodiles in the rivers
- Excessive costs involved in detailed manual surveys
- Particularly long duration of carrying out manual surveys in hostile environment.

1.3 Satellite remote sensing for forest monitoring

Remote sensing plays a crucial role in determining, enhancing and monitoring forest cover as well as its overall carrying capacity. In the last decade only, over 100 satellites have been placed in orbit for the purpose of earth observation of land, oceans and atmosphere and for strengthening the scientific understanding of the driving forces behind global change (king and Herring 2000).

Satellite Remote sensing technology is a potentially fast and efficient approach to mangrove management, mapping and monitoring, particularly in hostile forest environments decreased by limited accessibility, large spatial extension, and inefficiency of conventional means of ground survey is considered to have a great potential as an extremely valuable tool for detecting, assessing and analysing forest cover changes both qualitatively and qualitatively (Xiuwan et al. 1999, Turker and Derenyi 2000, Wyatt 2000, Held et al. 2003).

Remote sensing offers an efficient and reliable means of collecting spatial information required for assessing forest cover. The spectral reflectance of forest surfaces always varies with respect to the phenology, species type, and health condition of tree stands. It can be well measured by multispectral sensor systems. The fundamental assumptions that govern the use of digital remote sensing for change assessment in forest ecosystems are (Coppin and Bauer 1996):

(a) Phenomena, which are related to dynamics of changes of forest canopies cause significant changes in values of electromagnetic radiation being measured by remote sensing. These changes are related to changes in Electro Magnetic Radiation (EMR) caused by differences in atmospheric condition, illumination and background conditions over the same time interval.

(b) Any major variation over time in the remotely sensed values of EMR for a particular spot in a forest ecosystem can be associated to an alteration in its reflective/emissive characteristics, which are a manifestation of biophysical properties of the surface.

Satellite data have several important advantages compared to ground observations and thus foster the integration of satellite remote sensing in forestry. These advantages are:

- Synoptic view to achieve global observation (Franklin 2001, Nagendra 2001).
- Repetitive coverage to obtain uniform and reproducible, periodical and continuous observation (Pathirana 1999, Wyatt 2000).
- Multispectral data (Blaschke 2005, Peterson et al. 1999).
- Low-cost data (White 1998, Lunetta et al. 2004).
- Digital processing (Peterson et al. 1999).

Owing to the versatility of remote sensing and scale, it is a valuable tool in all stages of forest management. Because of the synoptic and repetitive data acquisition capabilities, satellite based sensors hold the potential to detect, identify and map changes effectively (Coppin and Bauer 1996, Pathirana 1999, Turker and Derenyi 2000, Wyatt 2000). Many exploratory investigations were instigated to determine the applicability of various remote sensing systems for mapping and monitoring the changes of the mangrove forest (Mas 1999, Berlanga-Robles and Ruiz-Luna 2002, Bauer et al. 2003, Cornejo et al. 2005, Muttitanon and Tripathi 2005).

The concept of sustainable forest management continues to gain momentum all over the world. There need to update spatial information on the current state of the forest and the changes occurring in order to plan regulations are obvious. Timely acquisition of remotely sensed data for monitoring the forest condition can provide better understanding of the relationships and interactions between human impact and state of forests for making decisions and plans in timely manner. Various impacts on SRF have intensified and diversified and therefore needs for establishing a sound monitoring approach using satellite imagery.

For the research eight compartments of SRF have been selected as study areas. The potential of satellite imagery for setting up an operational appropriate monitoring scheme of state and changes of SRF has to be critically analysed. Landsat TM imagery of January 1989 and Landsat ETM imagery of November 2000 were used to assess the forest cover and its trends of changes in the respective study areas of SRF.

1.4 Research objectives

The general objective of the research is to

Develop a monitoring scheme for operational use to allow assessment, mapping and evaluation of forest cover and its changes for sustainable management.

In addition to the general objective, the research has formulated some specific objectives such as to

(a). develop an appropriate classification system to represent the forest cover according to the existing management plan,

(b). develop an appropriate methodology for forest cover assessment and mapping,

(c). evaluate the forest cover change in study area for the period of 1989 – 2000.

1.5 Research approach

The research is designed to critically investigate the potential of satellite remotely sensed data for temporal assessment and mapping of forest cover and its changes in the SRF. The general methodology followed for this research is presented below (figure 1.2).

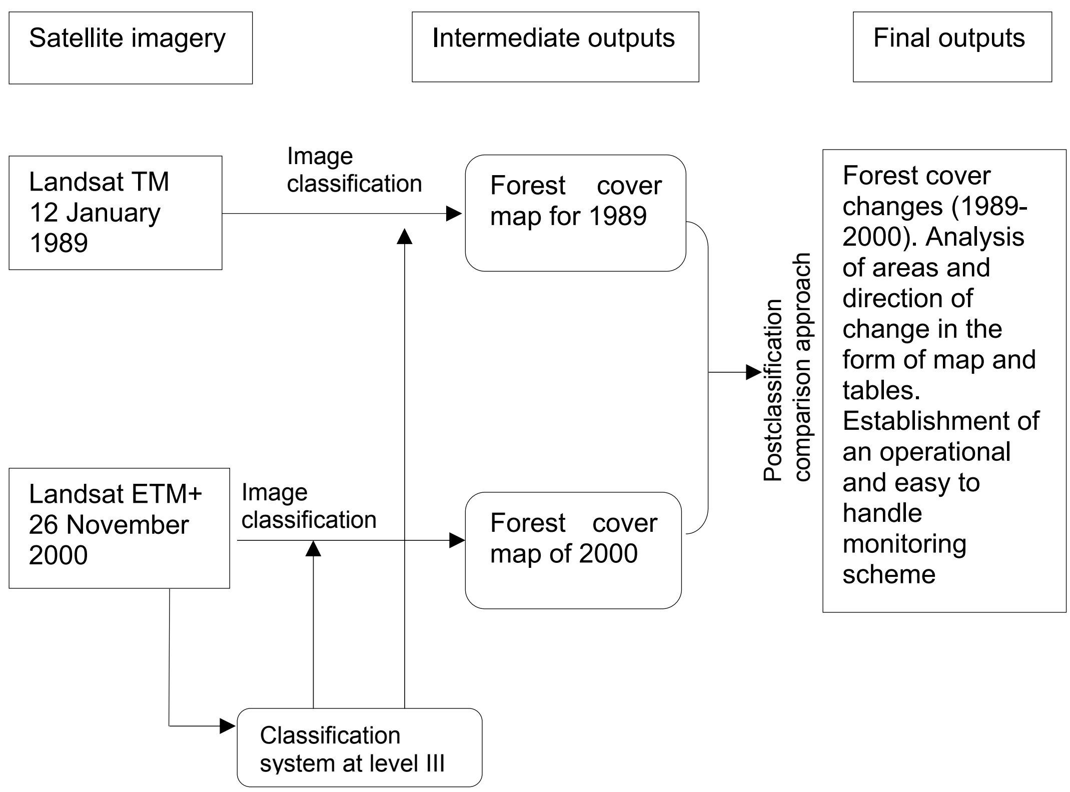


Figure 1.2: General methodology for the forest cover mapping and monitoring

1.6 Thesis structure

The research has assessed and evaluated the forest cover and its changes in the study areas of SRF using multitemporal Landsat imagery of the years 1989 and 2000 respectively. The PhD thesis comprises seven chapters. **Chapter 1** introduces the research by focusing the background introduction on the concept of problems of the study area, different aspects of the topic and the concept of the monitoring approach in the study areas (SRF). **Chapter 2** presents the study area (SRF) and describes its physical and geographical characteristics. Image acquisition of the study area is discussed along with the important characteristics of the Landsat sensor system. **Chapter 3** includes the presentation of concept of atmospheric correction and discussion of the selected method applied in the research. This chapter describes the advanced image processing steps for information extraction. Also discusses the classification system and generated a level III classification system. Supervised classification approach is applied for the forest cover class's extraction. Several classification methods of Landsat imagery is investigated for mapping the mangrove forest. Comparisons of the classified maps are analysed and the optimum classification for change assessment is determined. **Chapter 4** discusses the methods of assessing the mapping accuracy and the selected assessment of the classification performance of the respective satellite data analysis. Overall classification accuracy and Kappa Coefficient statistics are derived. Factors affecting classification accuracy are also discussed. **Chapter 5** describes the approaches of change detection. The postclassification comparison approach is used to derive forest cover change. The changes are identified and summary statistics of change are produced using maps, tables and change matrix. The factors influencing change are elaborated. Results of change assessment are affected by the positional and thematic errors are also discussed. **Chapter 6** provides the outline of setting up and maintaining the appropriate monitoring scheme after analysing the actual situation. This monitoring scheme will allow Bangladesh Forest Department for proper execution of monitoring of Sundarban Reserved Forest based on satellite imagery. **Chapter 7** presents the research findings, highlights the research limitations and provides recommendations for establishment and maintaining of monitoring effort using satellite imagery.

Chapter 2

Study area and research data acquisition

2.1 Location of the study area

The study analyses the forest cover of an area of natural mangrove forest of Sundarban Reserved Forest located in the southwest part of Bangladesh. The north east part of SRF, which stands between latitude 22°30'25''N and 22°15'35''N, longitude 89°26'E and 89°46'E is selected as study area (figure 2.1). The human communities, their agriculture and commercial activities surround the north part of the study area. The other parts surrounded with forests and rivers. Study area represents 8 compartments (25, 26, 27, 28, 30, 31, 32, 33) of the Chandpai and Khulna ranges and covered an area about 44,327 hectares of the SRF.

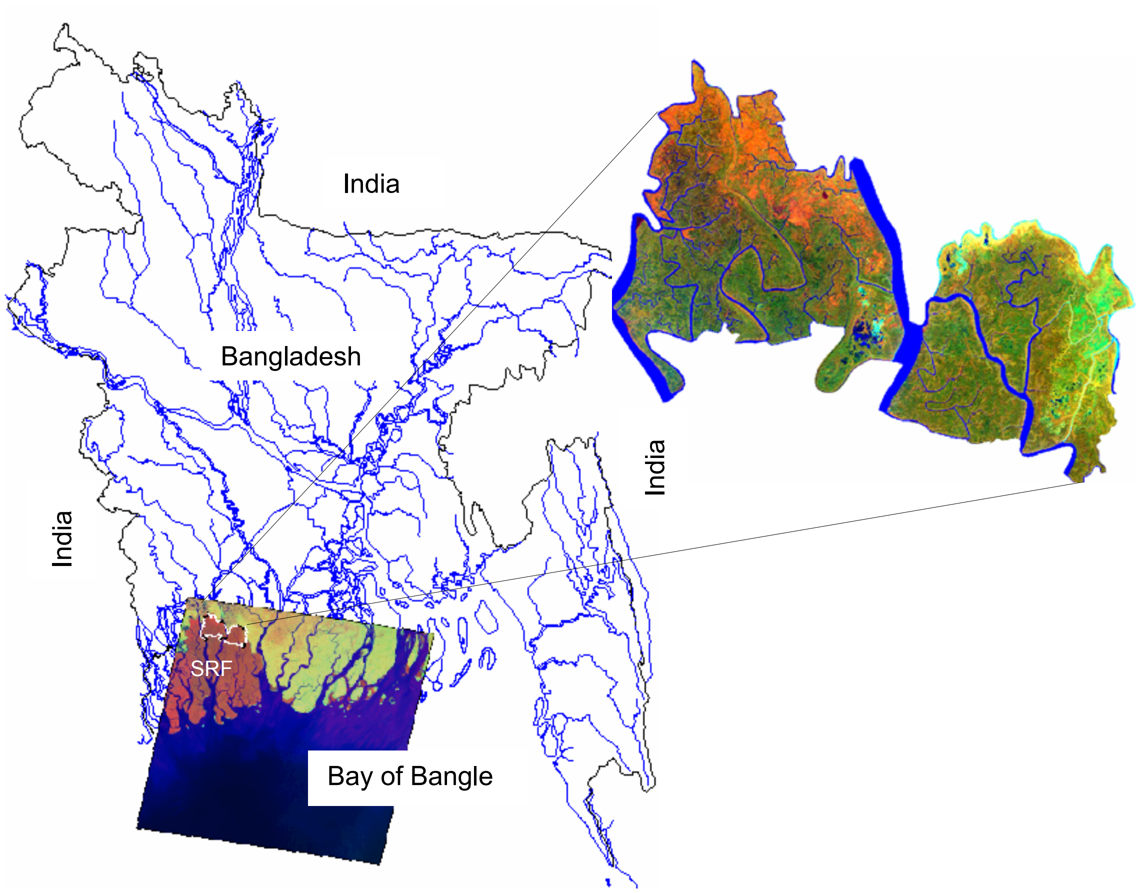


Figure 2.1: Location of study area in Sundarban Reserved Forest

Forest cover analysis requires detail information about the study area in order to interpret the remote sensing data and the results of changes that have occurred. The following sections describe the Sundarban as study area.

2.2 Characteristics of the Sundarban Reserved Forest

Figure 2.2: Sundarban Reserved Forest, Bangladesh

2.2.1 Topography

The Sundarban forms the southern most of the Ganges and Brahamaputra river deltas and is shaped by the complex drainage structure. Topographic variation within this delta is very low. The forest floor lies between 0.9 m to 2.1 m above sea level (Canonizado and Hossain 1998).

2.2.2 Geology

The SRF surface geology consists entirely of quaternary sedimentary layers of sand, silt and clay. Some studies in adjacent areas of Khulna and Barishal district confirmed earlier views that there was a sea level regression about 12000 years ago but there is now a trend in sea level rise, the effect of which may be exacerbated by relative stability to the west compared with active sedimentation accompanied by tectonic activity and ongoing subsistence to the east (Umitsu 1991).

The present delta is thought to be a combination of the Ganges delta, the old Brahmaputra-Megna delta and the Ganges-Jamuna-Meghna delta. It is difficult to determine the geomorphologic contacts of these deltas since these are obscured by deep sediments, which are overlain by very recent sediments. The Ganges is by far the greatest builder of the delta with estimates of 80% of the surface sedimentation coming from this source only (Khan 1991).

2.2.3 Soil

Soils of the SRF are derived from a mixture of deltaic floodplain deposits and tidal marine deposits. The surface soil is a silty clay loam overlying alternating layers of clay and sand. In general the soil fertility decreases from east to west and north to south. In the north and east portions of the SRF, relatively high fertility is maintained by annual silting (Canonizado and Hossain 1998, FAO 1998a). Silt appears to be the most common textural class and grain size is larger in the eastern forest than in the west. Pyrite may occur on localised depressions containing higher amount of organic matter. Presence of biotite, carbonates and feldspars may protect the soil from becoming acid sulphate where drainage is not impeded (FAO 1998a, Bhuiyan 1994).

Pedologically, soils of the SRF are very young, very poorly drained and poorly oxygenated (FAO 1998a). The percentage of organic matter appears to be generally low. It varies in the range 0.8 to 3.3% in top layer and 0.2 to 2.9% in bottom layers (Bhuiyan 1994). The soil pH varies from 6.8 to 8.4. But most soils fall in the alkaline pH range between 7.0 – 8.0 throughout the SRF (FAO 1998a).

2.2.4 Climate

The climate of SRF is divided into three distinct seasons, which are heavy monsoon rains, a cool winter and a dry season. The monsoon normally starts in mid May and continues until October. This is a time when mean temperature reach as 35°C with a maximum of over 40°C and with a relative high humidity (above 80%). During this season, short duration thunderstorms over the landmasses and severe cyclonic storms generated in the Bay of Bengal. Nearly 80% of the major storms, which strike the SRF occur during these months (FAO 1998a). The monsoon declines with a change in wind direction in cool winters, which last until February. During this time rainfall, temperature and relative humidity remain low. The dry season is short which is from March to April. During this period gradual rise of temperature to levels often above 35°C which introduces low pressure system and monsoonal conditions of the rains.

2.2.5 Hydrology

The open hydrological system of SRF encompasses global, regional and local factors due to shared catchments, shared access and global hydrological cycles. This holistic view of hydrology leave it inextricably linked to upstream water shades, shared drainage lines and natural and manmade processes in the Bay of Bengal and along the SRF's long western boundary.

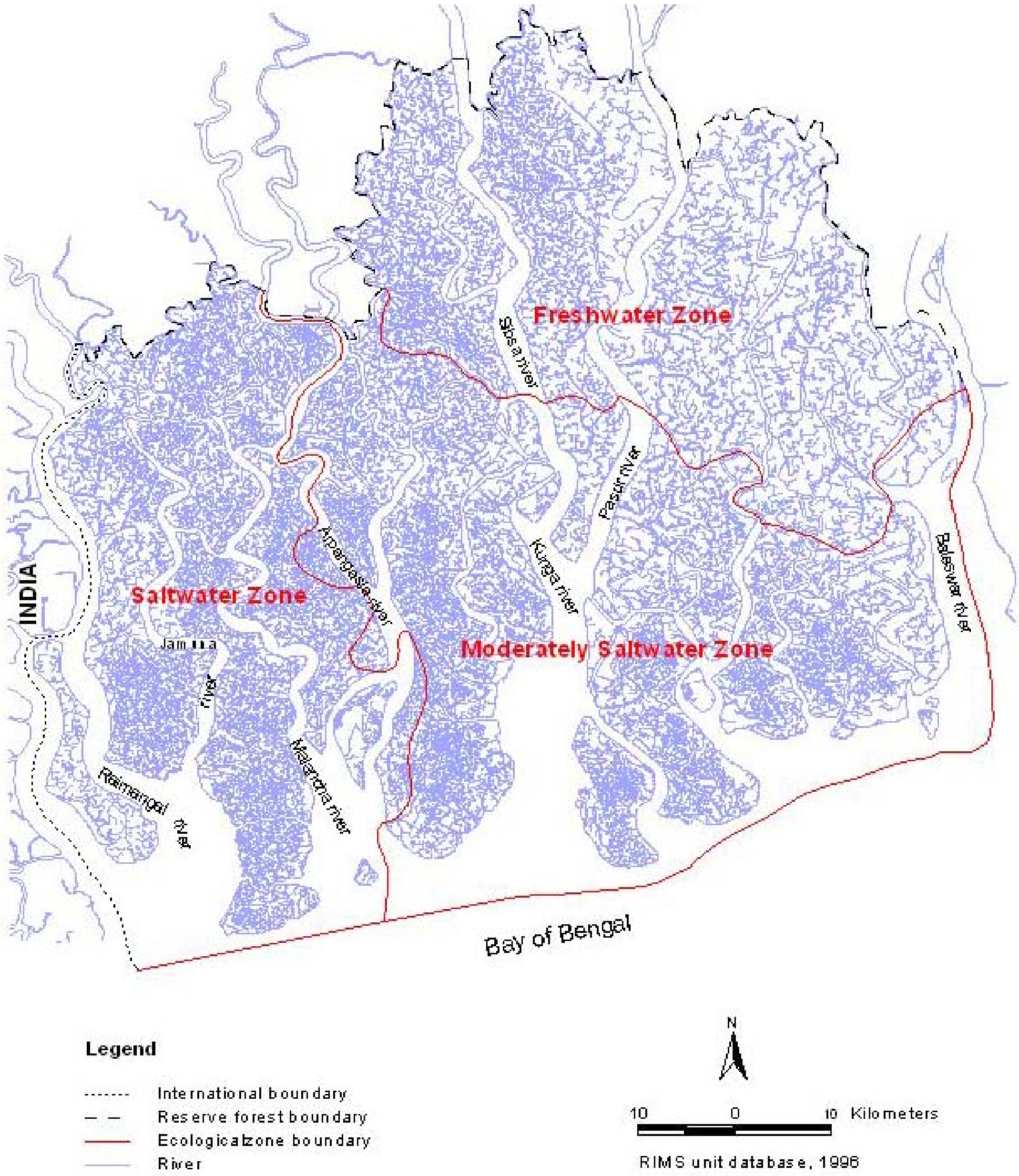


Figure 2.3: Map displaying the rivers and the ecological zones within the SRF

The SRF drainage system has three sub systems to the east, centre and west, which formed the estuaries of Bangra, Kunga and Raimangal. The whole area is dissected by large tidal river, notably the Baleswar, Passur, Kobadak-Sibsha, Arpangasia and Raimangal with innumerable small channels and creeks (figure 2.3).

Tides affecting the SRF are predominantly semi diurnal with a tidal period of about 12 hours 25 minutes. It takes approximately 2.5 hours for the tide to traverse the SRF. From the coast the tide flows the main estuaries, the Raimangal, Jamuna, Malancha, Passur, Sibsa and Balewar rivers. From these main rivers, the tidal waves spread into the smaller tidal channels (FAO 1998a). Based on the river flows inside the SRF are classified by three different series. They are Raimangal-Sibsa series, Passur-Sibsa series and Passur-Baleswar series.

2.2.6 Ecological zone

The relative site preferences of the various mangrove species are essentially passive in that they reflect differing degrees of tolerance of water logging and salinity (Chaffey et al. 1985). The proportion of salinity and the distribution of tree species composition define the zonation of SRF. These are the freshwater zone, moderately saltwater zone and saltwater zone (figure 2.3) (Chaffey et al. 1985). Sundri (*Heritiera fomes*) is the characteristic species of the freshwater zone. The zone provides good conditions for the abundance of sundri. The forest of the moderately saltwater zone is mixture of gewa (*Excoecaria agallocha*) and sundri with varying amounts of goran (*Ceriops decandra*) and other species. The forest in the saltwater zone is dominated by goran with a diapered overstorey of gewa (*Excoecaria agallocha*), passur (*Xylocarpus mekongensis*) and dhandal (*Xylocarpus granatum*).

2.2.7 Vegetation

The emergent stratum of east of SRF where the freshwater is available often occupied by sundri (*Heritiera fomes*) and interspersed with gewa (*Excoecaria agallocha*), kankra (*Bruguiera gymnorrhiza*), baen (*Avecennia officinalis*), passur (*Xylocarpus mekongensis*). Below to this, the stratum is either composed of pure sundri or a mixture of gewa and/or kakra. In this stratum, tree crowns of the canopy are usually tall and narrow and form a continuous layer. The next stratum consists of saplings of the canopy trees and medium sized trees and amur (*Amorra cucullata*) with occasional appearance of shingra (*Cynometra ramiflora*). Frequently, trees in the upper canopy have spreading branches while tree crowns in the lower strata are mostly slender. Light demander species usually form pure stands such as keora (*Sonneratia apetala*) (FAO 1998a, IUCN 1994). The forest canopy with scattered dominants attaining a height of up to about 15 to 20m and stem diameters are generally less than 20cm at breast height. But the dbh can reach up to 45 cm in favourable site condition (Zabala 1990). Gewa is the dominant woody species in SRF south, which an area of moderate salinity. It is often mixed with sundri. The canopy height is generally less then 10m, although species such as sundri, passur, dhandal and baen may attain a greater height. It is also frequently associated with a dense understorey of goran and passur. SRF west, in areas, which support sparse gewa and dense stand of goran and discontinuous patches of hantal palm (*Phoenix paludosa*) on drier ground and riverbanks. The goran grows predominantly in saline areas and is generally reaches a height about 4m.

2.2.8 Significance of the SRF

SRF has a great significance from the economic and ecological context of Bangladesh. This forest is rich in biodiversity along with a great variety of wild life. Sundarban Forest contains a considerably high floral diversity. There are about 334 plant species available in SRF. According to Seidensticker and Hai (1983) 62 principal plant species of 53 genera were found in the Sundarban. This forest has been an important source of timber, fuelwood, pulpwood and many non-timber forest products like, thatching materials, honey, wax and fish. According to an Economic and Social Commission for Asia and the Pacific (ESCAP) survey, 500,000 to 600,000 people depend directly on the Sundarban for their livelihood (ESCAP 1988). There are several commercial and industrial enterprises in the vicinity of the forest which dependent on the forest products. Furthermore, this forest is protecting and stabilizing the coastal areas and as well as serving as safeguard to the local peoples from cyclones, tidal surges are living around to the coastal areas.

The more prominent and important tree species found in the SRF includes the sundri (*Heritiera fomes*), gewa (*Exoecarea agallocha*), keora (*Sonneratia apetala*), goran (*Ceriops roxburghiana*), singra (*Cynometra ramifloral*), garjan/jhana (*Rhizopora mucronata*), dhundal (*Xylocarpus granatum*), amur (*Amoora cucullata*), passur (*Xylocarpus mekongenesis*) and kankra (*Bruguiera gymnorhiza*). Sundri is a fairly sized tree species, which has a wood that is durable and good for poles, posts, rafters, masts, oar handles and planking. Gewa is a medium-sized tree, the wood of which is the main raw material of the paper mill and match factories in Khulna district. This tree is also suitable for box planking and dunnage in ships. Keora is a tall tree and its timber is extensively used for baling boards in packing paper. It is also suitable for box planking, bobbins and centering in building construction. Goran is widely used for fuel wood as well as small house posts, cores of mud walls and fencing. Bark of this tree yields tannin. Singra is the most popular fuel wood in the Sundarban. Amur is much sought after for small house post. Garjan, dhundal, passur and kankra are rich in tannin.

The more prominent and important palms available in the Sundarban Forest include golpatta (*Nypa fruticans*), hantal (*Phoenix paludosa*). Golpatta is widely gathered for thatching material. Hantal is used extensively in the construction of small huts as roof rafters and frame of walls.

The important grasses exist in SRF are Sungrass (*Imperata* spp.), hogla (*Typa elephantine*), nalkhagra (*Orundo karka*). Sun grass is widely gathered for thatching in addition to being the main fodder species for deer's in the wildlife sanctuaries. Hogla, a bulrush is gathered and split for cheap fencing. Nalkhagra grass is used extensively for making mats.

The important shrubs available in SRF are hargoja (*Acanthus ilicifolius*), hodo (*Acrostichum aureum*), ora (*Sonneratia acida/caseolaris*). Hargoza, hodo together with ora are stream bank protection species by holding deposited silt and clay with their numerous roots. They are prominently growing along riverbanks in the interior areas of the wildlife sanctuaries.

Like on floral diversity, SRF is rich also in faunal diversity. It possesses three wildlife sanctuaries; namely Sundarban south, Sundarban east and Sundarban south. Sundarban provides a habitat for more than 450 animal species: 40 mammal species including 5 species of whales and dolphins, more than 270 different species of birds, 45 species of reptiles, 120 species of fish, including species of rare shark (Anon, 2001). SRF is the unique natural habitat of the world famous Royal Bengal Tiger (*Panthera tigris*), spectacular spotted deer (*Axix axix*), jungle fowl (*Gallus sp.*) and rhesus monkey (*Macaca mulata*). Over 270 species of birds have been recorded in the Sundarban including 95 species of waterfowl. Common residents include *Phalacrocorax niger, Anhinga melanogaster, Ardeola grayii, Bubulcus ibis, Butorides straiatus, Egretta gargetta, E. intermedia, E. alba, Esacus recurvirostris, Vanellus indicus, Gelochelidon nilotica* and *Sterna acuticauda*. The area is also ecologically important as a staging and wintering area for migratory shore birds, gulls and terns (Rahman and Banu 2000).

Fishes, shrimps, lobsters, crabs, sea snakes, crocodiles and turtles (green and olive) are very profile in the entire sundarban. The water bodies of SRF support a very rich and diverse fish fauna of which 120 species are of commercial importance. The most important species are *Eleutheronema tetradactylum*, *Polynemus paradiseus*, *Liza tada, Mystus gulio, Hilsa ilisha, Ilisha megaloptera, Coilia ranncarati, Lata calcarifer, Septipinna phasa, Thrysa purava, Harpodon nehereus* etc (Rahman and Banu 2000).

SRF has been for quite sometime a favourite eco-tourism area to foreign and local tourists as this forest have several unique and interesting attributes for domestic and international eco-tourism. During the winter and spring seasons in every year, tourists tour the SRF by boat, viewing from the boat the landscape, the vegetation, the birds, some mammals, sometimes a tiger, the mellifluous wide rivers, the dreary but dreadful narrow channels, partaking the cool, fresh and healthful breeze.

2.2.9 Legal status

There is a long and varied chronicle of legal status of the mangrove forest recorded as far back as the mughul period (1203-1538) when the area was leased to local kings (IUCN 1994). Records on reclamation, forest clearing and settlement stem from the late eighteenth century and the first management legislation was the charter of Indian Forests and Forest Act which declared the Sundarban as reserve forest by the government of British India in 1875-76 under the Forest Act of 1855. Subsequently the systematic management became official policy (FAO 1998a). Heinig (1892) in his working plan described important events in the legal background for establishing the Forest Act of 1927 that makes provision for reserved forests and their legal position. The boundaries of the reserved forest were all natural with minor exceptions. After the partition of India in 1947, the Pakistan portion of the Sundarban became a forest division, which later became a gazetted area of reserved forest under the Bangladesh Forest Department.

In 1994, the National Forest Policy was formulated and provided the foundation for all future policy, acts and rules, which are used to govern the administration of the SRF. There are other 11 principal policies and legislation that also affect the integrated forest management in SRF.

2.2.10 Management Units

The basic management unit in the SRF is the compartment. All the management prescriptions are formulated on a compartment basis. There are 55 compartments in the four forest ranges of SRF. Khulna, Chandpai, Sarankhola and Satkhira ranges are clearly demarcated by the natural features such as rivers, canals and creeks. Table 2.1 and the figure 2.4 are showing the distribution of compartments among the four ranges of SRF.

Table 2.1: Ranges and distribution of compartments in SRF

Name of the ranges	Area of Ranges (ha)	Compartment number
Sarankhola	130,998	1,2,3,4,5,6,7,8,11,12b, 24, 45
Chandpai	100,021	9,10,11,12a, 13, 14, 15, 21, 22, 25, 26, 27, 28, 29, 30, 31,
Khulna	161,345	16,17,18,19,20,32,33,34,35,36,37,38,39,40,43,44
Satkhira	184,992	41,42,46,47,48,49,50a, 50b, 1a, 51b, 52, 53, 54, 55

Source: Canonizado and Hossain (1998).

The Forest Department maintains permanent offices throughout the SRF. These are range offices, field stations and patrol posts. Seasonal stations are set up during harvesting periods of Goran (*Ceriops decandra*) and Golpatta (*Nypa fruticanns*) resources.

2.2.11 Existing forest management

The present management plan was formulated for the SRF up to the year 2010, after the completion of the inventory in 1996. The main objectives of the management plan are sustainability, conservation and protection of the forest. Thus, different management prescriptions for the operations e.g. annual allowable cut, non-timber forest product extraction etc. have been suggested in order to meet the objectives of management plan.

The forest management system of SRF is based on the division of the management unit into working circles, which have specific management objectives (Cannonizado and Hossain 1998). Prior to the latest management plan this consists of

i) Sundri working circle – timber production

ii) Gewa working circle – industrial wood production

iii) Fuelwood working circle – production of fuel wood (Goran, Bhola, Singra and others)

iv) Golpatta (palm) working circle – production of thatching materials

v) Wildlife and recreation working circle – recreation and tourism, game reserves, and preservation of biological diversity

vi) Aquatic resource working circle – Covers the water body of Sundarban (Fish, Crustaceans, Mollusks and others

vii) Keora working circle – timber production (indoor planks, furniture, boxes)

viii) Miscellaneous working circle – other forest products (honey/bees wax, hantal (palm), grass, cane and other minor products).

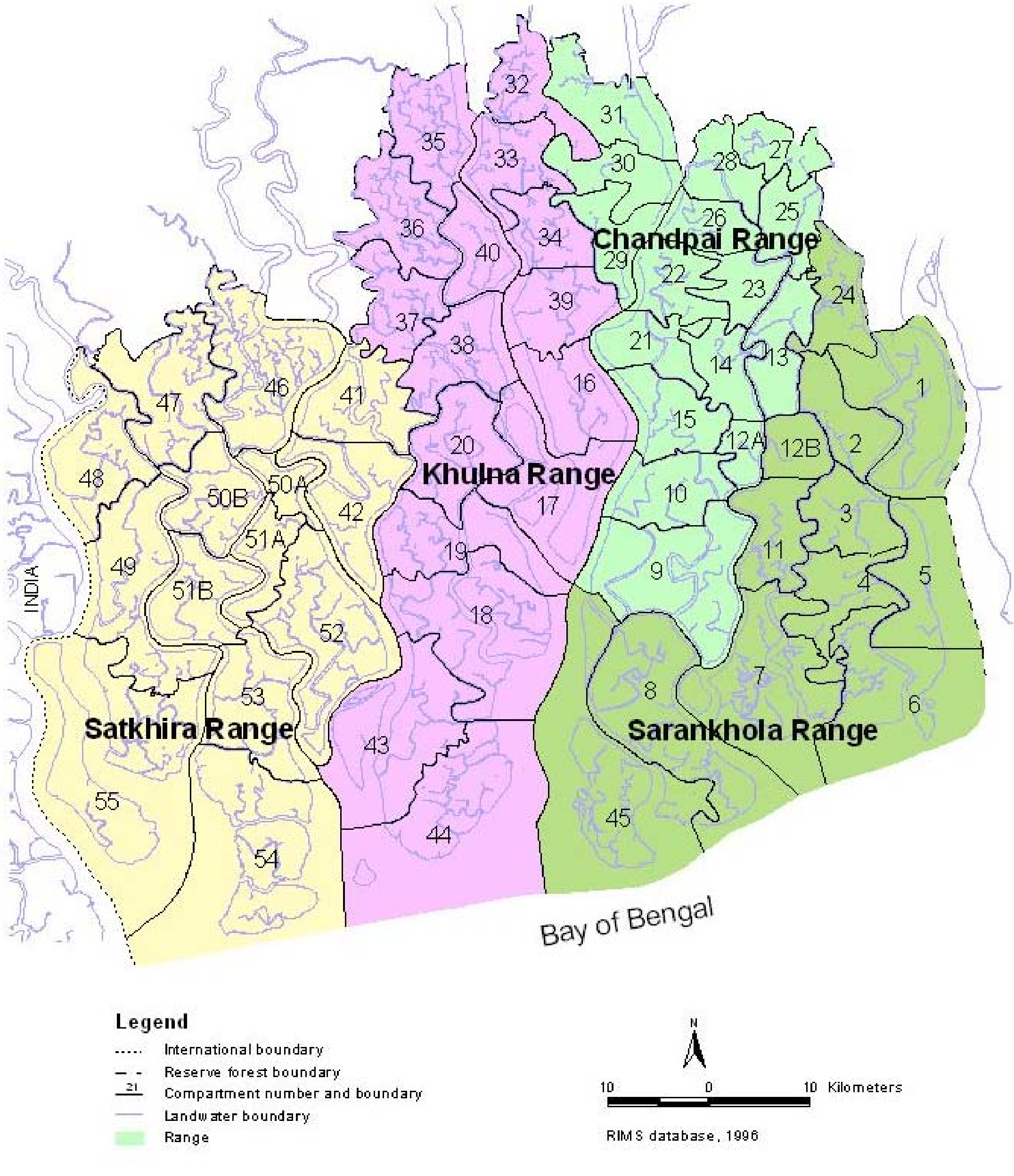


Figure 2.4: Figure showing the ranges and the compartments within SRF

2.3 Previous remote sensing initiatives for the management of SRF

The initial database of SRF was prepared based on the result of stereoscopic interpretation of black and white aerial photography of the year 1981 in scale 1:30,000 for forest inventory and mapping and forest type map of 1985 in scale 1:50,000 were produced under the project of Overseas Development Agency (ODA) of Bangladesh Forest Department. The land water boundary and rivers in the forest were mapped by the visual interpretation of multispectral SPOT satellite imagery of 1989 (Chaffey et al. 1985).

Later the database of SRF was updated using black and white aerial photograph of the year 1995 in scale 1:15,000 under the Forest Resources Management Project (FRMP) of Bangladesh Forest Department funded by World Bank. At that period a detailed inventory was conducted for the forest and the growing stocks was assessed to formulate a management plan. Also forest classification maps of 1995 in scale 50,000 were derived from the field survey and stereoscopic interpretation results of aerial photography.

The Resource Information Management System (RIMS) unit of Bangladesh Forest Department has been upgraded in 1995 under the World Bank project FRMP aiming to assist in forest management and planning of the forest resources. Accordingly the unit is equipped with Geographical Information System (GIS) and Remote Sensing (RS) hardware and software to solve the complex management problems. The unit built the digital database of SRF during 1996-98, which includes the detailed vegetation classes, their standing volume, detailed river networks, office locations, compartment, block and range boundaries, wildlife sanctuary boundary etc. Integrating forest inventories, photo interpretations and existed various map sources were the main inputs of the database (Runkel 1997). Further update of the RIMS database for the forest was not conducted, though the extraction of the forest resources legally or illegally is common all the year round.

2.4 Spectral characteristics of vegetation (in satellite imagery)

The launch of Landsat 1 in 1972 was the beginning of satellite based remote sensing for monitoring earth resources application (Coppin and Bauer 1996). The Landsat missions provided the longest period of Earth observation by a specific satellite system. More than 30 years since the launch of Landsat 1, 7. It is Landsat 7 with its ETM sensor system, which continues to provide multispectral imagery of the earth for applications in various fields of research (Goward and Masek 2001). The archives of landsat imagery are also extensively using in the assessment of land cover change (Caccetta et al. 2000; Rechards and Furby 2002).

Various vegetation types have different characteristic properties with respect to the response of the reflected energy (radiation). The reflectance characteristics of vegetation depend on the properties of the leaves including the orientation and the structure of the leaves canopy. The proportion of the radiation reflected in different parts of the spectrum depends on the leaf pigmentation, leaf thickness and structure (cell structure) and on the amount of water in the leaf tissue. In the visible portion of the spectrum the reflection of blue and red light is comparatively low since these portions are absorbed by leaf pigments in the plant, mainly by chlorophyll for photosynthesis and thus for biomass production. Vegetation reflects a relatively maximum of green light in the visible spectrum. The reflectance in the near infrared is highest but the amount depends on the leaf development and the cell structure of the leaves. In the middle infrared the reflectance is mainly determined by water stored in the leaves result is less reflectance. The reflectance is lower than in NIR, especially with two absorption bands of water in the ranges of approximately 1.4 and 1.9 μm wavelength (figure 2.5) (Lillesand and Kiefer 2000).

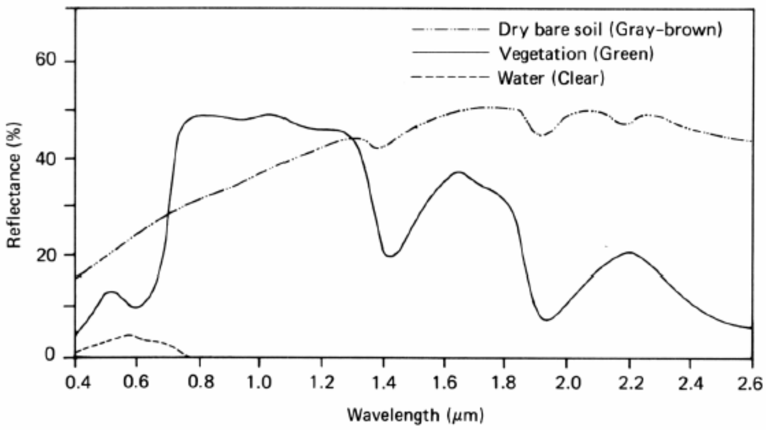


Figure 2.5: Spectral reflectance of different natural surfaces (Lillesand and Kiefer 2000)

Different species respond differently to electromagnetic radiation (Verbyla, 1995). The estimations of relationships between spectral values and species distributions is useful for the purpose of indicating areas of species diversity and can be applied over a large spatial extent. Remote sensing data of adequate spectral resolution are used to distinguish between plants of different species. Digital approaches to satellite data interpretation rely upon the development of analysis techniques, which utilize the unique quantitative characteristics of the digital data.

2.5 Data collection for study area

2.5.1 Landsat Imagery

Landsat ETM of 26^{th} November of the year 2000 was obtained from RIMS unit of Bangladesh Forest Department. Landsat TM data of 12^{th} January of the year 1989 was acquired from the web based data archives of the Global Land Cover Facility (GLCF). This data is offered by the USGS and University of Maryland for natural resources research. Data specifications are described in table 2.2 and 2.3.

Table 2.2: Satellite imagery and its specifications used for bi-temporal change detection of SRF

Sensor mode	Sensor	Platform	Date	Path/row	Band	Spatial resolution
Pan and MS	ETM+	Landsat 7	26-11-2000	138/43	1-5, 7 6 Pan	28.5m 59.5m 14.5m
MS	TM	Landsat 5	12-01-1989	138/43	1-5, 7 6	28.5m 59.5m

Table 2.3: Landsat specification

	Spectral Resolution	
Band	**TM**	**ETM**
1 (Blue	0.45-0.52 μm	0.45-0.52 μm
2 (Green)	0.52-0.60 μm	0.53-0.61 μm
3 (Red)	0.63-0.69 μm	0.63-0.69 μm
4 (Near IR)	0.76-0.90 μm	0.78-0.90 μm
5 (Middle IR)	1.55-1.75 μm	1.55-1.75 μm
6 (Thermal IR)	10.4-12.5 μm	10.4-12.5 μm
7 (Middle IR)	2.08-2.35 μm	2.09-2.35 μm
8 (Panchromatic)		0.52-0.90 μm
Swat width of TM and ETM	185 km	
Revisit capability of TM and ETM	16 days	

Source: NOAA 2005

2.5.2 Geometric information of the data sets

The images obtained for the study were rectified and geo-referenced to the World Geodetic System 1984 and projected to the Universal Transverse Mercator (UTM) map projection system (zone 46). The projection was changed to Bangladesh Transverse Mercator (BTM) system during research with the following specification

Spheroid	Everest
Datum	Indian (Bangladesh)
Scale factor at central meridian	.9996
Longitude of central meridian	90 E
Latitude of origin of projection	00 N
False easting	500000m
False northing	-2000000m

2.5.3 Ancillary data

Table 2.4 presents the additional spatial databases acquired from Bangladesh Forest Department, which supported image analysis for the research.

Table 2.4: Ancillary vector data available for the study

Description of the vector data	Format	Purpose for this research
1. Compartment boundary	Digital	To subset the study area from satellite data
2. Vegetation data layer of aerial photo interpretation of the year 1995	Digital	To have an preliminary idea about the vegetation types of the SRF
3. Office locations	Digital	To place the offices into study area map
4. Ecological zone boundary	Digital	To show the ecological zones into SRF map
5. Range office boundary	Digital	To display the ranges into SRF map
6. River networks	Digital	To prepare a map for SRF for viewing the rivers

2.7 Summary

The north-eastern part of the SRF was selected as study area because this section is subjected to considerable change in forest cover both in term of change in species distribution as well as deforestation during the last decade.

Analysis of forest cover classes of remote sensing data requires good in-situ knowledge of the study area. In this regard, a brief description of the SRF ecosystem, its significance, management etc. has been provided in this chapter. Previous initiatives to assess the forest cover of SRF have been taken place using the aerial photography of 1981 and 1995 under the frame of project by the Bangladesh Forest Department are also discussed.

This study used multispectral satellite imagery to assess and monitor the study area of SRF. For this purpose geometrically and radiometrically corrected Landsat ETM and TM imagery was obtained for the study. Data specifications and spectral behaviour of vegetation are provided for an understanding of specific properties of the Landsat satellite imagery.

Chapter 3

Image preparation, analysis and mangrove forest mapping

3.1 Introduction

Satellite data preparation is essential to establish a more direct linkage between the data and biophysical phenomena. It requires several processing steps for better identification of the image features. Image processing of remotely sensed data for feature identification relates to the range of image enhancement and information extraction procedures. The goal of image enhancement is to improve the interpretability of an image by increasing the apparent distinction between features (Lillesand and Kiefer 2000). A wide range of enhancement techniques is available from simple contrast stretching to transformation images as a precursor to subsequent digital image analysis. The ideas behind the transformation of remotely sensed image are

- To reduce the number of information channels,
- To attempt to transform the information content of interest into the reduced number of bands (Franklin 2001).

The research takes consideration of the atmospheric correction of the data sets as several studies on the assessment of changes in land cover indicates any omission of atmospheric correction during temporal assessment will give unreliable results (Jensen 1996, Hadjimitsis et al. 2004). Within research study the processing techniques followed to the extent necessary to provide data of consistent quality suitable for land cover classes identification. Contrast stretching and formation of colour composite were performed as an aid in identification of the cover classes. The fusion techniques for Landsat ETM, Normalized Difference Vegetation Index for the Landsat ETM and TM imagery were examined in order to identify the classes investigated for the study area.

Evaluation of the information content of remotely sensed data and its application to land cover mapping relies upon careful definition of the land cover classes. Remote sensing spectral properties combining with the ground information, a classification system was generated for the study area. Much attention has been directed towards the development of signatures for the classes form training samples and spectral separability of the corresponding classes. Supervised classification was applied to several methods and investigated their reliability in identifying the level III classes from the Landsat ETM and TM imagery.

3.2 Atmospheric correction

Several factors independent of ground cover can significantly affect spectral reflectance as measured by the sensor. Electro Magnetic Radiation (EMR) used for remote sensing passes through atmosphere of the earth. The effects of the atmosphere on the signal are mainly caused by scattering and absorption. They vary with the path length, the atmospheric conditions and the wavelength. Atmospheric absorption results in the loss of energy to atmospheric constituents. Scattering, the redirection of electromagnetic energy by particles suspended in the atmosphere, is the reason why the radiation arriving at the sensor consists of the following components (Campbell 1996, Lillesand and Kiefer 2000):

- radiance reflected from the earth's surface
- radiation scattered directly to the sensor without reaching the earth's surface
- radiation scattered to the ground (diffuse radiation, skylight) being reflected to the sensor
- surface-reflected radiation, partly scattered both directly to the sensor and to the ground.

Thus a sensor will receive not only the directly reflected or emitted radiation from a target, but also the scattered radiation from a target and the scattered radiation from the atmosphere, which is called path radiance (Lillesand and Kiefer 2000).

De Haan et al. (1991), Cracknell and Hayes (1993), Campbell (1996), Jensen (1996) describe and attempt to categorise several atmospheric correction methods. There are two major categories, absolute correction and relative normalisation. Absolute corrections include image based atmospheric corrections, which have been performed for the Landsat imagery in this study. Many correction methods have been proposed in several studies to remove the atmospheric effects. Song et al. (2001) made evaluation of several correction methods based on land cover classification and change detection accuracies applied on a multitemporal dataset of seven Landsat TM images. They found that the best overall results with respect to their impacts on image classification and change detection accuracies were achieved using the simpler DOS (Dark Object Subtraction) method, rather than the more complex atmospheric corrections that combine both atmospheric models and the Dark Pixel (DP) principle.

DOS is perhaps the simplest and most widely used image based atmospheric correction approach for classification and change detection applications (Campbell 1996, Schowengerdt 1997, Song et al. 2001). However, there is no commonly accepted correction for Landsat data for operational applications at regional scale. Thus in this study it has been decided to perform the DOS method for atmospheric correction.

3.2.1 Dark Object Subtraction method

Atmosphere has an additive effect on brightness to the overall image, resulting in higher Digital Number (DN) values reducing the contrast. For the correction of each band the minimum DN value is estimated as atmospheric contribution and subtracted from each band on a pixel-by-pixel basis resulting in left shifted histograms with minimum values of zero as shown in figure 3.1. This procedure is also known as haze removal method (Sabins 1987, Jensen 1996).

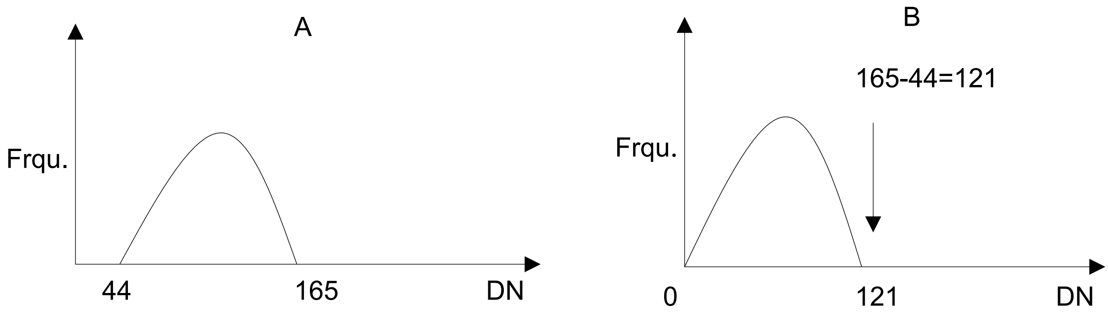
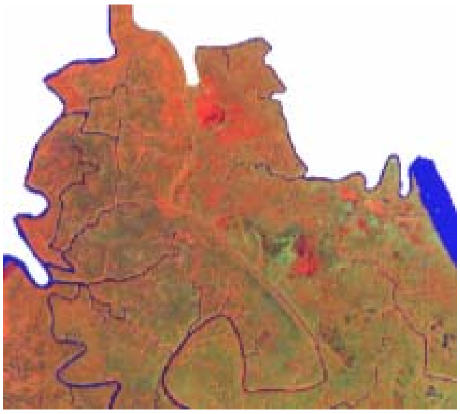


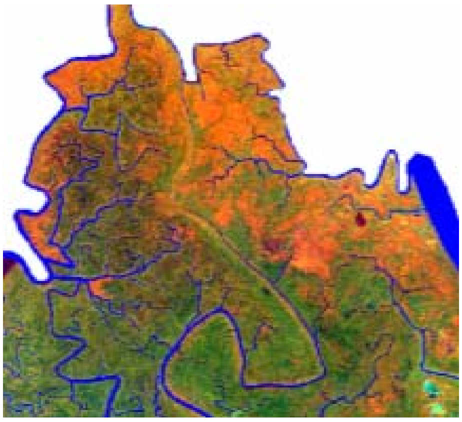
Figure 3.1: Atmospheric Correction per band: (A) original histogram, (B) resulting change.

This method has been applied in both Landsat TM and ETM images of the study area. Each band of a scene is shifted by the respective DN value, which finally produces a better quality images compared to the respective colour composite images (figures 3.2).

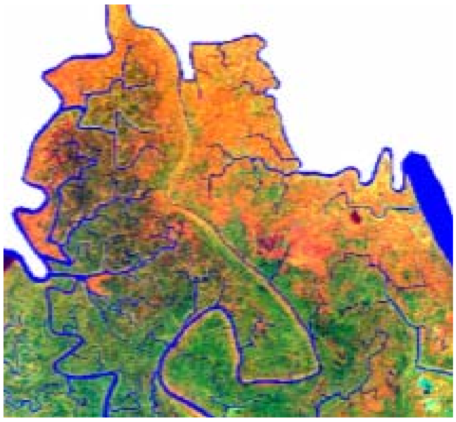


Colour Composite of the study area compiled from Landsat TM bands (4, 5, 3) (1989)

Atmospherically corrected Landsat TM imagery (bands 4, 5, 3) (1989)



Colour Composite of the study area compiled from Landsat ETM bands (4, 5, 3) (2000)



Atmospherically corrected Landsat ETM imagery (bands 4, 5, 3) (2000)

Figure 3.2: Subsets of atmospherically corrected images with the corresponding colour composites of study area

3.3 Image analysis support functions

3.3.1 Image fusion

Image fusion can be considered as the combination of two or more different images to form a new image by using algorithms (Van Genderen and Pohl 1994). Data fusion techniques have emerged as key tools for visualisation as well as providing improvements in classification accuracy, image sharpening, data substitution, change detection, geometric correction and overcoming data gaps due to clouds (Solberg 1999, Pohl and Van Genderen 1998). In general, image fusion methods can be grouped into two classes: (1) colour-related and (2) statistical/numerical methods

(Pohl and Van Genderen 1998). This study attempts to use the colour-related Intensity Hue Saturation (IHS) and the statistical Principal Component Analysis (PCA) method for checking the performance in defining the various land cover classes of study area. Fusion techniques are implemented to monitoring coastal zones by means of remote sensing all over the world. Due to its spatial enhancement detailed land use distribution was performed with a good percentage of reliability and was then used for setting up new coastal zone plans (Guerra 2003). For this study higher resolution panchromatic band (14.5m) were merged with the respective multispectral bands (28.5m) of Landsat ETM in order to produce high resolution image, while the spectral resolution of medium resolution multispectral image is preserved in the final IHS and PCA fusion image.

3.3.1.1 IHS fusion

Intensity Hue Saturation (IHS) has become a standard procedure in image fusion (Chavez et al. 1991, Ehlers 1991, Shettigara 1992, Zhang 1999). This technique was successfully applied in several studies in forest cover mapping. Leckie (1990) used SAR and optical data together in a forest type discrimination study in northern Ontario that was aimed at separating general species classes, and got significant benefit in forest cover mapping. This technique was also used to combine multitemporal ERS-1 and mutispectral Landsat TM data and thus increased the classification accuracy of the Swedish land cover maps (Michelson et al. 2000). Pellerin et al. (2004) used Landsat TM data with Spot HRV pan data to establish a classification of river Tavares mangrove vegetation in Santa Catarina Island, Brazil and experienced minimal distortion of spectral visible characteristics of the fusion data, which offered more accurate mapping for the vegetation. Prasad et al. (2001) examined IHS method in identifying the forest classes as well as non forest areas of Pathri reserved forest in Uttaranchal, India and found distorted the spectral characteristics of the forest classes.

IHS method transforms data from RGB space into their related intensity, hue, and saturation components, where intensity refers to brightness of colour, hue refers to the dominant or average wavelength of light contributing to a colour, and saturation specifies the purity of a colour (Jensen 1996, Sabins 1997, Pohl 1999).

The IHS images can be expressed as described below.

$$I = \frac{1}{3}(R + G + B) \tag{3.1}$$

$$S = 1 - \frac{3}{(R + G + B)}[\min(R, G, B)] \tag{3.2}$$

$$H = \cos^{-1}\left[\frac{\frac{1}{2}[(R - G) + (R - B)]}{\sqrt{(R - G)^2 + (R - B)(G - B)}}\right] \tag{3.3}$$

where $R\ G\ B$ stands for red green and blue respectively.

During IHS transformation, bands 2,3,4 were used because these bands most closely covered the same portion of the electromagnetic spectrum as the panchromatic image (Ghassemian 2001). The steps followed to produce an IHS fusion image are highlighted in figure 3.3.

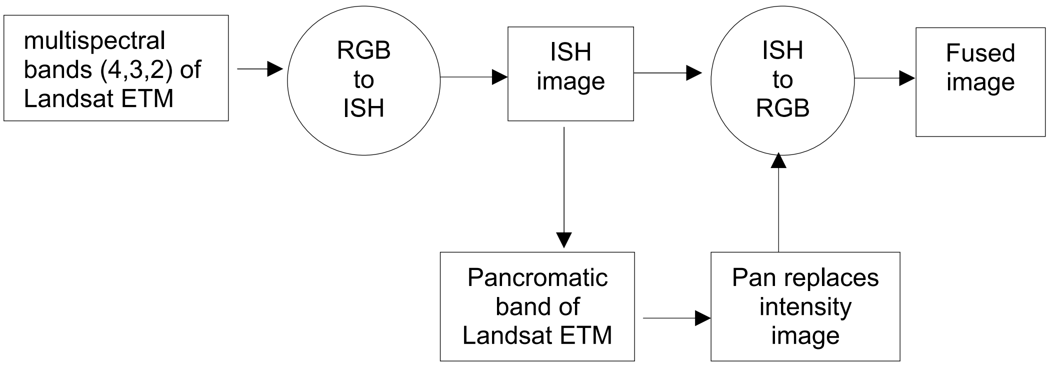


Figure 3.3: Steps followed during IHS transformation

3.3.1.2 PCA fusion

PCA is the most widely used technique for reducing dimension. The purpose of PCA is to compress all of the information contained in original n (any number) band data set into fewer then n new bands. Components are computed by linear combinations of the original images. None of the components is linearly correlated with the others because these n components are orthogonal. The total variance of original images is mapped onto new components. The first principal component (PC1) has the greatest percentage of the total variance and succeeding components (PC2, PC3,….,PCn) each contain a decreasing percentage of the total variance (Lillesand and Kiefer 2000, Wald 2002).

Several studies used PCA fusion and experienced the improvement of the classification accuracy of the natural vegetation as well as land cover types (Francis and Canisius 2003). Zhang (2002) found maximum increase in detail and minimum discrepancy of spectral properties of the land use types after PCA fusion. Prasad et al. (2001) used PCA fusion image for delineating the forest and non-forest areas of Pathri reserved forest in Uttaranchal, India and moreover used it successfully in determining the forest classes and canopy density.

PCA was used in this research for two purposes; that is to reduce data dimension and to implement data fusion. PCA transforms the original Landsat ETM dataset (bands 1-5 and 7) into a new coordinate set to reduce the data dimension. The first principal component (PC1) is highlighting the overall brightness. It has the largest percentage of the overall data variance and contains most of the relevant information inherent to a scene. The following principal components, from component number 2 to 6 contain a decreasing percentage of total data variation (Table 3.1). The higher components appeared noisy because they contained very little variance, much of which was due to noise in the original spectral data.

Table 3.1: Eigenvector and Eigenvalue from Principal Component Analysis

PC	ETM bands						Eigenvalue and %	
	Band1	Band2	Band3	Band4	Band5	Band7	Eig_val.	%
PC1	0.530	0.354	0.195	0.673	-0.136	-0.291	3478.83	88.21
PC2	0.389	0.364	-0.026	-0.106	0.126	0.830	402.94	10.22
PC3	0.322	0.481	-0.233	-0.616	0.117	-0.466	52.97	1.34
PC4	0.584	-0.583	0.457	-0.318	-0.093	-0.030	6.65	0.17
PC5	0.312	-0.392	-0.628	0.233	0.546	-0.047	1.32	0.03
PC6	0.162	-0.131	-0.551	-0.025	-0.804	0.083	1.03	0.03

The data fusion procedure based on the PCA approach integrated the Landsat ETM multispectral and the panchromatic band according to the following steps, which are also presented in figure 3.4:

a) transforming Landsat ETM multispectral bands into six Principal Components

b) re mapping the panchromatic image into the data range of PC1

c) substituting the PC1 with the panchromatic image and

d) applying an inverse principal components transformation to the data.

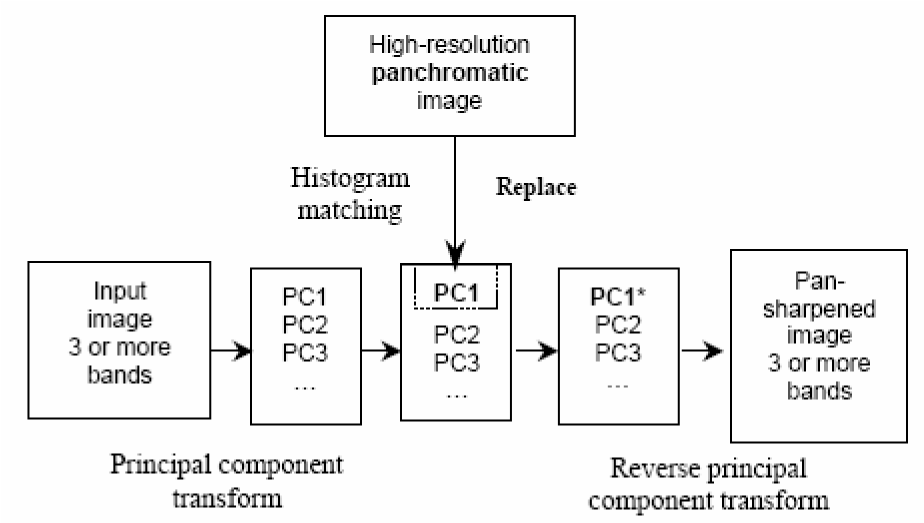
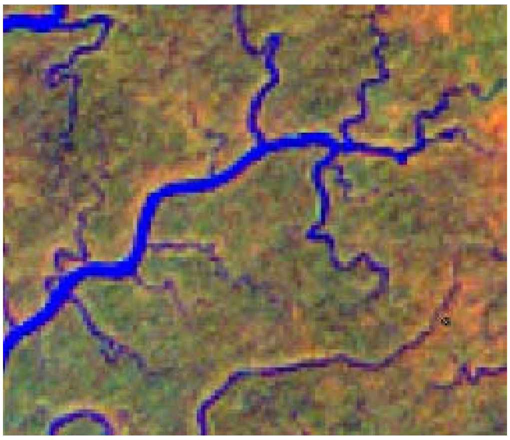


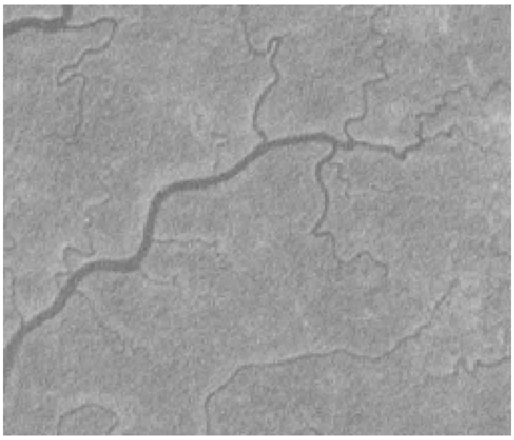
Figure 3.4: Flowchart of PCA image fusion (Zhang 2002)

3.3.1.3 Fusion image performance

Figure 3.5 compares the results of PCA and IHS data fusion with the original Landsat image data. The panchromatic image provided more detailed textural information due to its higher spatial resolution. Comparing the results of data fusion with the original Landsat ETM bands, it is clear that the river courses became smooth and also sharpened the edges of land and water boundary for the study area.

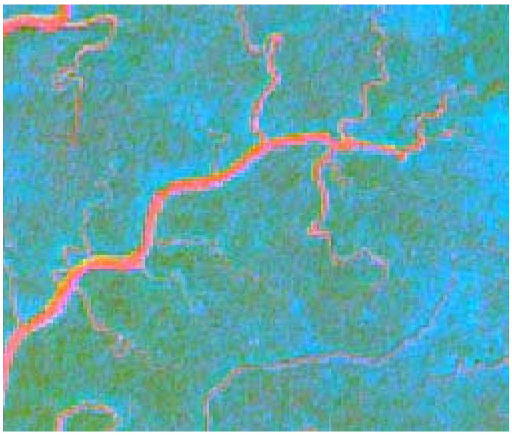


Colour composite map of Landsat ETM 4, 5, 3 as RGB of the original image (28.5m resolution)



Panchromatic band of Landsat ETM. (14.5m resolution)

IHS fusion image of the multispectral bands (used band 4, 3, 2 as RGB) and the panchromatic band of the Landsat ETM



PCA fusion image of the multispectral bands and the panchromatic band of the Landsat ETM

Figure 3.5: Landsat ETM composite bands, panchromatic band and IHS and PCA fusion images

3.3.2 Normalized Difference Vegetation Index (NDVI)

A Vegetation Index (VI) is a dimensionless, radiation based measurement computed from some spectral combination of remotely sensed data (Asner et al. 2003). As illustrated in figure 2.5 (chapter 2), healthy green vegetation generally reflects very little solar energy in the visible wavelengths (0.4 - 0.7 μm), with a sharp increase in reflectance in the near infrared wavelength region (0.7-1.1 μm). This unique spectral property is used in various indexes ranging in complexity from applying correlation coefficients to brightness values of a near infrared band to multi band rationing combined with complex algorithms (Jensen 1996).

In order to derive valuable information on vegetation classes NDVI values have been extracted from both Landsat ETM and TM imagery for the study. The NDVI is a common and widely used transformation for the enhancement of vegetation information (Rouse et al. 1973, Tucker 1979, Tucker et al. 1985, Nogi et al. 1993, Riano et al. 2002). NDVI has been used to measure vegetation cover characteristics and incorporated into many forest assessment studies (Wulder 1998, Tole 2002, Roy and Joshi 2002, Levent and Scot 2003). It can be used for accurate description of land cover, vegetation classification and vegetation phenology (Tucker et al. 1982, Tarpley et al. 1984, Justice et al. 1985). In some cases, multi resolution imagery and integrated analysis method were included along with NDVI for land cover classification (Lambin and Ehrlich 1995, Cihlar et al. 1996, Laporte et al. 1998, Moody 1998). Temporal dynamics of the NDVI or adding a NDVI image with the multispectral image is also useful in differentiating the vegetation types (Hensen 2000, Levent and Scot 2003).

NDVI combines a multivariate data set of observations to a single index that is related to the amount of chlorophyll present in leaves of vegetation. It is an indicator of vegetation amount. NDVI computed as the difference of the Near Infra Red (NIR) and red band reflectance divided by the sum of reflectance for those same bands. The algorithm isolates the significant increase in reflectance from the visible red to near infrared wavelengths, and normalises it by dividing by the overall brightness of each pixel in those wavelengths. Specifically NDVI is:

$$NDVI = \frac{NearIR\ (Band\ 4) - red\ (Band\ 3)}{NearIR\ (Band\ 4) + red\ (Band\ 3)} \tag{3.4}$$

The result of this algorithm is a single band data with NDVI values ranging from -1 to 1 (Sabins 1997, Jensen 1996).

NDVI can highlight and enhance specific spectral differences, which cannot be observed in the display of the original colour bands. NDVI is less influenced by sun angle and illumination and thus provides relatively reliable information about vegetation discrimination (Gutman 1991). Generally, most vegetation indices eliminate shadowing effects through highlighting the difference in reflectance between bands. Removal of shadow and albedo effects from vegetation indices can offer improvements in classification (Qi et al. 1995, Huemmrich 1996).

3.4 Field visit and classification system generation

Forest classes can be generated by explaining the forest according to the component species, floristic composition or by the canopy structure from remote sensing data (Franklin 2001). One of the objectives of this research is to investigate the application of medium resolution satellite data for the determination of forest cover classes by generating an appropriate classification system for the study area. The application of a standardised classification system provides a fundamental framework for the establishment of information for local and national purposes.

The most widely utilised land use and land cover classification system was developed by USGS (Anderson et al. 1976) comprising of four levels (I, II, III, IV) and has found wide acceptance as the basis for digital classification using remote sensing (Jensen 2000). Application of the classification levels (table 3.2) depends on the characteristics of the available remote sensing data.

Table 3.2: Example of forest classes and levels used in Landsat image classification

Level I	Level II	Level III	Level IV
	General	Species levels	Crown density classes (4)
Forest Land	Deciduous forest	Red pine	High (>60%)
	Evergreen forest	Black spruce	Medium (40-60%)
	Mixed forest	Mixed swamp conifer	Low (25-40%)
	Forested wetlands	Northern white cedar	Very low (10-25%)

Source: Adopted from Anderson et al. (1976), North America - classification; Wolter et al. (1995), Northern Midwest U.S. - classification; Cihlar et al. (1997), Northern Saskatchewan, Canada - classification

A range of studies (Martin et al. 1988, Trietz et al. 1992, Wolter et al. 1995) has derived level II information from medium resolution satellite data but in a few cases, level III classification has been reported using medium resolution imagery (Franklin 1994, Wolter et al. 1995). The study takes consideration of the system due to its reliance on remote sensing data to determine the forest cover classes. However the success has been dependent upon the heterogeneity and contrast of spectral characteristics of different classes.

The classification system for the SRF as applied by Bangladesh Forest Department is explained in table 3.3 and 3.4. It was developed by the interpretation of aerial photography of the year 1981. Classification for the forest was based on dominancy of species and their composition with other species at stand level. The classification system was followed later in 1996 during mapping the forest using aerial photography. A new forest type Gewa Mathal (coppice) added with the others is described in table 3.3. It introduced another two non-forest types - water body and sandbars and excluded cultivation (Opena et al. 1995).

Table 3.3: Forest types of SRF (stereoscopic interpretation of the aerial photography of 1981)

Forest types	Composition by species (%)						
	Sundri	Gewa	Passur	Kankra	Baen	Goran	Keora
Sundri	>=75						
Sundri-Gewa	50 - 70	25 - 50					
Sundri-Passur	50 - 75		25 - 50				
Sundri-Passur-Kankra	25 - 50		20 - 40	20 - 40			
Gewa		>=75					
Gewa-Sundri	50 - 75	25 - 50					
Gewa-Garan		50 - 75				25 - 50	
Goran						>=75	
Goran-Gewa		25 - 50				50 - 75	
Passur-Kankra			40 - 60	40 - 60			
Passur-Kankra-baen			20 - 40	20 - 40	20 - 40		
Baen					>=90		
Keora							>=90

Source: Chaffey et al. 1985

Table 3.4: Non-forest types of SRF (stereoscopic interpretation of the aerial photography of 1981)

Non Forest Type	Description
Scrub	Height <5ft
Tree plantation	Principally Keora, ora grass, Kankra and Kalshi
Cultivation	Rice
Grass & bare ground	Vegetation cover <10%

Source: Chaffey et al. 1985

The management plans for SRF were formulated according to the working circle of the dominant species existing in the forest (detail in chapter 2). Therefore these detailed forest type maps were not usable on field level, as the forest types were not mapped according to the management plans. Accurate representation of the forest classes in maps according to their management plan is essential and urgent for planning and decision making.

The classification system of the study area is designed to utilise remotely sensed satellite data as the primary information source. Ancillary data, which were collected from the Bangladesh Forest Department, as well as the data collected during field visits were used in the understanding of image data for detailed interpretation at species level. Locating training sites was depending mainly on the easily accessible areas covered by the classes. Without the logistics provided by the Bangladesh Forest Department it would have been impossible to conduct the fieldwork. A small team of forest guard to protect safeguard, boatman and a responsible officer took part in the field visits. Due to the presence of anthropophagous tigers in SRF, shooting was a must before entering the forest. The forest floor near the rivers or creeks was often covered by deep mud especially during low tide. It was also covered by small to large aerial roots, seedlings, bushes and grasses, which made difficulties while walking inside the forest. The task of field verification of Landsat ETM data for classification system generation and for accumulating the training samples was very difficult as the area is large. Trawler was the only means to move around in the study area. It was therefore impossible to cover the whole area for collection of the training samples. Selected locations were visited during field visits (figure 3.6). GPS (Garmin 12) was used to identify the locations and also to check any differences in position of an object identified in the ground compared to the imagery. Three accessible water ponds (marked areas in figure 3.6) have been identified in the Landsat ETM image.

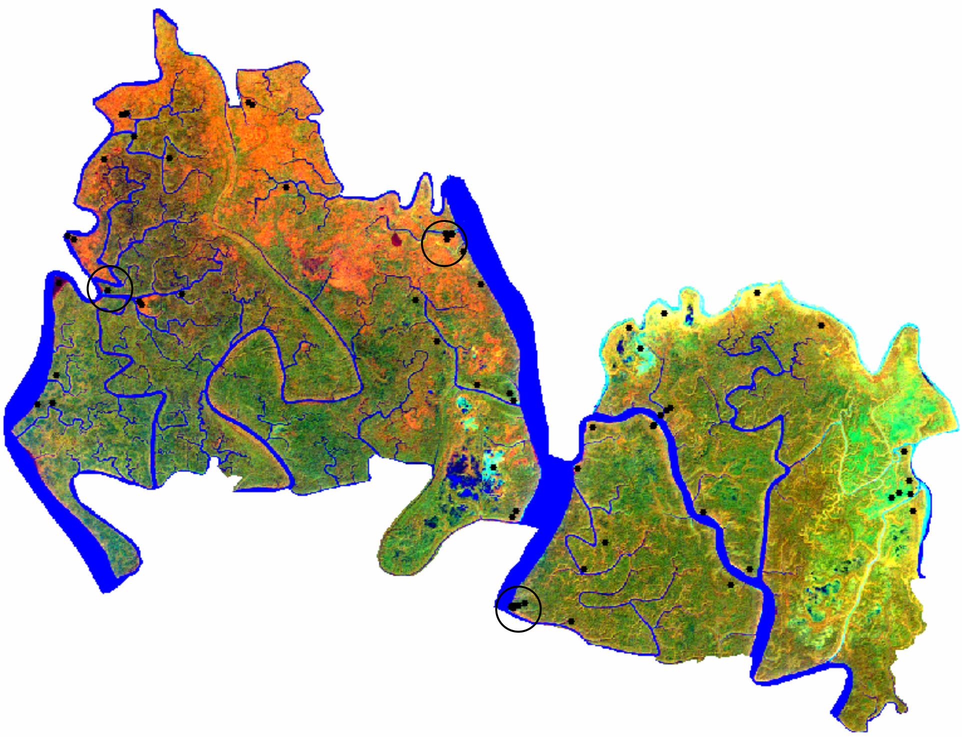


Figure 3.6: Ground locations visited in the study area

The coordinates of the individual pond corners were collected and comparison with world in the geo-referenced image showed shifts about of ± 0.6 pixel.

Depending on the characteristics of remote sensing data efforts has been made to produce usable maps for planning. A level III classification system has been developed in this study for mapping the classes according to existing management plan based on unique spectral reflectance of the multispectral Landsat ETM data. The classification system developed for the study area is illustrated in table 3.5. The classification is hierarchical with classes at level I, II and III in order to accommodate the various level of detail which can be extracted in the satellite data. The pixel size of Landsat offered adequate resolution to identify eight classes for ETM data inside the study area. Two types of grass layer have been identified in Landsat ETM due to their significant difference in reflectance characteristics. One was representative of marshy land and another comparatively drier land. Grass layers in the drier areas have been created after 1996, according to the aerial photo interpretation of 1996 as derived by the Bangladesh Forest Department. During field visit it was realised that the drier grass areas are increasing. The Bangladesh Forest Department initiated effort for management of these areas in the later part of 2000. The authority partially burned this grassland and planted exotic species. As the Landsat ETM image was acquired in the later part of 2000, it was possible to identify the whole drier grassland from the data. This grassland was actually a gap created after removal of trees from the forest. Drier grass areas classified separately as Bush land in the classification system for separate presentation of two grass layers in the classified map.

Table 3.5: Land cover classification system developed for the study area

Level I	**Level II**	**Level III classes for Landsat ETM**
Forest land	Mangrove Forest	Gewa
		Sundri
		Kankra
		Keora
	Shrub	Shrub
	Grassland	Bush land
		Marshy grassland
Water	Rivers, creeks, canals, ponds	

The representing colours for the classes were identified in colour composite Landsat ETM imagery (RGB = 4, 5, 3) shown in figure 3.7. Details of interpretation, training area acquisition and signature derivation from the training data for the classes are discussed in the following sections.

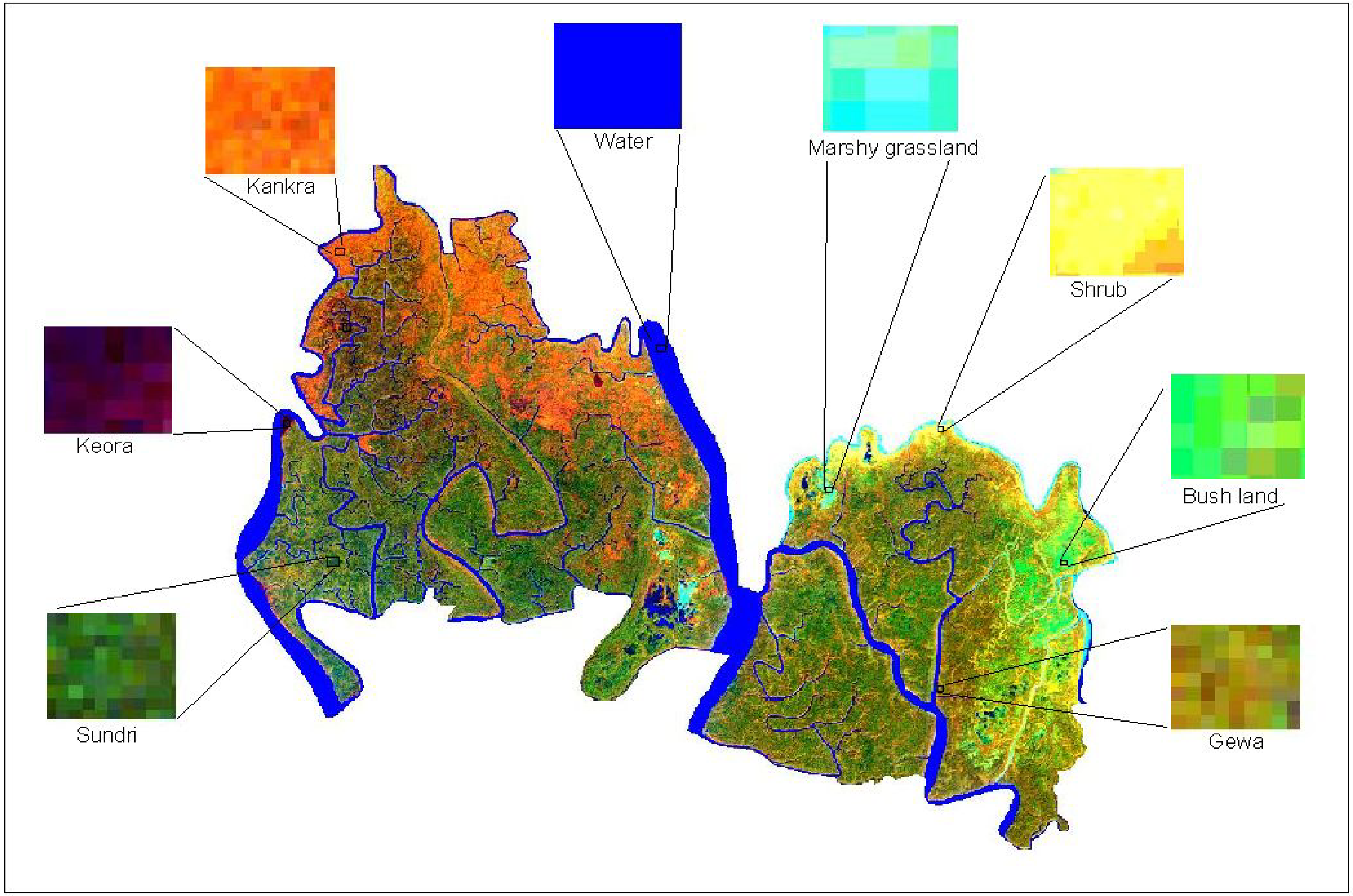


Figure 3.7: Subset samples representing the land cover classes according to the spectral radiance of Landsat ETM (RGB = 4,5,3) in the study area

3.4.1 Building an interpretation key of forest cover classes

The objective of an interpretation key is to ensure the interpretation quality in order to reproduction of the classification system and standardisation of the interpretation process. It is necessary to document the connection between the extracted signatures in satellite data and the appearance of the classes in-situ to make this classification system usable.

The interpretation key is provided examples for the classes and descriptive rules for interpretation work. The following figure (figure 3.8) presented the resulting interpretation key.

Class description	Photographs
Class: Sundri Local name of the species: Sundri Scientific name: *Heritiera fomes* Areas are dominated by sundri and mixed with gewa (*Excoecaria agallocha*), baen (*Avecennia officinalis*), kankra (*Bruguiera gymnorrhiza*), passur (*Xylocarpus mekongensis*), shingra (*Cynometra ramiflora*); dense canopy; understorey is characterising by the germination of the canopy species; ground is covered by dense phenumetophores (aerial roots).	
Class: Gewa Local name of the species: Gewa Scientific name: *Excoecaria agallocha* The areas are dominated by gewa and mixed with sundri (*Heritiera fomes*), kankra (*Bruguiera gymnorrhiza*), baen (*Avecennia officinalis*), keora (*Sonneratia apetala*); more or less close canopy; understorey covered by the sapling or seedling of the canopy species.	

Class description	Photograph
Class: Keora Local name of the species: Keora Scientific name: *Sonneratia apetala* Pure keora; close canopy; usually occurs in small patches; grows in newly accreted land.	
Class: Kankra Local name of the species: Kankra Scientific name: *Bruguiera gymnorrhiza* Mostly kankra, some times mixed with gewa (*Excoecaria agallocha*), sundri (*Heritiera fomes*), keora (*Sonneratia apetala*), passur (*Xylocarpus mekongensis*); close canopy.	
Class: Shrub Area covered by perennial shrub less than 1m height; mainly bola (*Hibiscus tiliacious*) species.	
Class: Marshy grassland Areas are covered by grasses. They are nolkhagra (*Eriochloea procera*), 1.5 – 2m height; malia (*Cyperus javanicas*), <1m height and hargoja (*Acanthus ilicifolius*); they are growing independently or in mixture with each other in marshy areas; not all of them are included in the photograph.	
Class: Bush land Area covered by Hogla (*Typha elephantia*) 1.5m height, nolkhagra (*Eriochloea procera*) 1.5 – 2m height; they occur independently or in mixture.	

Class description	Photograph
Class: Water This category includes any open water area larger than the minimum mapping unit or 28.5*28.5m resolution. Rivers, canals, creeks and ponds are all included.	

Figure 3.8: Interpretation key of the SRF on Landsat ETM imagery

3.4.2 Training area acquisition

These classes mentioned above were used to derive the training areas based on ground data. They were used to examine the spectral characteristics of each class to achieve an optimal separability. It is crucial to get a unique signature for each class and thus carefully supervised the pixel categorisation process.

The quality of the training data highly determines the classification effort and the value of generated results. Reliable training statistics depend upon inclusion of sufficient samples to provide an accurate measure of the target mean and covariance. Swain (1978) indicates that $10n$ pixels should be used, where n is the number of spectral bands, and Richards (1993) recommends $100n$ as an appropriate number. Table 3.6 summarises the number of training pixel used to analysis the Landsat data for the study. According to Swain (1978) the minimum number of training pixels per class for Landsat TM is 60. Hildebrandt (1996) refers 25-30 pixels for single areas and a minimum of 100 pixels in heterogeneous object classes.

Training samples extracted for the ETM data was depended on the field data and observations of the study area. Acquisition of the training data was constrained by the area covered by each class. Comparatively larger training samples could be extracted for large area covering classes while small area covering classes allowed only for a small number of training samples to be extracted e.g. for Keora, shrub and marshy grassland types. A relatively low number of training samples have been extracted carefully from historical Landsat TM data. Because the experience gained from the field visits for ETM data were also used in selecting the training samples for

TM data (table 3.6). Training areas for both images were selected as small polygons, which had been delineated manually.

Table 3.6: Number of training pixels for the classes used for derivation of training statistics for maximum likelihood classification

Class	**Landsat TM**	**Landsat ETM**
Gewa	248	859
Sundri	330	1072
Kankra	71	456
Keora	24	43
Shrub	32	81
Marshy grassland	36	56
Bush land		168
Water	1300	2726

3.4.3 Signature analysis for the training area

Ground verified training areas for Landsat ETM data were used to develop signature for the classes. The uniqueness of extracted spectral signatures of the training data enabled identification of the target classes. Accurate extract of specific spectral characteristics and their documentation is needed to characterise each class, such as each pixel compared to a library of spectral signatures, should be allocated to the appropriate class (Jensen 1996). Figure 3.9 is representing the spectral properties extracted from the mean values of training samples for the classes of the study area based on ETM data. Steps followed to derive the unique spectral signatures with maximum separibility are:

- identification of the informational classes in the satellite image,
- locations of sample sites of the informational classes for extraction of training statistics,
- identification and comparison of distinct spectral pattern of the informational class,
- extraction of pixel groups as training sample,
- extraction of training statistics from the satellite data for each informational class,
- acceptance of the training sample or redefinition in order to achieve better statistics of the informational classes.

There are various means to control the quality of signature for the classes, such as scatter plots, coincident spectral plots, histogram of the training samples and the separability index. A contingency matrix was generated for the trainings in order to examine the separability among the classes.

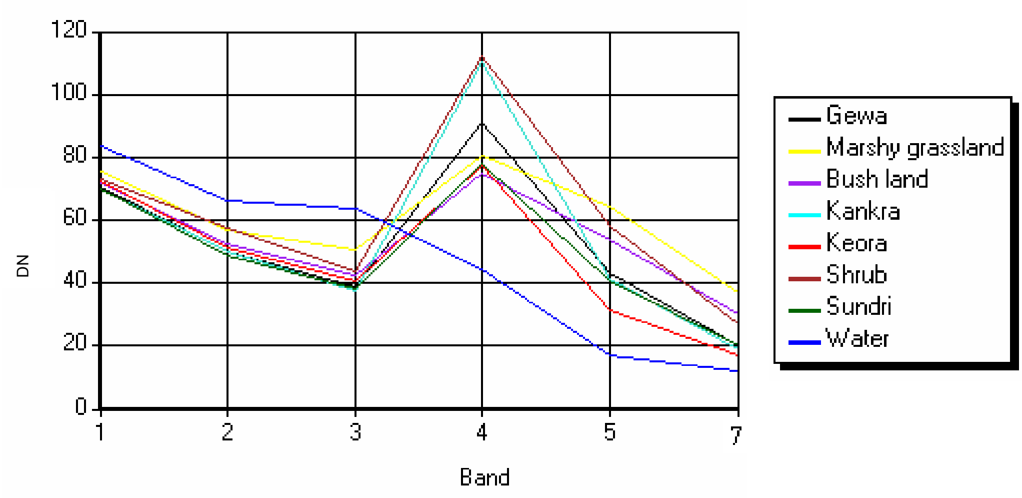


Figure 3.9: Mean spectral radiance extracted for the land cover classes

3.5 Information extraction from Landsat imagery

In order to extract the appropriate information supervised method was applied, which involved the identification and labelling of the land cover classes. A separate classification was also performed for the water bodies to extract the smooth river course using visual interpretation of Landsat ETM bands.

3.5.1 Supervised classification

Classification is the most appropriate approach for predicting the categorical class membership (e.g. land cover classes) of an observation (pixel), based on its intrinsic traits (measurement vector of spectral band responses) (Franklin et al. 2003). Supervised classification requires prior knowledge about the spectral properties and/or the statistical nature of the categorical classes to be determined (Mather 1987) or access to ancillary data, which can be used to build spectral statistics (Franklin et al. 2003). Knowledge about the spectral information is often derived from fieldwork, aerial photo interpretation or from the study of appropriate large scale maps. Supervised classification procedure provides an opportunity for the analyst to intervene and direct the classification process. A priori selection of categorical classes, analyses of training site statistics, specification of sampling approaches and of training site geometry are possible during the supervised classification.

The classification algorithm, which is based on the training sample information, is needed to classify the image. Algorithms like the parametric classifier require statistical information and are categorised as parallelepiped, minimum distance, and maximum likelihood approach. In this study the maximum likelihood algorithm has been applied. It is the most common approach and is frequently used in research and application (Jensen 1996, McGwire et al. 1996, Ediriwickrema and Khorram 1997, Richards and Xiuping 1999, Heikkonen and Varjo 2004).

3.5.1.1 Theoretical approach

The maximum likelihood algorithm assumes that pixels, which comprise target classes are normally distributed and that each class may be completely described by its mean vector and covariance matrix of all bands included in the data set (Lillesand and Kiefer 2000). A multivariate application of the normal probability distribution function is used to model the distribution of pixels to the available classes (Haralick and Fu 1983). Pixels are allocated to the class with the spectral distribution showing the greatest probability of membership.

The multivariate application of the normal probability density function is derived from the univariate algorithm given below (Swain 1978):

$$p(x \mid \omega_i) = \frac{1}{(2\pi)^{1/2}\sigma_i} \exp\left[-0.5\frac{(x-\mu_i)^2}{\sigma_i^{\;2}}\right] \qquad 3.5$$

Where

$p(x \mid \omega_i)$ = Probability of a pixel at a location x being a member of class ω_i

$\mu_i \leq E[x|\omega_i]$ = Mean value of pixels in classes i

$\sigma_i^{\;2} = E[(x-\mu_i)^2|\omega_i]$ = Variance of pixels in class i

Training samples are used to estimate the values of μ_i and $\sigma_i^{\;2}$ from the remotely sensed data. It is important at this stage to define unimodal samples in line with the Gaussian assumption and to ensure that a sufficient number of samples are collected for parameter estimation (Swain 1978).

Remote sensed data, which require the implementation of a multivariate probability density function are collected from multispectral systems:

$$p(X \mid \omega_i) = \frac{1}{(2\pi)^{n/2} \mid \Sigma_i \mid^{1/2}} \exp\left[-0.5(X - U_i)^T \Sigma_i^{-1} (X - U_i)\right] \qquad 3.6$$

where

X = Measurement vector containing the value of the unknown pixel in each band

U_i = Mean vector for class i

Σ_i = Covariance matrix for class i

Equation 3.6 represents the multivariate probability density function $p(X \mid \omega_i)$, which defines the probability of pixel X being classified over n bands into a class ω_i. This function relies upon the covariance matrix being non-singular and requires at least $n+1$ training sample pixels to be evaluated.

Classification of pixel X into class ω_i occurs when the probability of belonging to this class is greater than the probability of belonging to all other classes as follows:

$$x \in \omega_i \quad \text{if } p(\omega_i \mid X) > p(\omega_j \mid X) \quad \text{for all } j \neq i \qquad 3.7$$

Values of $p(\omega_i \mid X)$ are a posteriori probabilities and are not available, but may be estimated from the training data class probabilities - $p(X \mid \omega_i)$:

$$p(\omega_i \mid X) = \frac{p(X \mid \omega_i) p(\omega_i)}{p(X)} \qquad 3.8$$

Where

$p(\omega_i)$ = probability that class ω_i occurs in the image

$p(X)$ = probability of finding a pixel from any class at location X

The value $p(\omega_i)$ is termed as a priori probability and takes a value of 1.00 for all classes if no other information regarding the distribution of classes is available. Incorporation of prior probabilities into equation 3.7 and removal of $p(X)$ as a common factor results in the classification rule as follows:

$X \in \omega_i$ if $p(X \mid \omega_i)p(\omega_i) > p(X \mid \omega_j)p(\omega_j)$ for all $j \neq i$ 3.9

The maximum likelihood decision rule may be stated in terms of discriminate functions for X in the form:

$$g_i(X) = \ln[p(X \mid \omega_i)p(X)]$$
$$= \ln p(X \mid \omega_i) + \ln p(\omega_i) \qquad 3.10$$

Thus substituting the discriminate functions in equation 3.9 the maximum likelihood decision rule is stated as:

$X \in \omega_i$ if $g_i(X) > g_j(X)$ for all $i \neq j$ 3.11

The multivariate probability density function defined in equation 3.6, when operated by the natural logarithm, is stated as:

$$\ln p(X \mid \omega_i) = -0.5\ln(2\pi) - 0.5\ln\left|\sum i\right| - 0.5(X - U_i)^T \sum_i^{-1}(X - U_i) \qquad 3.12$$

The constant $0.5n\ \ln(2\pi)$ may be ignored and for types of analysis with an assumption of equal prior probabilities for all classes, equation 3.11 is modified to provide the final form of the discriminate function for the maximum likelihood classification:

$$g_i(X) = -\ln|\Sigma_i| - (X - U_i)^T \sum_i^{-1}(X - U_i) \qquad 3.13$$

Each pixel within an image will therefore be classified into one of the target classes for which training data have been defined, regardless of how small the actual probabilities of membership for any class are (Richards 1993, Richards and Jia 1999). Classification accuracies of 100 percent are rarely achieved. Careful selection and redefinition of training samples can provide results of an acceptable standard.

3.5.2 Classification results

The process of developing a classification methodology using supervised approaches has been discussed in previous sections. The objective of this sub chapter is to present the classification results for Landsat TM and ETM data and to describe the specific considerations of the classifications. Steps followed to perform supervised classification for the data sets of the study area in SRF are shown in figure 3.10.

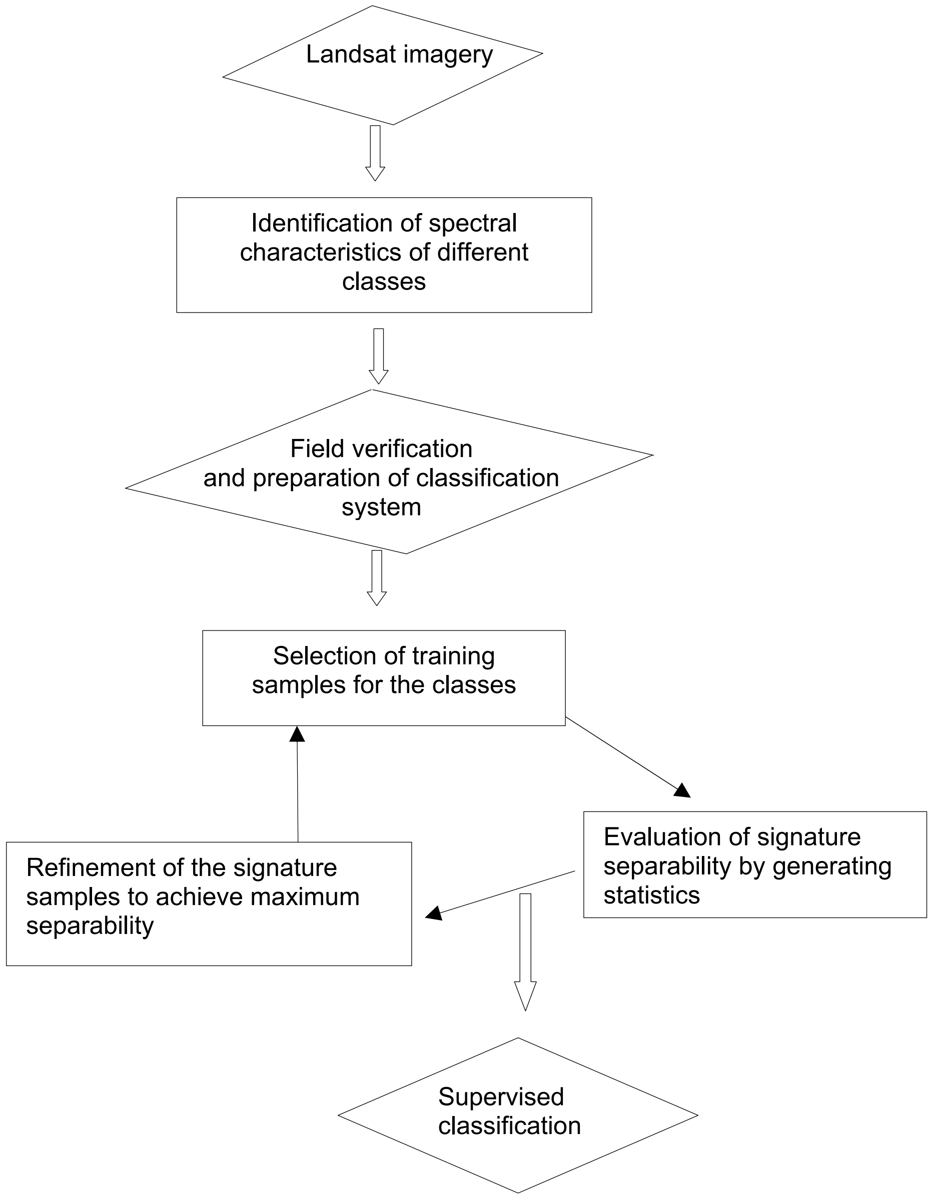


Figure 3.10: Workflow of the classification procedure for the study area of SRF

Georectified Landsat ETM data of 26 November 2000 and Landsat TM data of 12 January 1989 were obtained for the study. Atmospheric correction has been applied for the data sets. In order to enhance the image features an IHS and a PCA fusion technique were applied by using the panchromatic and multispectral bands of Landsat ETM data. NDVI images for both years have also been extracted using the NIR and red bands of Landsat TM and ETM imagery for better interpretation of the forest cover information.

Supervised classifications of all multispectral bands as well as NDVI layer, fusion images and the atmospherically corrected images for both years have been examined for Landsat ETM and TM data. Different image processing routines were designed (table 3.7) to perform classification in order to improve the classification accuracy as well as identify the most suitable method for the study area.

Table 3.7: Image classification methods investigated in the study

No.	Methods
1	Combination of 6 bands (excluding thermal band)
2	Combination of 7 bands (all spectral bands)
3	Combination of 7 bands (NDVI image and 6 spectral bands excluding thermal band)
4	Combination of 8 bands (NDVI image and all spectral bands)
5	Combination of 6 bands (atmospherically corrected image excluding thermal band)
6	Combination of 7 bands (NDVI image and atmospherically corrected image)
7	IHS fusion image based on multispectral bands (2,3,4) and panchromatic band
8	PCA fusion image based on multispectral bands and panchromatic band

All the methods were applied to Landsat ETM data and methods 1 to 6 were applied to Landsat TM data classification. Method 1, 2, 3, 4, 7 and 8 were used spectral data without atmospheric correction for both data sets.

Signature developed for the classes was used as input to the maximum likelihood classification. Following the classification process all output files were statistically filtered using majority function filter in a 3*3 window size in order to remove speckle and smooth the classified images. Only one pass was applied in order to minimise the generalisation of details. Scattered classified Keora pixels were merged with the major area cover classes. Likewise pixels of classified river areas for tiny rivers have also been merged to other classes after filtering.

Increasing the number of bands in the classification process has increased the accuracy of interpretation of classes. Adding the thermal band as well as NDVI band all together with multispectral bands was found effective in identifying the classes. The thermal band assisted to achieve more accuracy for the classes. Radiant energy emitted by the land cover classes is different, which probably helped to increase the accuracy of the classification. Herold et al. (2003) also found that Landsat ETM thermal band has greatly increased the accuracy in forest canopy classification.

In 1989 the study area was mainly covered by the two dominating classes Sundri and Gewa (figure 3.20), while, in 2000 Kankra class increased its area of coverage by partly replacing the two dominant classes (figure 3.16). An increase of grassland in the study area during 1989 to 2000 was identified. This is the result of illegal removal of Sundri and Gewa, which has been more accelerated due to drying of Bhola River and Kharma cannel near the forest boundary.

Evaluation of the classification results of different methods was done by field observation (and experience) of the composite images of Landsat ETM. The choice of the most accurate method for monitoring the classes was dependent upon the accuracy of detecting the spatial distribution and the expansion of different classes in the study area. The results achieved for the methods are critically analysed and represented in the following sub chapters.

3.5.2.1 Landsat ETM

The classification results of the land cover classes based on table 3.7 of Landsat ETM data do not coincide at level III in quite a number of locations. Instead of presenting classification results for all methods for the whole study area, few subsets have been selected in order to present the dissimilarity of the classification results.

Figure 3.11 represents the differences in identifying specific areas, as marked by circles. During field visits small areas of Keora were documented beside Kalabogi Station, which have been successfully classified by the method combination of 6 bands (excluding thermal band) and combination of 8 bands (NDVI image and all spectral bands). Combination with 8 bands (NDVI image and all spectral bands) showed a reasonable representation of Keora and the marshy grassland around Kalabogi Station proving the significant increase of accuracy.

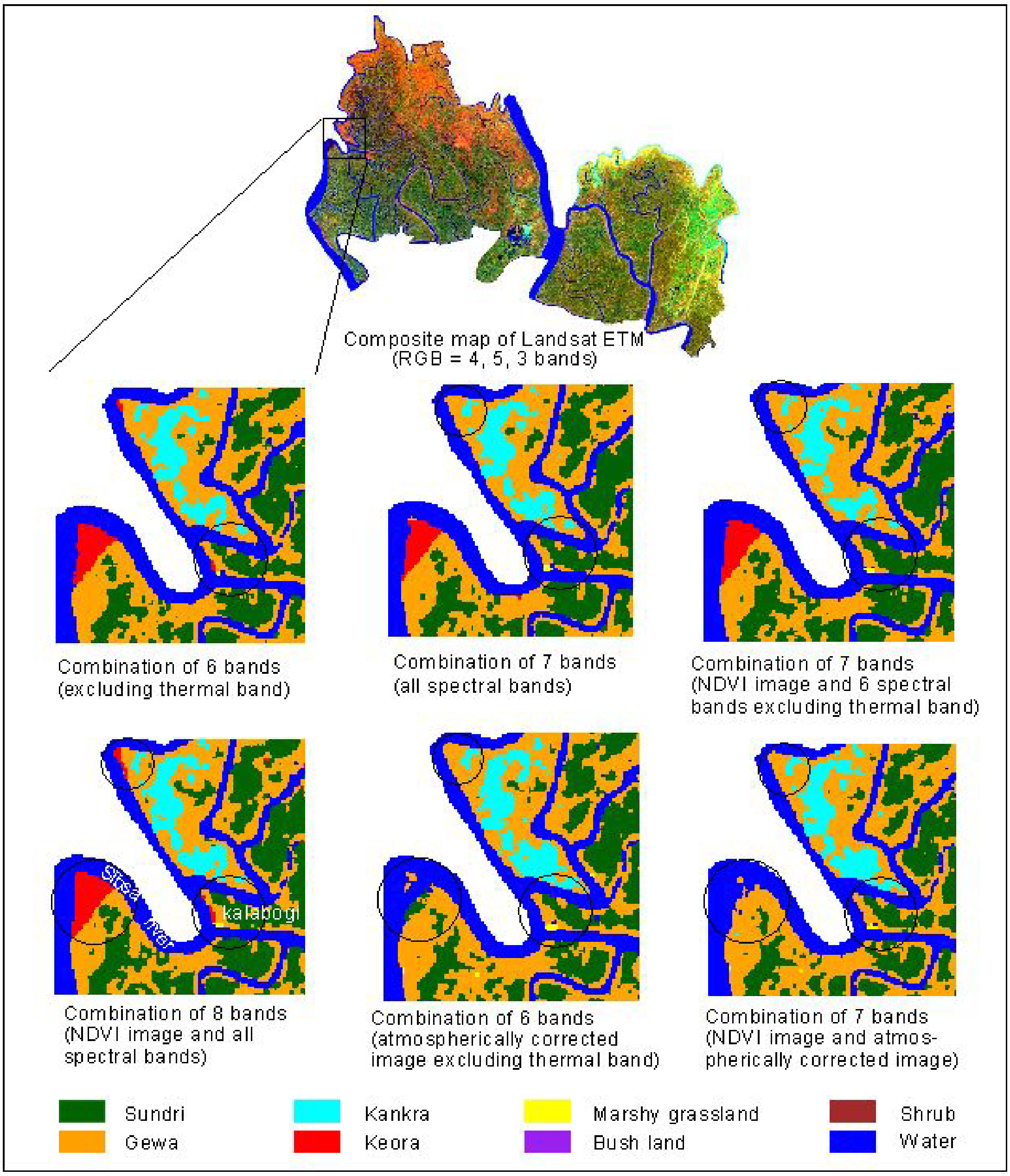


Figure 3.11: Subsets of classification results of several methods of the Landsat ETM

Keora patches have been observed in the bend of the Sibsa river towards Kalabogi and beside Sibsa river during field visit. These patches have been identified in the classification result of the combination of 8 bands (NDVI image and all spectral bands) (figure 3.11 and 3.12) are conserving their shape as observed during field visit as well as colour composite of the original image. Other methods have not detected these features accordingly.

Atmospherically corrected imagery and its combination with NDVI image failed to detect the Keora during classification and misclassified these areas as water (figures 3.11, 3.12).

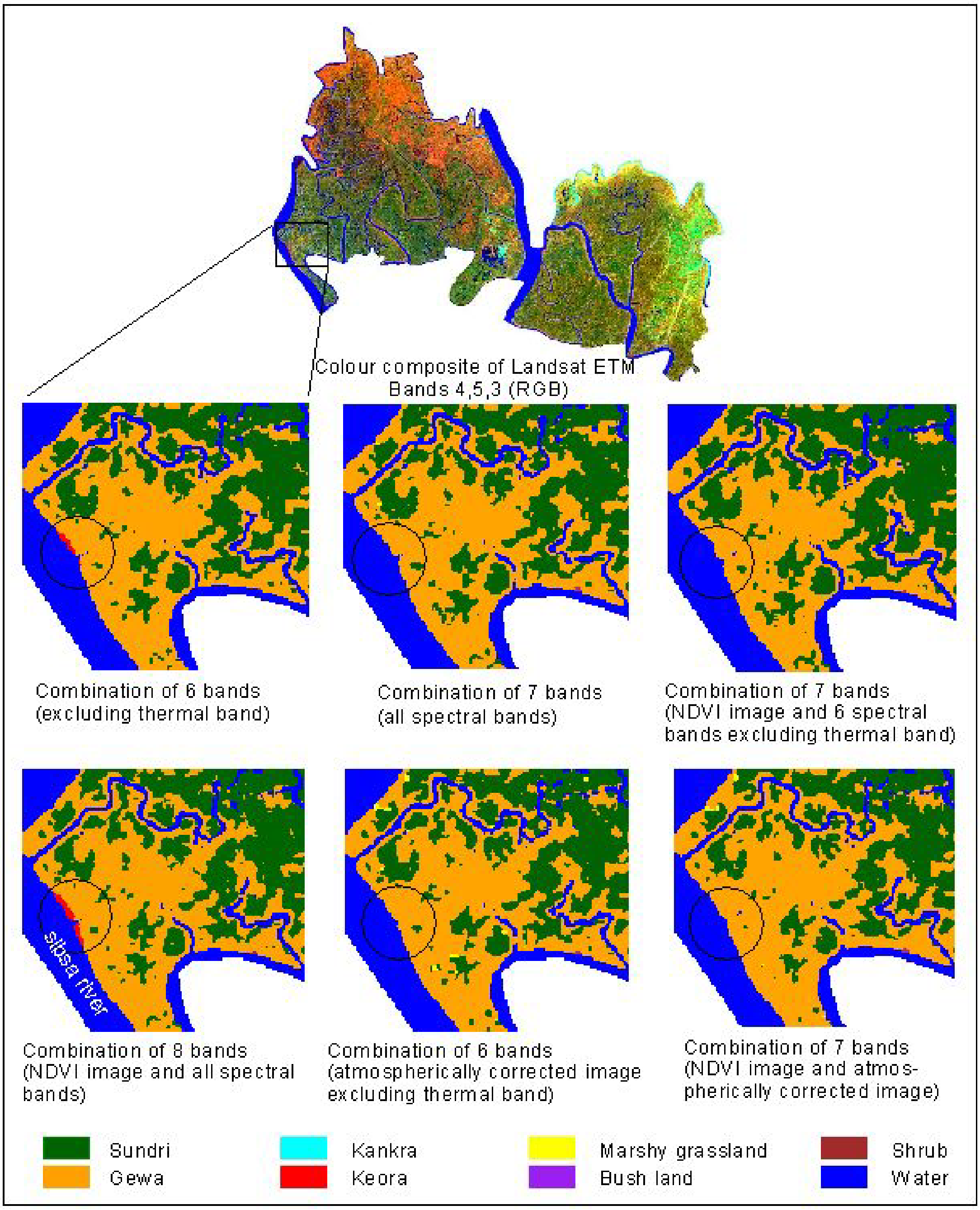


Figure 3.12: Subsets of classification results of several methods of the Landsat ETM

Figure 3.13 showed that the method combination of 6 bands (atmospherically corrected image) and combination of 7 bands (NDVI image and atmospherically corrected image) wrongly identified marshy grassland inside areas of Sundri. The low performance of the atmospherically corrected image of the study area was unexpected as it was assumed that atmospheric corrections are critical components for the improvement of radiometric generalisation and will thus improve the classification accuracy.

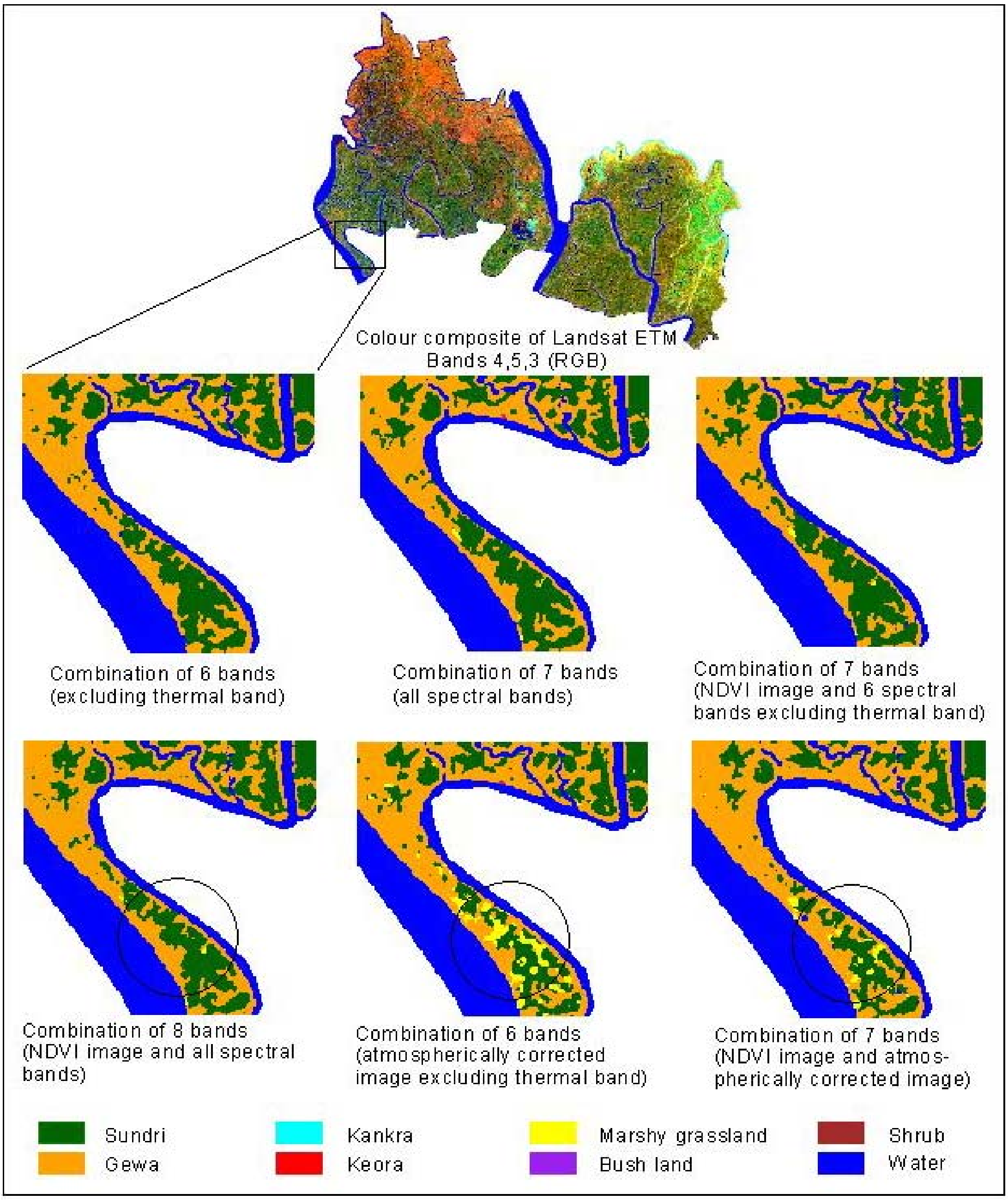


Figure 3.13: Subsets of classification results of several methods of the Landsat ETM

Results of the classification of the fusion images

IHS image

The spatially enhanced IHS fusion image was not useful in identifying any of the classes properly (figure 3.14). It confused all defined spectral characteristics of the classes with each other. Bush land and Keora appears all over the image, Kankra was identified for less area. Gewa has been identified in more areas than in reality. The IHS fusion image was apparently affected by anomalies in spectral characteristics of the defined classes. The reason is probably the high distortion of the original spectral information during IHS transformation, which was present in the multispectral images.

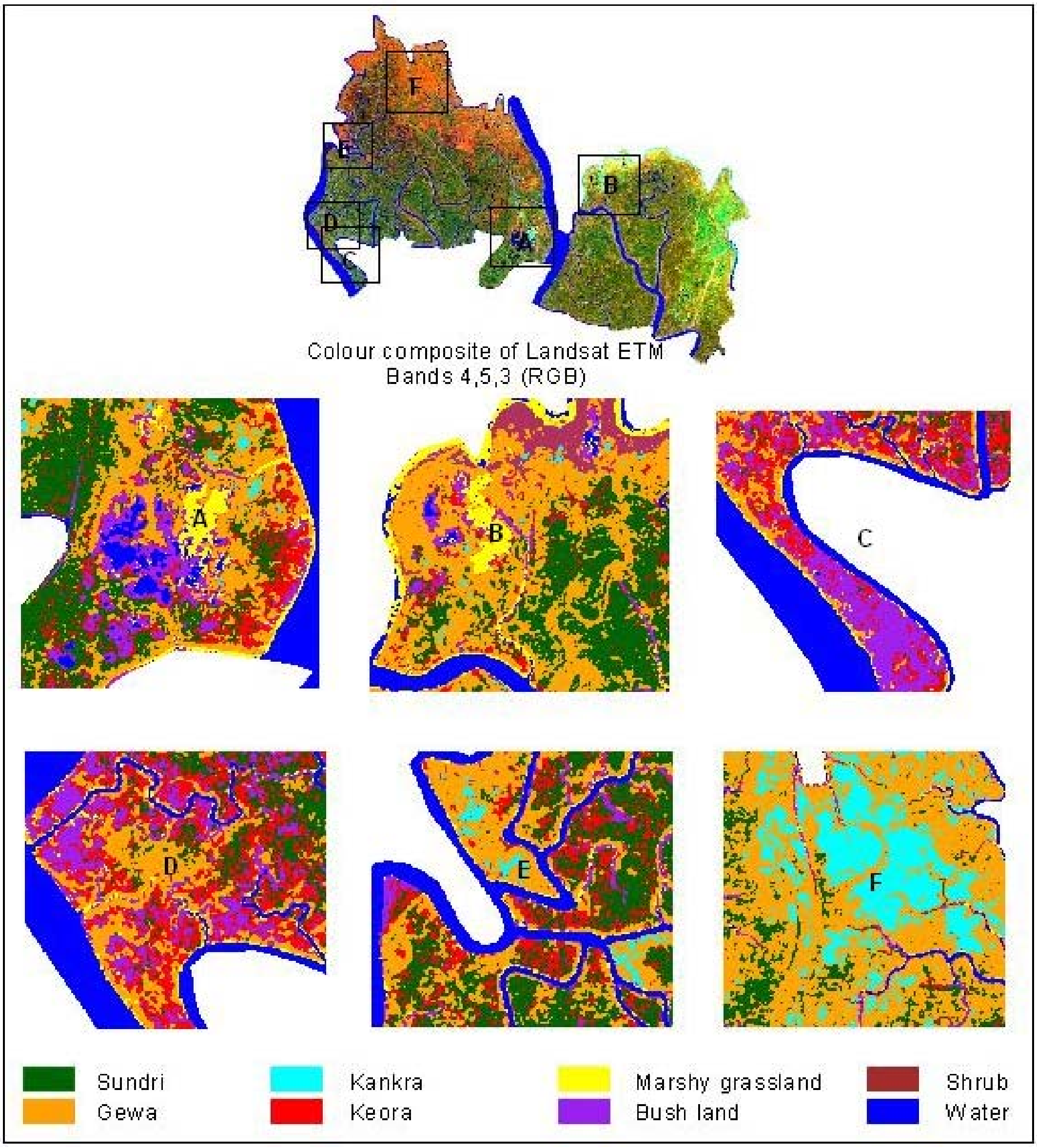


Figure 3.14: Subsets of classification results of the IHS fusion method (A, B, C, D, E, F areas of composite map are representing the subset areas respectively)

PCA image

PCA fusion performance in defining the classes during classification process appears to be reliable for separating 7 classes. It identified Keora class along most of the river courses (figure 3.15). From experience and field observation it is known that Keora species naturally grows along the river ways and in newly accreted land. It is possible that the mixed pixel of water and Keora class may be identified as Keora in the classified image. If it is assumed that the horizontal extension of Keora areas and open river is about 7m within one mixed pixel then it is obvious that the detection of Keora along the river courses is inaccurate. For further use of the classification needs ground verification for this class.

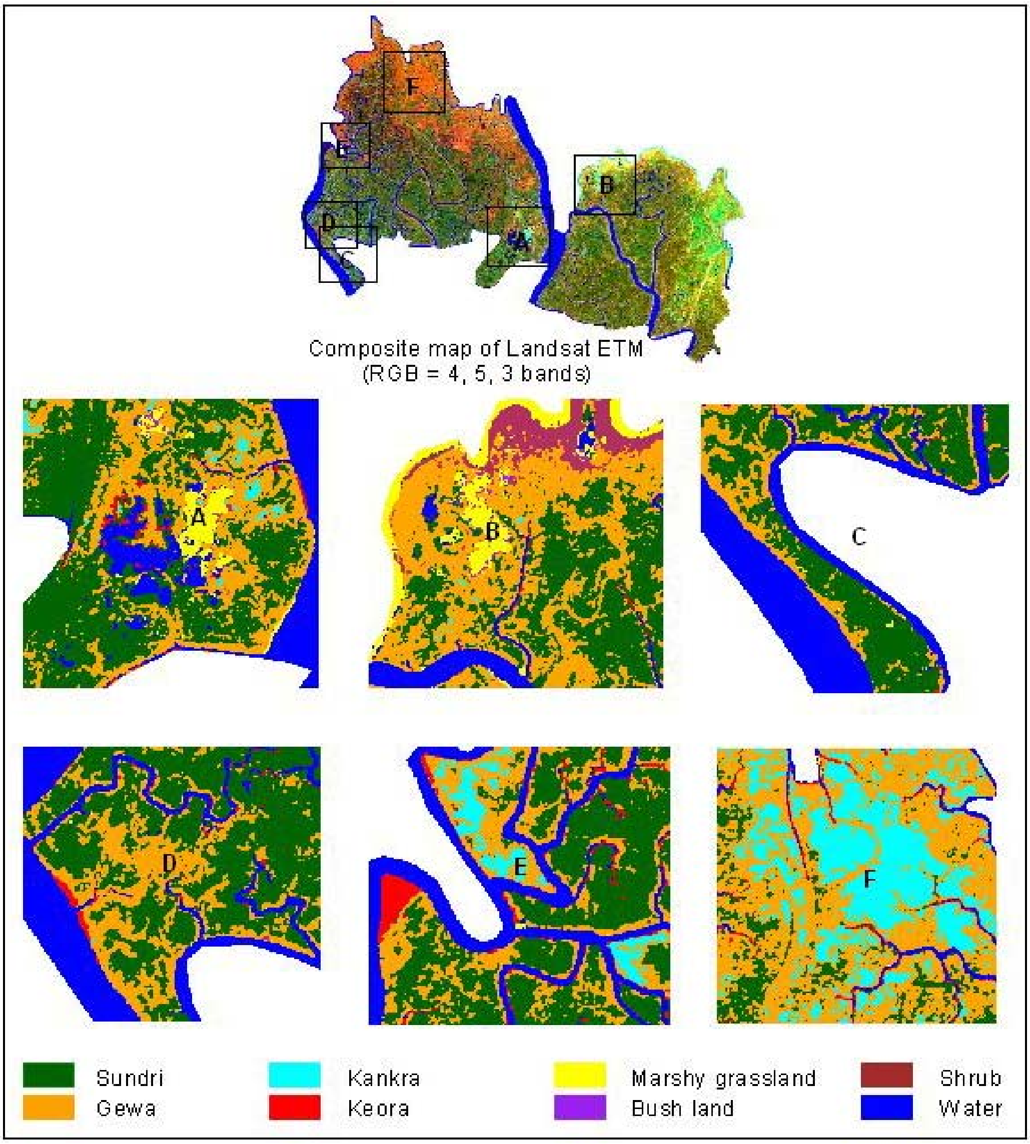


Figure 3.15: Subsets showing the classification result of the fusion image (A, B, C, D, E, F areas of composite map are representing the subset areas respectively)

Refinements of the training samples for Keora class could eventually improve the classification performance of PCA fusion image. A large amount of image pre-possessing steps prior to fusion is needed and takes a huge amount of time. Also a large data volumes generated in image processing constitute a limitation. By comparing all the methods, combination of 8 bands (NDVI image and all spectral bands) for Landsat ETM performed well to maximize the reliability of the identification of the respective land cover classes (figure: 3.16).

Classification of water bodies

Separate classification was done by on screen interpretation and digitisation of the areas of all the main rivers including creeks, canals from the composite map of the original bands of the November 2000 of Landsat ETM in order to provide a smooth representation of the water bodies as vector layer. The separately classified river courses were combined with the final classification result of Landsat ETM data to improve its readability (figure 3.16).

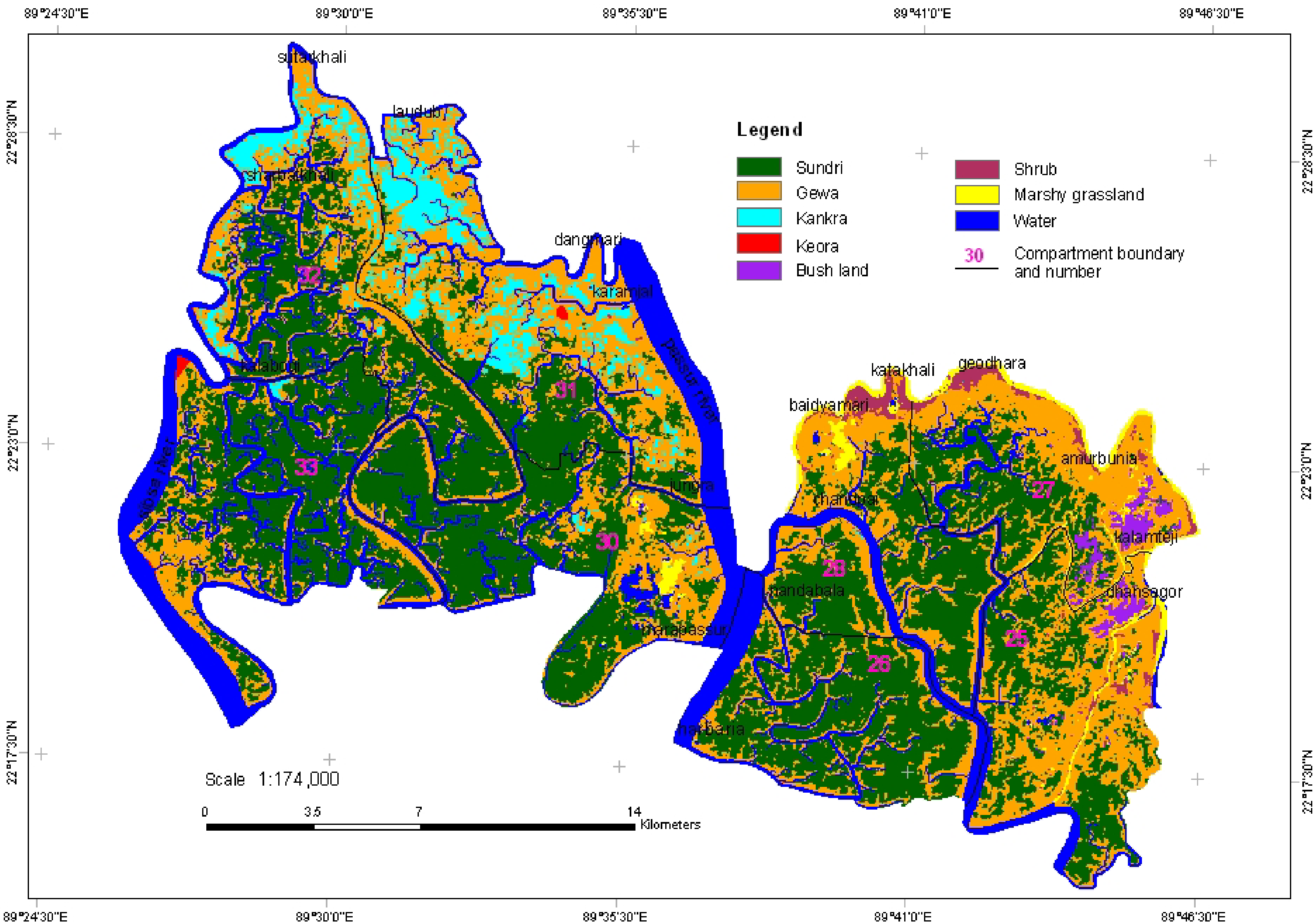


Figure 3.16: Land use and land cover map of the study area in SRF, derived from Landsat ETM spectral bands and NDVI image of November 2000

3.4.2.2 Landsat TM

As with Landsat ETM data, the methods listed in table 3.7 were also applied for Landsat TM data. The level III classification scheme was also applied for supervised classification of all respective band combinations in order to find out the most reliable results for assessment of changes in the study area during the last decade. Evaluation of the classification results of the methods was made and demonstrates dissimilarities among each other. Subsets of some representative areas are presented in order to demonstrate these significant differences.

The Gewa was classified using all methods, but the method combination of 8 bands (NDVI image and all spectral bands) detected the Gewa class adequately as it can be observed in the original composite image (figures 3.17, 3.18, 3.19).

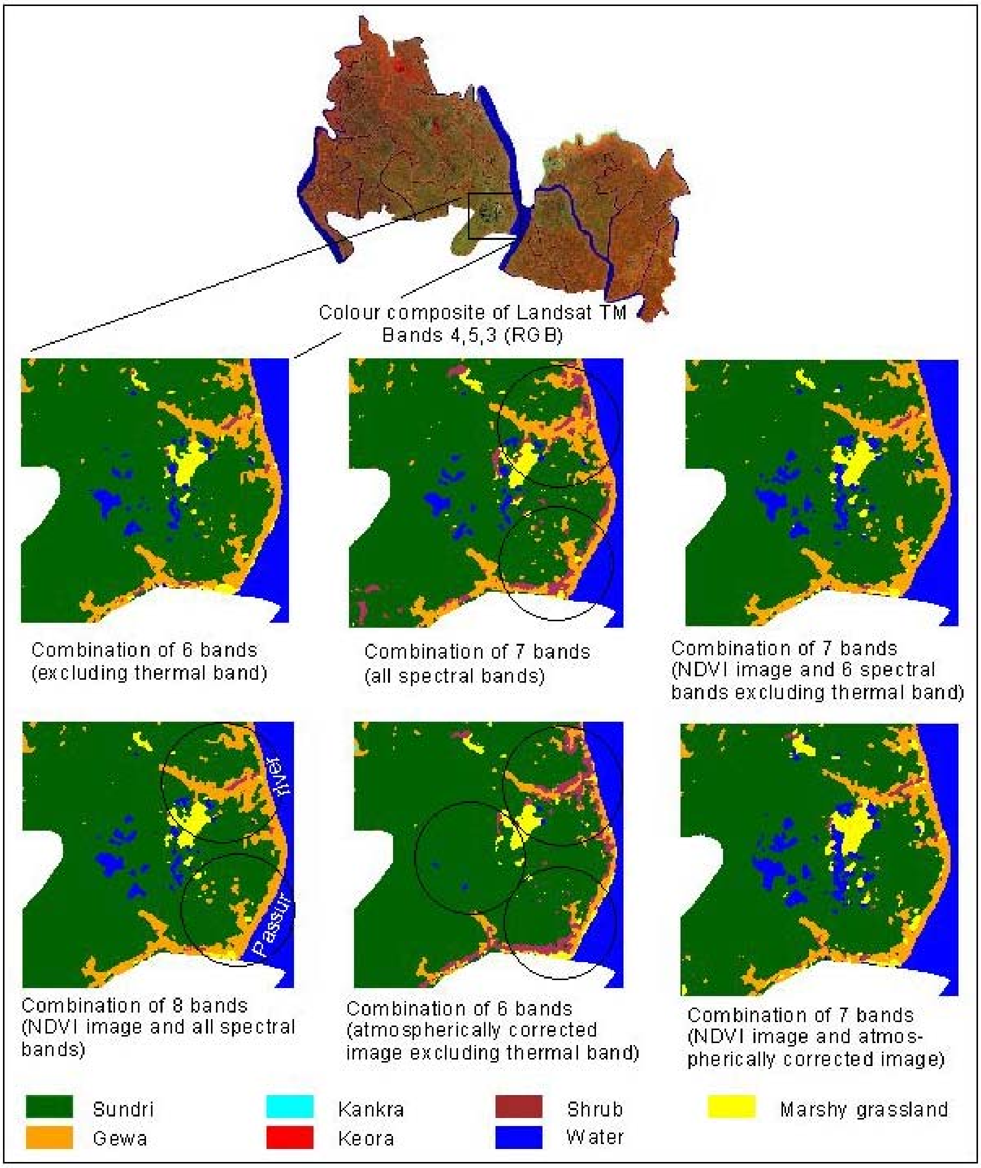


Figure 3.17: Subsets of classification results of several methods of the Landsat TM

Shrubs are detected by all methods applied in Landsat TM data. But the method combination of 6 bands (atmospherically corrected image) and combination of 7 bands (all spectral bands) misclassified shrub to a certain extent. As a result plenty of shrub areas are present in the classified image (circles in figure 3.17 and boxes in figure 3.18), which was not the case in reality as well as documented by the original RGB image.

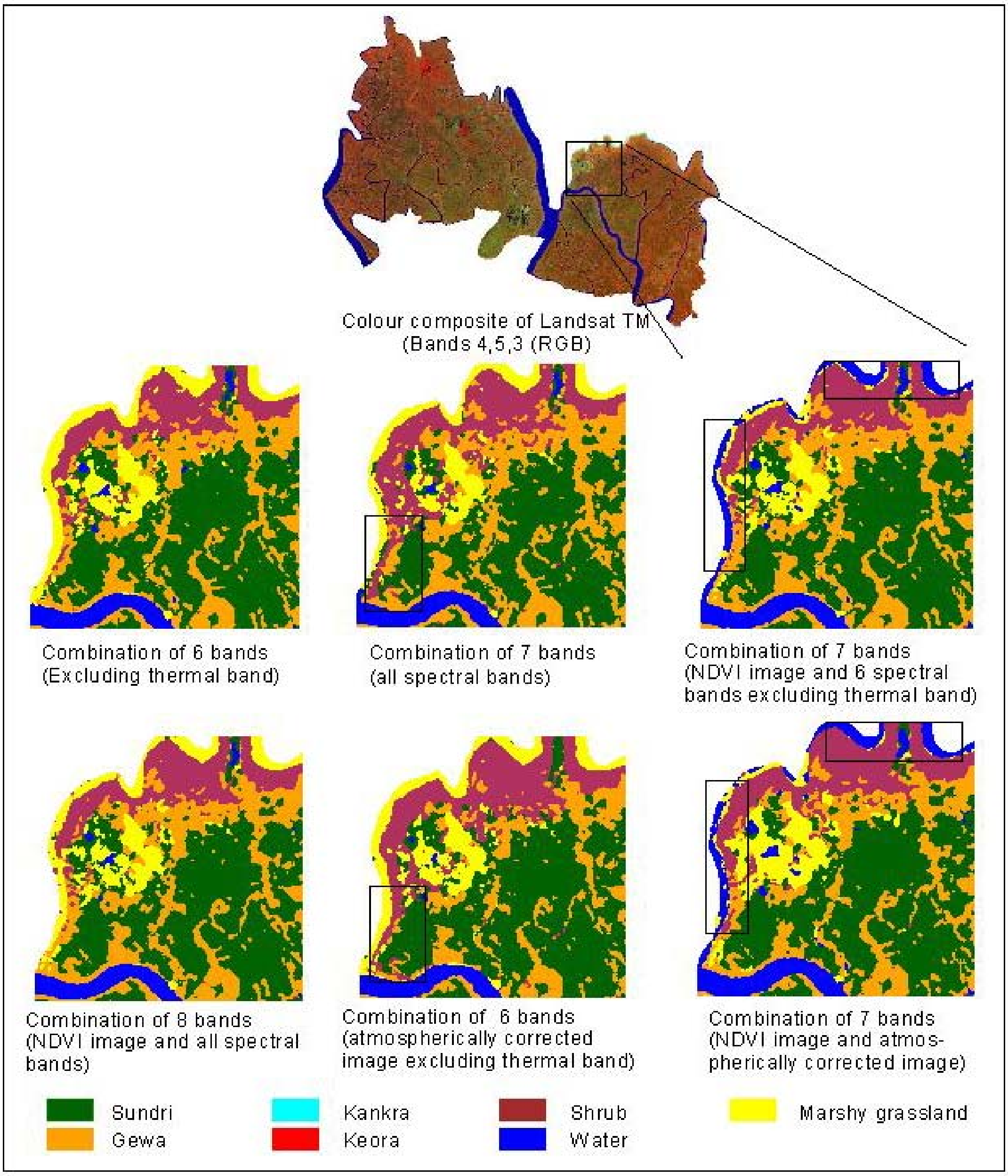


Figure 3.18: Subsets of classification results of several methods of the Landsat TM

The method of combination of 7 bands (NDVI image and 6 spectral bands excluding thermal band) as well as combination of 7 bands (NDVI image and atmospherically corrected image) misclassified a dry riverbed as a water body (boxes in figure 3.18).

Kankra stands are identified by five methods (figure 3.19). The method combination of 7 bands (NDVI image and atmospherically corrected image) failed to detect Kankra areas and confused it with Keora. Other two methods combination of 6 bands (excluding thermal band) and combination of 6 bands (atmospherically corrected image) identified this class for comparatively more areas according to colour composite of the original bands of Landsat TM.

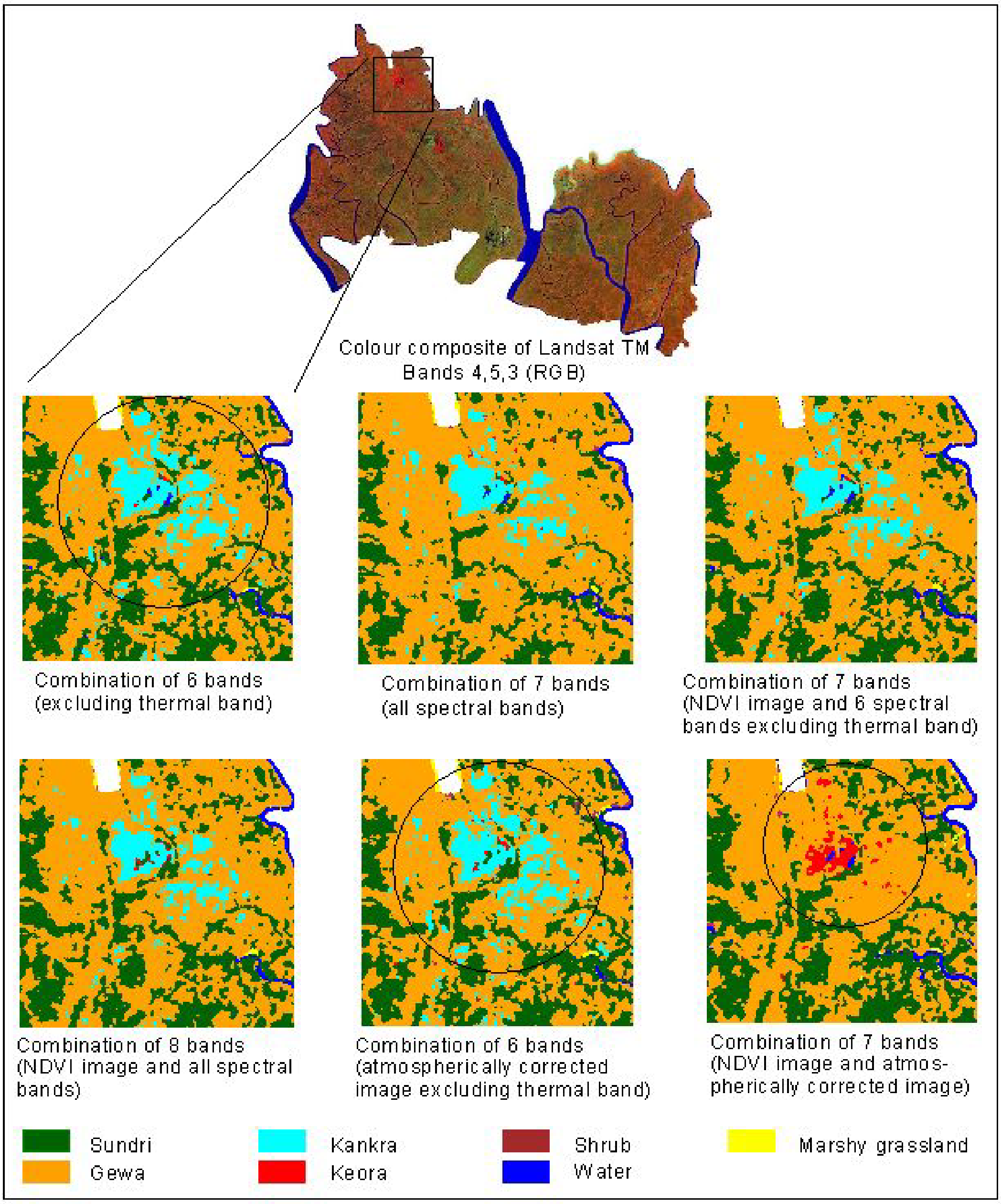


Figure 3.19: Subsets of classification results of several methods of the Landsat TM

The method combination of 8 bands (NDVI image and all spectral bands) showed relatively acceptable results for mapping the classes of the study area (figure 3.20). Likewise Landsat ETM, integration of the NDVI image as an additional layer and as well as the thermal band with other multispectral bands for Landsat TM improved the accuracy in identifying the respective classes according to their shape and size as observed in the original image.

The results are also explained in a table (table 3.9) briefly to clarify the dissimilarity among the methods for both data sets. Areas covered by the respective classes in classified imagery are shown in table 3.8.

Table 3.8: Areas in classification of Landsat TM and ETM imagery (Combination of 8 bands - NDVI image and all spectral bands)

Land cover classes	Areas of Landsat TM of January 1989 (hectare)	Areas of Landsat ETM of November 2000 (hectare)
Sundri	23027.77	19308.51
Gewa	15184.45	15828.41
Kankra	190.55	1906.06
Keora	43.78	81.69
Bush land		386.67
Shrub	569.55	463.27
Marshy grassland	558.67	772.24
Water	4726.56	5580.98

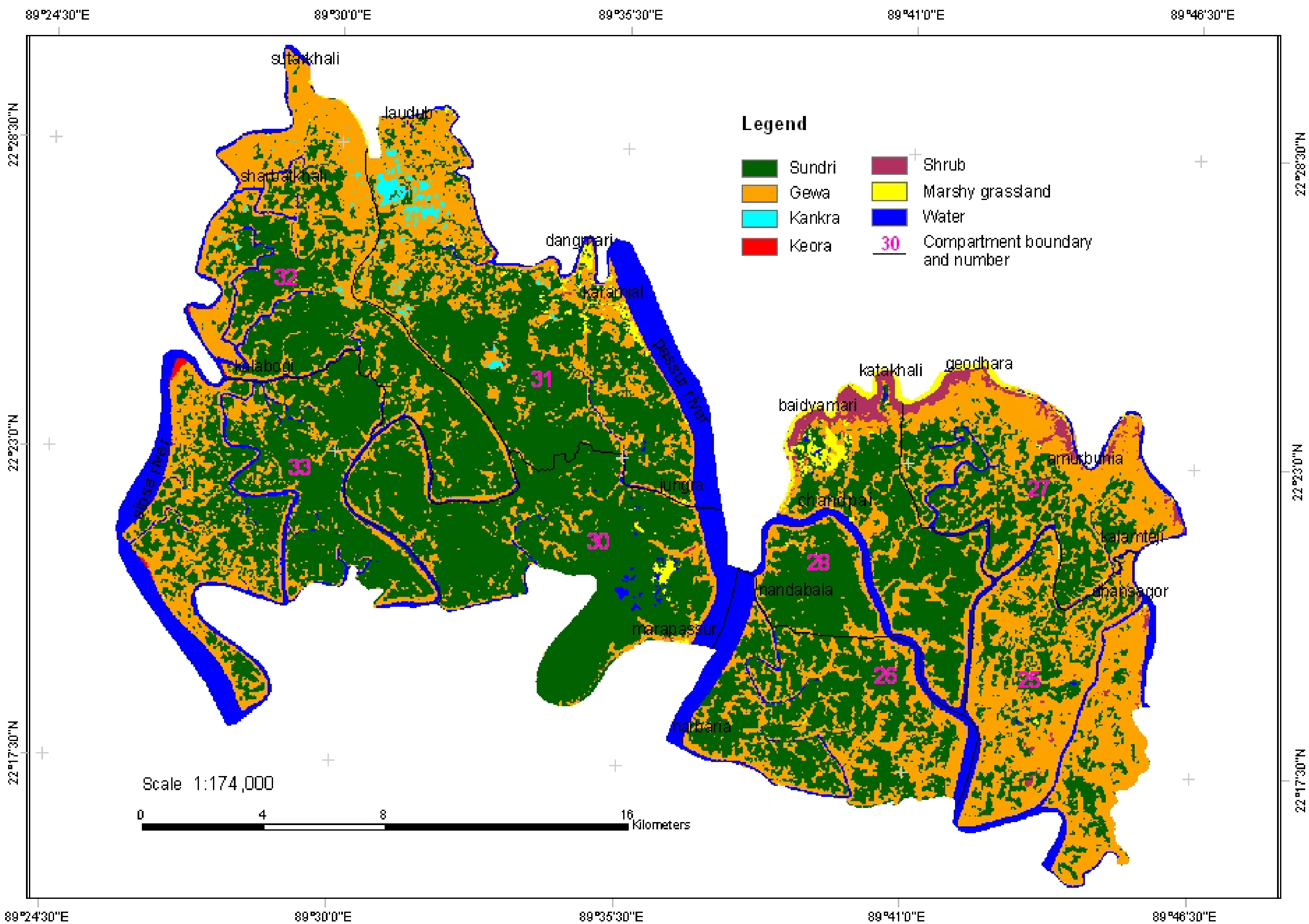


Figure 3.20: Land use and land cover map of the study area in SRF, derived from Landsat TM spectral bands and NDVI image of January 1989

Table 3.9: Descriptive results of the classification methods

Classification methods	**Results in the classified data of Landsat ETM**		**Results in the classified data of Landsat TM**	
	Description	**Field observation**	**Description**	**Visual evaluation**
Combination of 6 bands (excluding thermal band)	Separation of all classes according to the classification scheme was possible. Problem occurs in detecting Keora and marshy grassland (e.g. figure 3.11, 3.12).	Considered as not reliable for change monitoring	Separation of all the land cover classes was possible. Interpretation of more area for Kankra during classification (e.g. figure 3.19).	Considered as not reliable for change monitoring
Combination of 7 bands (all spectral bands)	All classes were identified, but Keora could not be detected in some areas (e.g. figure 3.11, 3.12).		Separation of all the classes was possible, but wrong identification of shrub all over the classified data (e.g. figure 3.17, 3.18).	
Combination of 7 bands (NDVI image and spectral bands excluding thermal band)	Identification of all the classes was possible, but Keora was not identified in some areas (e.g. figure 3.11, 3.12).		Separation of all the classes was possible but misinterpretation of a dry riverbed as water (e.g. figure 3.18).	
Combination of 8 bands (NDVI image and all spectral bands)	Separation of all the land cover classes was possible. Representation for all the classes was satisfactory according to field observation and colour composite map (e.g. figure 3.11, 3.12, 3.13).	Considered as reliable for change monitoring	Identification of all the classes in classified data and satisfactory representation of all the classes were possible according to colour composite map (e.g. figure 3.17, 3.18, 3.19).	Considered as reliable for change monitoring
Combination of 6 bands (atmospherically corrected image)	No detection of all the classes was possible. Misinterpretation of Keora class as water and wrong identification of marshy grassland inside Sundri areas (e.g. figure 3.11, 3.12, 3.13 respectively).	Considered as not reliable for change monitoring	Detection of all the classes was derived. Misinterpretation of the shrub occurred (e.g. figure 3.17, 3.18) and over classified Kankra (e.g. figures 3.19).	Considered as not reliable for change monitoring

Table 3.9: Descriptive results of the classification methods (continued)

<table>
<tr><th rowspan="2">Classification methods</th><th colspan="2">Results in the classified data of Landsat ETM</th><th colspan="2">Results in the classified data of Landsat TM</th></tr>
<tr><th>Description</th><th>Field observation</th><th>Description</th><th>Visual evaluation</th></tr>
<tr><td>Combination of 7 bands (NDVI image and atmospherically corrected image)</td><td>No identification of all the classes was possible. Misinterpretation of Keora and marshy grassland (e.g. figure 3.11, 3.12, 3.13).</td><td rowspan="3">Considered as not reliable for change monitoring</td><td>Separation of all the classes was not possible. Misidentification of Kankra as Keora (e.g. figure 3.19). As well as identified a dry riverbed as water (e.g. figure 3.18).</td><td>Considered as not reliable for change monitoring</td></tr>
<tr><td>IHS fusion method (for Landsat ETM data)</td><td>Confusion occurred among all the classes during classification. It was not possible to correctly interpret any of the land cover classes (e.g. figure 3.14).</td><td></td><td></td></tr>
<tr><td>PCA fusion method (for Landsat ETM data)</td><td>Due to the spatial richness in the PCA fusion image it was possible to identify 7 classes with sufficient accuracy (figure 3.15). Identification of areas of Keora along the rivers would need specific ground verification for its further use.</td><td></td><td></td></tr>
</table>

3.5 Summary

In this chapter the performance of advanced Image processing tasks has been examined in order to enhance the interpretability of the images by increasing the apparent distinction between features. An IHS and a PCA fusion image of Landsat ETM multispectral bands with the panchromatic band are produced. These spatially enhanced fusion image sharpened edges of land and water boundaries, smoothened the river course and image features. NDVI image have also been extracted for Landsat ETM and TM data using the NIR and red bands of the respective images for advanced extraction of the valuable spectral thematic information. Since atmospheric influences are particularly significant within multitemporal studies of land cover change, the DOS method has been applied for atmospheric correction.

Furthermore investigated on the derivation of an appropriate classification system for the study area of SRF is done, which has been subject to significant change during the last decade. According to the spectral properties of satellite imagery as well as the existing management plan of SRF of Bangladesh Forest Department has been used to delineate a variety of land cover classes. A level III classification system was developed based on the widely accepted USGS classification structure. Descriptions of the classes for level III classification are also documented to explicitly focus on the spectral characteristics of the land cover. Training statistics are derived from extracted groups of pixels of the classes based on progressive sampling strategies.

Supervised classification by maximum likelihood approach was applied to the Landsat ETM and TM data according to the classification system defined for the study area. Several classification methods are conducted by representative combinations of bands for the images in order to improve the classification accuracy. Classification is applied to the IHS and PCA fusion image of Landsat ETM separately. A separate classification of the water bodies is also undertaken by digitising the rivers, creeks and canals with the help of visual on screen interpretation of the Landsat ETM imagery.

The analysis of the results has been assessed qualitatively by field observations and experiences as well as verified with colour composite maps of the respective imagery. Several dissimilarities were noticed among the classified results of the methods. Higher spatial resolution IHS data distorted the spectral properties of the land cover classes, which leading to lower classification accuracy. PCA fusion approach was improved classification accuracy of 7 classes excluding Keora as per ground experience and onscreen visual interpretation. The integration of atmospherically corrected imagery for analysis was expected to improve the classification result but at the end accuracy decreased and identification of Keora explicitly failed for Landsat TM. NDVI images were used as an additional band with all the respective Landsat multispectral bands and improved the accuracy of classification. Different thermal response among different land cover classes may be improved the classification accuracy. The methods, which were applied only to the multispectral bands of Landsat TM and ETM imagery did not extend the accuracy up to satisfactory level for the classes.

In order to find a most suitable operational method for classification and also in terms of benefit and cost evaluation the method combination of 8 bands (NDVI image and all spectral bands) is taken into consideration. Adding the NDVI and thermal band together with all the multispectral bands are found successful to improve the accuracy of classification. This classification method showed reliable accuracy in representing all the land cover classes according to the field observation as well as verification by visual interpretation. A significant improvement in extraction of spatial information on the classes from the two Landsat images is achieved using this method. This result is evaluated quantitatively in chapter 4.

Chapter 4
Mapping accuracy assessment

4.1 Introduction

Accuracy assessment is the procedure of quantification of the reliability of a classified image. It allows the user to assess the data suitability for the particular application. Moreover it allows the producer to learn more about errors in data and to improve the process of classification. Integration of geographical information derived from remote sensing has led to the requirement for increased knowledge of errors and their contribution to the overall quality of the final map. During image processing and the process of classification remotely sensed data are affected by both positional and thematic errors. This chapter has focused on discussion of the assessment of thematic errors of the classified Landsat data, which occur due to the mislabelling of pixels into land cover classes.

Classification differences between remotely sensed and reference data arise for a range of reasons (Davis and Simmonett 1991):

(i) Misregistration of satellite data to the cartographic coordinate system
(ii) Misregistration of reference data to the cartographic coordinate system
(iii) Spectral confusion between information classes for training and test data
(iv) Inappropriate classification algorithm
(v) Poor definition of information class for training and test data
(vi) Information classes containing several spectral classes
(vii) Sub pixel variations causing mixed pixel and boundary effect.

Understanding the above factors can lead to refinement of the classification approach and improvements in the quality of classification. Analysis of overall classification performance and analysis of performance by the classes will be used to evaluate the contribution of these factors. Accuracy analysis of this study is especially focusing towards a statement about the errors for individual cover classes.

Statistically sound approaches to set up sample size and sampling design are required to perform valid assessments of classification accuracy for landscapes of varying spatial diversity (Congalton 1991). Considering the most recognised sampling approaches, random sampling was selected and implemented for evaluation of the accuracy of land cover map derived from Landsat imagery (chapter 3).

4.2 Accuracy assessment approaches

Precision is defined as the degree of detail in reporting of a measurement, which is often determined by the characteristics of the measuring equipment, while accuracy is defined as a measure of the difference between a measured value and a known or true value (McGwire and Goodchild 1997). From a thematic mapping perspective, precision is related to the level of detail (or generalisation) inherent in the thematic mapping classification system (Janssen and van der Wel 1994). In the context of thematic mapping accuracy relates to the agreement of the classified image with a source of reference data of greater accuracy than the primary remotely sensed information. It is often derived out of field investigations.

Analysis in this study directed towards assessment of the accuracy of the method combination of 8 bands (NDVI image and all spectral bands) achieved by supervised classification of the Landsat satellite data (chapter 3). The level of the classification system as described in the previous chapter determines the detail of the classification. As the degree of detail increases from level I to level III, the possibility of errors also increases, which may lead to more and more uncertain results and logically lower classification accuracies (Janssen and van der wel 1994).

4.2.1 Descriptive techniques

The standardised land cover classification systems for remotely sensed data generated significant interest in approaches to assess classification accuracy. Application of a random sampling scheme (section 4.3) for the study area enabled the acquisition of representative samples of each class and provided relevant data for studying the error matrix (table 4.2).

The overall classification accuracy is the percentage of correctly classified samples of an error matrix. It is computed by dividing the total number of correctly classified samples by the total number of reference samples. It can be expressed by

$$\text{Overall accuracy} = \frac{1}{N}\sum_{k=1}^{n} a_{kk} \qquad 4.1$$

where, a = individual cell values

a_{k+} = row total

a_{+k} = column total

n = total number of classes

N = total number of samples

The mapping accuracy of each class may be derived in two ways, either by producer's accuracy or by user's accuracy (Story and Congalton 1986, Congalton and Green 1999). Producer's accuracy is calculated by the division of the number of accurate classified pixels in a category and the number of reference set pixels in that category. This is a measure for the probability of a reference data being correctly classified. The equation can be expressed as:

$$\text{Producer's accuracy} = \frac{a_{ii}}{\sum_{i=1}^{n} a_{+i}} \qquad 4.2$$

where, a_{ii} is the number of samples correctly classified and

a_{+i} is the column total for class i.

User's accuracy can be obtained by dividing the number of accurately classified pixels in each category by the row total. This indicates that the classified pixel actually represents the real condition on the ground. It can be expressed by the equation,

$$\text{User's accuracy} = \frac{a_{ii}}{\sum_{i=1}^{n} a_{i+}} \qquad 4.3$$

where, a_{ii} is the number of samples correctly classified and

a_{i+} is the row total for class i.

The greatest significance may be attached to these separate measures of accuracy when the producer's and user's accuracies are dissimilar (Story and Congalton 1986). The user's accuracy is a measure of the reliability of the classification because it measures the proportion of pixels that are classified as one category, but actually belong to other categories. The producer's accuracy gauges the proportion of pixels that actually belong to a category, but have been classified as other features. The user's and producer's accuracies also permit a more complete understanding of the intra-class confusion for the purposes of signature refinement in supervised classification.

Aronoff (1982) has integrated these values through statistical analysis for comparison of classifications with accuracy standards of thematic maps. The user's accuracy specifies the probability that a map of unacceptable accuracy will pass the accuracy test, and the producer's accuracy specifies the probability that a map of some acceptable accuracy will be rejected. Acceptable levels of accuracy for the user's and producer's accuracy have been defined in this study as a part of the analysis.

4.2.2 Analytical techniques

The error matrix was developed to evaluate classification accuracy of remotely sensed data. Normalisation of the error matrix facilitates comparison for the classification result both overall and by class. Conversion of pixel counts to percentages is possible, however uncertainty exists about whether the divisor should be the row or column total. An iterative procedure is available which normalises all rows and columns of the error matrix (Congalton 1991). Differences in the number of samples are eliminated and individual cells within the matrix are directly comparable. Determination of classification accuracy using other accuracy estimation approach also taken into consideration is described in this section.

Accuracy assessments, which include all elements of the error matrix, may be undertaken using the Kappa coefficient of agreement (Cohen 1960). The Kappa Coefficient was developed for comparison of data according to nominal scales. The overall level of agreement for an error matrix (Kappa Coefficient) is based upon the deference between the actual agreement of the classification compared with the reference data (measured by the matrix diagonal) and the chance agreement, which is indicated by the product of the row and column margin values.

The application of the Kappa Coefficient to the analysis of classifications of remotely sensed data was first proposed by Congalton et al. (1983), and has been widely reported (Rosenfeld and Fitzpatrick-Lins 1986, Fung and LeDrew 1988, Gong and Howarth 1990, Fitzgerald and Lees 1994, Lo and Watson 1998). The method may be used to evaluate an error matrix as a whole or for individual classes.

The value of the overall Kappa Coefficient (K) is computed from (Congalton, 1991):

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} * x_{+1}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+} * x_{+1}\right)} \qquad 4.4$$

where, r = number of rows/columns in the error matrix

x_{ii} = number of observations in row i and column i

x_{i+} = total number of row i

x_{+i} = total number of column i

N = total number of observations

The Kappa statistics provides a statistically valid assessment of the quality of classification and enables tests of significance between classifiers for determination of optimum algorithm performance (Fitzgerald and Lees 1994). The overall classification accuracy is considered to significantly overestimate classifier performance and has resulted in the general acceptance to the Kappa statistics (Congalton et al. 1983). Landis and Koch (1977) have used the qualitative descriptor shown in the table 4.1 to describe the strength of agreement based upon Kappa statistics. The values are mainly utilised in this study to evaluate classifier performance.

Table 4.1: Qualitative descriptors for the strength of agreement for Kappa statistics

Kappa statistics	Strength of Agreement
<0.00	Poor
0.00-0.19	Slight
0.20-0.39	Fair
0.40-.059	Moderate
0.6-0.79	Substantial
0.80-1.00	Excellent

Source: after Landis and Koch 1977

4.3 Sampling design

Assessment of the quantitative or qualitative aspects of map accuracy relies upon a sampling scheme with a common set of criteria based upon Ginevan (1979):

(i) a low probability of accepting a map of low accuracy
(ii) a high probability of accepting a map of high accuracy
(iii) requiring a minimum number of reference data samples.

The sampling scheme must ensure statistical validity and provide a practical means of implementation. The sampling procedure employed and the adequate number of sample points will determine statistical validity.

The sampling scheme generally follows a simple random or systematic selection protocol and utilises population, strata or cluster sampling structures. Experimental evaluation by Lo and Watson (1998) of each sampling design showed that the stratified random sampling is the most reliable approach for general application in classification accuracy assessment. This study utilised the stratified random sampling design for accuracy assessment of the classified Landsat TM and ETM data. In a stratified random sampling method each pixel within the population is assigned to a stratum prior to the application of simple random sampling within each stratum.

Field verification of the reference samples for classification accuracy assessment was not possible. The aerial photo interpretation database available for the year 1996 in Bangladesh Forest Department was not applicable as reference for the Landsat ETM classified data because the detailed classes of the database were found to be incompatible with the classes derived from satellite data. Therefore the method reported by Cohen et al. (1998) were utilised for developing reference data for building an error matrix for the study area. Reference pixels from classified images were displayed on-screen in composite (RGB = 4,5,3) imagery. Each pixel was then labelled according to its class by on-screen interpretation based on experience from field observations and expert knowledge both for Landsat ETM and TM data.

4.4 Sample size

Allocation of sample size for accuracy assessment of each land cover class was depended on the area covered by the respective class in the classified maps. Gewa and Sundri classes occupy large area in the classified Landsat TM and ETM imagery and adequate numbers of samples were selected for assessment. Kankra, Keora, marshy grassland, shrub, and bush land occupy relatively small areas for both images. As a result these classes were ignored in determining of required samples. Sampling was undertaken using automated sampling routines. For classified Landsat

TM imagery 273 pixels and for ETM 327 pixels were selected randomly to assess the accuracy.

4.5 Classification accuracy assessment

Results of supervised classification of TM and ETM imagery have been evaluated for the study area. Overall classification accuracy and Kappa Coefficient have been computed to provide measures of the accuracy of the classification. The user's and producer's accuracy as well as elements of the error matrix have been calculated to assess error patterns of the respective classification.

4.5.1 Landsat TM

Table 4.2 represents the result of supervised classification of Landsat TM data of the year 1989. The Kappa coefficient indicates substantial agreement with values of 66.8 percent and the overall accuracy is 77.6 percent (table 4.2) for level III classification. Areas highlighting Gewa class appeared with a user's accuracy of 87.8 percent and producer's accuracy of 67.3 percent (table 4.3). The sample pixels showed high spectral variability, which created difficulties in separating the class from all other classes, except Keora. Sundri displayed high producer's accuracy of 96.0 percent and user's accuracy of 69.3 percent. The spectral reflectance of the Sundi training data was heterogeneous and thus problem in separating the Gewa was the major source of misclassification. Erroneous boundary delineation among these classes due to mixed pixels may be the main reason for this problem. Marshy grassland and Kankra showed low producer's accuracy. Marshy grassland was confused by the spectral reflectance pattern of Sundri. Water and Kankra were confused by the similar reflectance pattern of Gewa.

Table 4.2: Error matrix of Landsat TM data

Classified as	Reference data							
	1	2	3	4	5	6	7	Training sample
1	72	1	1		1	3	4	82
2		5				1	1	7
3	1		1					2
4				4			1	5
5	1	1		1	3			6
6	33	4				97	6	140
7		1					30	31
Training sample	107	12	2	5	4	101	42	273

Overall accuracy = 77.6%

Overall Kappa Statistics = 66.8%

Classification description

Class no.	Land cover classes
1	Gewa
2	Marshy grassland
3	Kankra
4	Keora
5	Shrub
6	Sundri
7	Water

Colours representing the land cover classes in the tables

Table 4.3: Producer's and user's accuracy of the Landsat TM error matrix

Classes	Producer's accuracy	User's accuracy
1	67.3%	87.8%
2	41. 7%	71.4%
3	50.0%	50.0%
4	80.0%	80.0%
5	75.0%	50.0%
6	96.0%	69.3%
7	71.4%	96.8%

4.5.2 Landsat ETM

Table 4.4 represents the result of supervised classification of Landsat ETM data of the year 2000. The Kappa Coefficient indicates substantial agreement by a value of 73.7 percent and overall accuracy with 81 percent (table 4.4) for level III classification. In this classification Sundri and Gewa have shown the balance producer's and user's accuracy (table 4.5) and also considerable misclassification of these classes. The error may be due to the presence of mixed pixels in the boundary region among these classes. Producer's accuracy is relatively low for shrub and confusion may be result from the presence of low height Gewa stands in the forest as well as in the class boundaries. Water sample data appear to be well defined with a user's accuracy of 100 percent but producer's accuracy 79.5 percent indicates classification of water training samples into Gewa class as the main cause of errors.

Table 4.4: Error matrix of Landsat ETM data

Classified as	Reference data 1	2	3	4	5	6	7	8	Training sample
1	93	1	2	2		12	2	6	118
2		7					1		8
3	7		10						17
4	4			15					19
5	1				5			1	7
6	20					96		2	118
7	1						4		5
8								35	35
Training sample	126	8	12	17	5	108	7	44	327

Overall accuracy = 81.0%

Overall Kappa Statistics = 73.7%

Classification description

Class no.	Land cover classes
1	Gewa
2	Marshy grassland
3	Bush land
4	Kankra
5	Keora
6	Sundri
7	Shrub
8	Water

Colour representing the classes in the tables

Table 4.5: Producer's and user's accuracy of the Landsat ETM error matrix

Classes	Producer's accuracy	User's accuracy
1	73.8%	78.8%
2	87.5%	87.5%
3	83.3%	58.8%
4	88.2%	78.9%
5	100.0%	71.4%
6	88.9%	81.4%
7	57.1%	80.0%
8	79.5%	100.0%

.

4.6 Factors contributing to classifier performance

The 28.5m spatial resolution of Landsat ETM data has been used to analyse the land cover classes for the study area. The presented analysis of accuracy of classification provided an assessment of the performances of the supervised classifier for multispectral data at level III of classification detail. This section discusses the factors, which have contributed to the performance of the algorithm and represents important considerations relevant to the reliability of this research.

<u>Spectral resolution</u>

Consideration of spectral separation of the land cover classes is important to understand the classification patterns. The results of accuracy assessment of the supervised classification as represented in tables 4.2 and 4.4 demonstrate difficulties in separating the classes marshy grassland, Kankra and Gewa in Landsat TM data and the classes Gewa and shrub in Landsat ETM data due to similar spectral properties of training samples.

After comparing several methodologies (chapter 3), the method of combination of 8 bands (NDVI and all spectral bands) improved the classification accuracy for the study area. Confusion among the land cover classes still exists in separating the classes within this method. This is probably due to the presence of plenty of mixed pixels within the imagery for heterogeneous patterns of structure and species composition within the study area. Mixed pixels may include spectral characteristics of a number of classes and reflection of a mixed pixel is not representative of a particular feature but rather a composite of other features within the representative pixel. As a result, these pixels are of low efficiency to give information about the association to any specific class. Sub-pixel analysis using spectral mixture models, which un-mix an image into different fractions has demonstrated effectiveness for improving classification accuracy. Spectral un-mixing provides a more realistic representation of the true nature of a surface compared with that provided by the assignment of a single dominant class to every pixel by statistical model and is suitable to solve the mixture problem for medium to low spatial resolution data (Campbell 2002). This strategy requires a large amount of image processing work and time and is still not operationalised for appropriate use. Therefore this method was not investigated during this study.

To improve the spectral separability among the classes initiatives were undertaken by decorrelating the Landsat ETM bands, as correlation between bands is also responsible for reduction of the spectral separability of specific classes. Reduced spectral correlation of multispectral bands by analysing and PCA combination with the panchromatic band showed improvement of the spectral separability (chapter 3). A considerable time and extended image pre-processing work was needed. Still this method apparently misclassified especially the Keora class.

Though the study also investigated for improving the accuracy using the IHS and PCA fusion method, however, the intention was to find out an operational method as well as to achieve reliable results for the study area. The combination of 8 bands (NDVI image and all spectral bands) of Landsat imagery performed well for separating the representative classes. A further decrease of uncertainty for the classes may be achieved through refinement of training data (chapter 3) and a better adjustment of spectral signatures.

<u>Spatial resolution</u>

Boundary effects in remotely sensed data are mainly related to the interpretation of mixed pixels, determination of class boundary locations and reference data verification error. When mixed pixels occur, pure spectral responses of specific features are confused with the pure responses of other features, leading to the problem of composite signatures. Incorporation of spatially enhanced PCA fusion method for classification using Landsat ETM multispectral bands with the panchromatic band reduced the number of mixed pixels, resulting in an improvement of the classification accuracy for the 7 classes except Keora. By using higher spatial resolution data such as IKONOS, the derivation of improved accuracy as well as proper boundary delineation would be possible. Acquiring very high resolution satellite data is costly and thus not reliable for appropriate use.

<u>Reference data</u>

It was not possible to perform ground checking for the reference samples of the classified data due to constraints as mentioned in chapter 3 for training data collection. Though compatible and reliable reference data lack, error matrices was generated using onscreen interpretation based on field observations and expert knowledge for detecting and describing sample points as reference against the classified Landsat ETM and TM imagery for accuracy assessment. The influence of the quality of reference data on the assessment of classification accuracy of the land cover classes depends on their thematic accuracy. Reference data are assumed to be free of error, however this is not the case even for data collected directly (Congalton 1991, Kalkhan et al. 1998).

4.7 Summary

Assessment of the classification accuracy of remotely sensed data is essential if a thorough evaluation of change detection is undertaken. Thus investigations in this chapter have been directed towards the evaluation of the reliability of the supervised classification approach in identifying land cover classes in Landsat ETM data by means of generation and discussion of an error matrix. This is a commonly used method for the assessment of accuracy of land cover classifications of remotely sensed space borne digital imagery.

Methods of descriptive and analytical accuracy assessment are available for the evaluation of classified data. Descriptive methods have been applied by calculating the overall classification accuracy and the user's and producer's accuracy. Analytical approaches such as the calculation of the Kappa Coefficient provide statistically sound algorithms, which summarise all elements of the error matrix and compute an accuracy value and its variance. The Kappa Coefficient is computed to provide a representation of the statistics of the accuracy assessment of the land use and land cover classes of the study area.

A simple random sampling scheme was used in this study for error assessment of the classification. Sampling was undertaken using automated sampling routines. Selection of sample sizes for the land cover classes depended on their ground coverage. Classes covering large areas allowed for the selection of an adequate distribution of samples, but classes covering very small areas did not allow for a collection of a representative number of reference data (e.g. Keora, marshy grassland and shrub).

The discussion of the assessment of classification accuracy also focused on detecting the reason for errors and analysing the factors contributing to the resulting classification accuracy. Due to the capability of supervised classification reliable results of classification of Landsat TM and ETM data at level III have been achieved. These outcomes have thus been used for the study of change assessment as discussed in chapter 5.

Chapter 5

Evaluations of forest cover change

5.1 Introduction

Change in vegetation is defined as an alteration in the surface components of the vegetation cover (Coppin et al. 2004), or as a spectral/spatial movement of a vegetation entity over time (Lund 1983). Singh (1989) defines change detection as the process of identifying difference in the state of an object or phenomenon by observing it at different time. Detection of land cover change in satellite imagery is complicated due to adverse temporal factors. These include differences in band passes and spatial resolution, spatial misregistration, variations in the radiometric responses of the sensors, differences in the distribution of cloud and cloud shadow, variations in solar irradiance and solar angles, and differences in phenology (Yuan and Elvidge 1998). The preconditions in using remote sensing data for change detection the fact that changes in land cover must result in variations in radiance values and that variations in radiance due to land cover change must be significant large with respect to radiance variations caused by other system or environmental factors not related to land cover change (Mas 1999).

Classified Landsat ETM and TM data were used to assess the changes. There are four aspects of change detection, which are considered particularly important when monitoring natural resources (Macleod and Congalton 1998):

- Detecting the changes
- Identifying the nature of change
- Measuring the extent of change
- Assessing the spatial pattern of change.

5.2 Change detection approaches

The remote sensing change detection approaches relies on per-pixel classifiers. Approaches of the analysis of change detection analysis approaches can be broadly divided into postclassification and preclassification detection of spectral change (Nelson 1983, Singh 1989). A variety of techniques of preclassification change detection have been developed over the last two decades. Comprehensive summaries of methods of digital change detection are documented (Howarth and

Wickware 1981, Nelson 1983, Singh 1989, Jensen 1996, Gong and Xu 2003). These include mainly composite analysis, image differencing, principal component analysis, change vector analysis and spectral analysis methods. Most of the approaches are frequently used for monitoring vegetation canopies (Coppin et al. 2004).

Ridd and Liu (1998) used multitemporal Landsat TM data to determine patterns of land cover change in a near urban area by image differencing, image regression, Kauth-Thomas transformation and a X^2 - transformation developed by the authors. They found none of the algorithms was clearly superior to the others and concluded that algorithm selection should be soundly based on environmental conditions and objective of application. Muttitanon and Tripathi (2005) used Landsat TM data to identify land use changes in the coastal areas of Ban Don Bay, Thailand. They used image differencing, vegetation index differencing and the vegetation index composite method to identify changes over a period of 10 years. They concluded that the method of image differencing method was performing better in identifying the changed areas. Mas (1999) used six change detection procedures for detecting areas of changes in the region of the Terminos Lagoon, a coastal zone of the State of Campeche, Mexico, using Landsat MSS imagery. Image differencing, vegetation index differencing, Selective Principal Components Analysis (SPCA), direct multi-date unsupervised classification and postclassification comparison were applied. After evaluating the accuracy of the results obtained by each method the postclassification comparison was found to be the most accurate procedure presenting the advantage also indicating the direction of the changes. The postclassification method has also been successfully used by Cornejo et al. (2005) to assess the changes of mangrove forests in the Navachiste-San Ignacio-Macapule Lagoon Complex, Sinaloa, Mexico; by Bauer et al. (2003) to analyse the changes in land cover in the Twin Cities of Minnesota; by Berlanga-Robles and Ruiz-Luna (2002) to examine the land cover changes in a region north of Agua Brava, Mexico using Landsat data.

Townshend and Justice (1988) as well as Coppin et al. (2004) considered that the ability to detect changes in land cover classes over time by remote sensing depends on the spatial, spectral, radiometric and temporal properties of the sensor system. Also the specific methodology implemented can profoundly affect the qualitative and quantitative estimates of the change (Colwell and Weber 1981). Even in the same environment in different approaches may yield different change result in detection

(Coppin et al. 2004). The selection of the appropriate method is therefore of considerable importance.

All the preclassification methods are limited in identifying of change versus no-change and do not offer any quantitative results. Therefore it was decided to apply an approach of postclassification change detection to identify the nature of change and to measure the areas of changes in order to provide sound statistics of land cover change for the study area. This approach detects transitions between any classes as highlighting on the respective classification process.

5.2.1 Postclassification comparison

Postclassification comparison is the most commonly used quantitative method of change detection (Jensen et al. 1993). It involves independently produced classification results from each end of the time interval of interest, followed by a pixel-by-pixel or segment-by-segment comparison to detect changes in cover classes. It is possible to get a complete matrix of change and the change classes by adequately coding the classification results (Coppin and Bauer 1996, Coppin et al. 2004). Postclassification comparison provides the analyst with a significant degree of flexibility through selective grouping of classification results for presentation of customised change detection classes (Singh 1989).

The most significant issue related to change detection derived from postclassification comparison is concerned with the estimation of the thematic accuracy of the final product. Some results of research suggest that because each image is subject to thematic classification errors change detection contains much larger errors than either one of the component images and may therefore be less accurate than any other change detection method (Quarmby and Cushnie 1989, Singh 1989, Coppin et al. 2004). Therefore during the classification of each image, care must be taken in the analysis to ensure consistency in the classification process in terms of class allocation, signature extraction and classification quality.

Landsat TM and Landsat ETM data have been classified for the study area (chapter 3) and analysed to evaluate forest cover changes between the year of 1989 and 2000. Figure 5.1 highlighting the steps of postclassification were used to evaluate the changes for the study area.

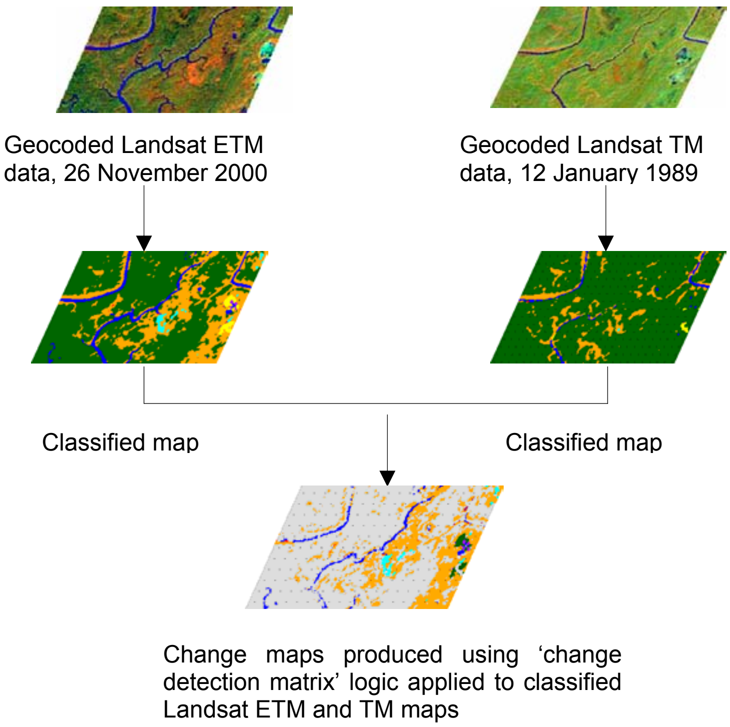


Figure 5.1: Change evaluation using postclassification comparison

5.3 Change statistics and presentation

A variety of approaches is available for reporting the changes derived from remotely sensed data. These approaches can be categorised either as area based or pixel based and utilise image or statistical techniques of representation. Area based methods rely upon extraction of area statistics for the classes derived at each sensing period and on comparisons made regarding the change in the area of each class. Pixel based methods provide data derived from a pixel-by-pixel comparison of imagery and summarisation of the observed change. Change data of these approaches are discussed in the following section.

5.3.1 Area change summaries

Change summaries measure the variation in areas occupied by each class between sensing periods and provide class-by-class reports of changes by area and / or percentage (Howarth and Wickware 1981). This study traces the recent history of (1989-2000) Forest cover change in the study area of SRF and provides the description of the changes. Table 5.1 summarises the details of the extent of forest change for each class. Areas are computed based on the classified imagery of Landsat TM and ETM and are showed as net change in area.

Table 5.1: Statistics of changes in areas of forest cover classes between the year 1989 and 2000

classes	1989		2000		change 1989-2000	
	Hectares	% Area	Hectares	% Area	Hectare	Net Gain-Loss %
Sundri	23027.8	52.0	19308.5	43.6	-3719.3	-8.4
Gewa	15184.4	34.3	15828.4	35.7	643.3	1.4
Kankra	190.6	0.4	1906.1	4.3	1715.5	3.9
Keora	43.8	0.1	81.7	0.2	37.9	0.1
Bush land			386.7	0.9	386.7	0.9
Shrub	569.5	1.3	463.3	1.0	-106.3	-0.2
Marshy grassland	558.7	1.3	772.2	1.7	213.6	0.5
Water	4726.6	10.7	5581.0	12.6	854.4	1.9

Table 5.1 shows loss of 8.4% area of Sundri during the period from 1989 to 2000. Area of Kankra increased and bush land was introduced within this 11 years period. Almost all the rivers in the study area have increased their width within the respective period. Figure 5.2 representing the areas covered by the classes for the period.

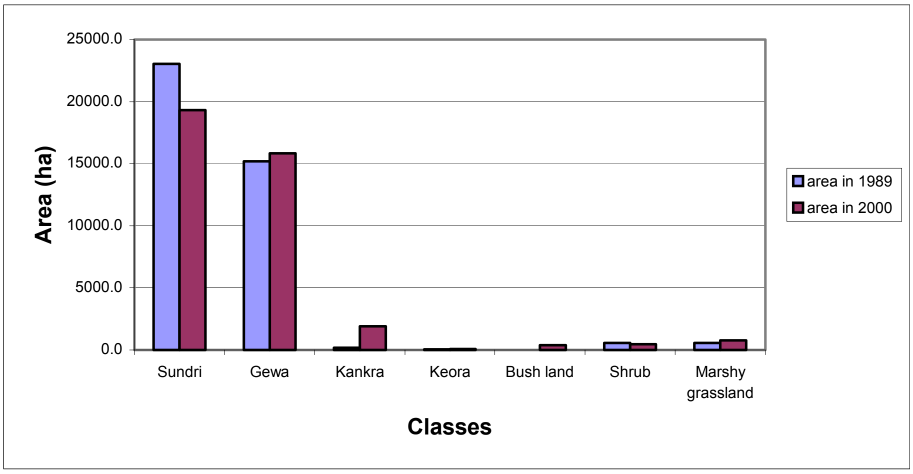


Figure 5.2: Representation of areas covered by the classes on the year 1989 and 2000

An alternative method of summarising changes by area is presented in table 5.2 and 5.3. These data are calculated from the change image derived through a pixel-by-pixel comparison of the classified images (Green et al. 1994). Consequently the data represent the summation of changes identified in individual pixels for each class and also the direction of change, which is recorded as gain or loss.

Locations of change are not reflected in these simple figures. For example for the period 1989 to 2000 the area of Gewa class shows a net increase of 643.3 hectare (table 5.1), yet following table 5.2 Gewa increased by 5898.3 hectare and decreased by 5239.0 hectare. Minor differences between results in calculation of areas are caused by the fact that summaries of changes are computed using two methods. The values in table 5.1 are computed directly from the differences between areas identified in each classified image, but the gain/loss areas are derived from a cross tabulation matrix between dates.

Table 5.2: Statistics of changes in area based on pixel-by-pixel comparison between 1989 and 2000

Forest cover class	Area 1989	Gain		Loss		Unchanged	
	Hectare	Hectare	%	Hectare	%	Hectare	%
Sundri	23004.5	3019.7	6.8	6715.7	15.2	16288.8	36.8
Gewa	15159.8	5898.3	13.3	5239.0	11.8	9920.8	22.4
Kankra	191.5	1726.7	3.9	10.9	0.0	180.6	0.4
keora	44.1	69.2	0.2	24.8	0.1	19.3	0.0
Bush land	-	386.7	0.9	-	-	-	-
Shrub	569.3	210.2	0.5	316.3	0.7	252.9	0.6
Marshy grassland	556.1	486.4	1.1	301.4	0.7	254.6	0.6
Water	4695.1	1274.5	2.9	463.5	1.0	4231.6	9.6

Table 5.3: Overall forest cover change from 1989 to 2000 in study area

Status	% of Study area	Hectare
No change	70.4%	31148.6
Change	29.6%	13071.8

This approach allows for the analysis of the direction of change in terms of gains and losses as well as of areas of change versus areas of no change. The method adequately describes the changes in area of each of the forest cover classes but it does not provide information regarding the spatial location of changes in area. Maps present the area of change regarding the representing specific forest cover classes.

5.3.2 Maps

Maps are used extensively for representation of forest cover change and provide a convenient summary of the overall extent and distribution of change within specific areas (Laba et al. 1997, Riley et al. 1997). Change maps rely on the representation of all change classes and of related legends.

Interpretation of the imagery at level III provides 56 change and no change classes overall, of which 49 classes are actually effected by change. The representation of change classes in one map with many colours or patterns including legends would produce a complex graphical visualisation. Therefore several maps have been provided to clearly visualise the change areas.

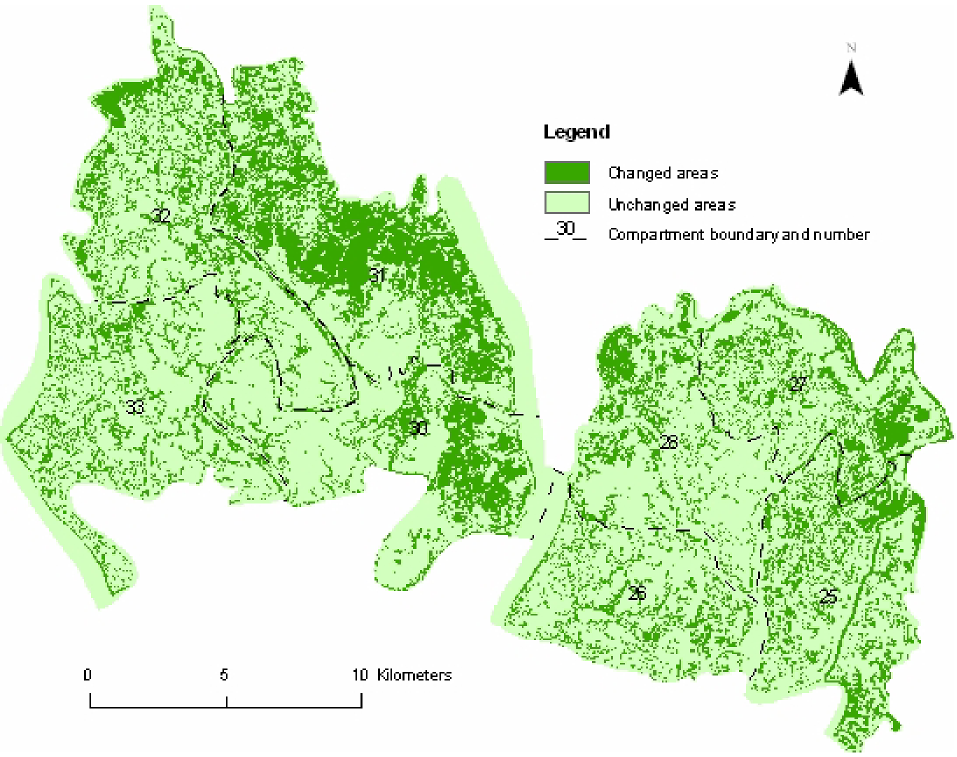


Figure 5.3: Study area showing changed and unchanged areas during 1989-2000

Figure 5.3 represents an overview of changed and unchanged areas throughout the study area. Figure 5.4 and 5.5 show the changed areas for the two largest forest cover classes Sundri and Gewa. Figure 5.4 shows that the area of other classes decreased and added to Sundri class in compartment 25, 26, 27 and 33, while decreased of most areas of Sundri to the classes Gewa, Kankra and bush land in compartments 25, 27, 28, 30 and 31 during the 11 years period of observation.

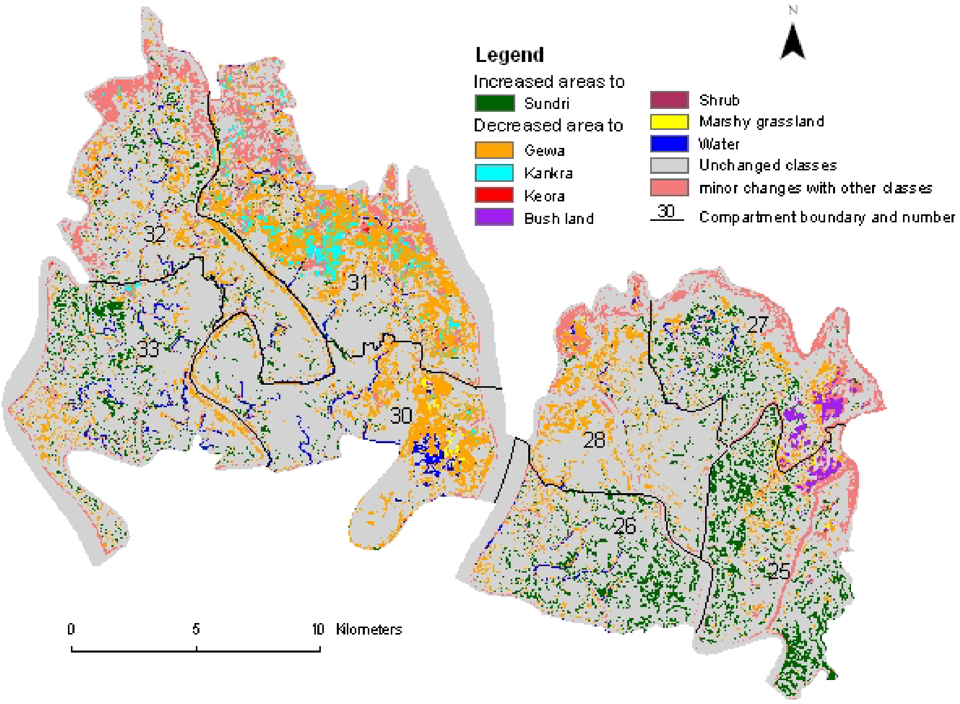


Figure 5.4: Representation of changed areas for Sundri during 1989-2000

Figure 5.5 shows the areas of other classes converted to Gewa in compartment number 28, 30 and 31 and the areas of Gewa converted to other classes Sundri and Kankra with the compartment 25, 26, 27, 31 and 32 respectively.

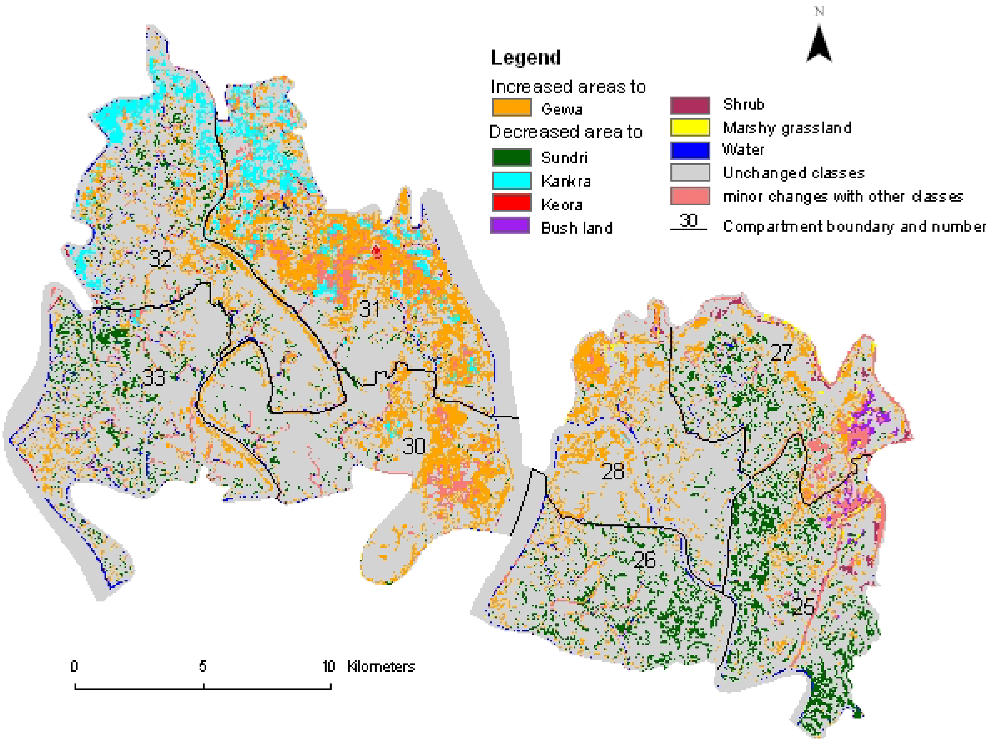


Figure 5.5: Representation of changed areas for Gewa during 1989-2000

5.3.3 Change matrix

Communication of information on forest cover change is complicated due to the large amount of detail available from the image analysis process. Where n (any number) classes are interpreted at each sensing period, n^2 change classes result and require interpretation and representation. Change assessment implies analysis of temporal transition, therefore it is advantageous to present the outcome of the analysis in a manner that fully communicates the results of this process. A change detection matrix provides a convenient means of summarising all forest cover changes between sensing periods (Martin and Howarth 1989, Jakubauskas et al. 1990, Jensen et al. 1993).

The following change detection matrix (table 5.4) represents 56 separate classes in the change matrix. The matrix arrangement permits assessment of change patterns amongst classes. It lists all classes from the first period on the left side and all classes from the second period across the top. Each element of the change matrix represents a transition sequence, the diagonals representing unchanged pixels and the off-diagonals representing pixels in transition. However the analysis is based upon pixel-by-pixel analysis rather than area based comparison so that recorded changes represent actual transitions from one class to another.

Table 5.4 represents changes in Forest cover classes from 1989 to 2000 using the results of the Level III classification of Landsat TM and ETM. The magnitude of change in hectares for each class is recorded and it is possible to determine the main change trends, which include the represented shifts of areas of the Sundri to Gewa or Gewa to Kankra. The change matrix provides the opportunity to highlight the classes and explain the relationship using a legend structure.

Table 5.4: Change matrix

Landsat	Year 2000 (hectare)							
Year 1989	Gewa	Marshy grassland	Kankra	Keora	Shrub	Sundri	Water	Total 1989
Gewa	9920.8	199.1	8.8	3.2	284.7	5238.9	163.6	15819.2
Marshy grassland	117.5	254.6	0.0	0.2	21.9	95.6	251.3	741.0
Kankra	1236.0	13.7	180.6	6.5	2.8	465.7	2.0	1907.3
Keora	34.9	0.6	1.3	19.3	0.0	27.4	4.9	88.3
Shrub	142.6	37.6	0.0	0.0	252.9	9.3	20.7	463.1
Sundri	2988.3	7.1	0.5	0.7	3.0	16288.8	20.2	19308.5
Water	578.4	42.3	0.3	14.3	2.8	636.5	4231.6	5506.1
Bush land	141.3	1.1	0.0	0.0	1.2	242.3	0.8	386.7
Total 2000	15159.8	556.1	191.5	44.1	569.3	23004.5	4695.1	44220.4

No change areas   Introduced between 1989 and 2000

5.4 Error influence on data sets

All data within a GIS contain a certain amount of error due to measurement, classification, recoding, generalisation, interpolation or interpretation errors (Heuvelink 1998). Walsh et al. (1987) consider errors in spatial data to arise from inherent and operational sources. Heuvelink et al. (1989) describes operational errors in terms of processing and modelling errors, and inherent errors as source errors. From the results of image processing, Hord and Brooner (1976) suggest errors arise mainly from boundary location, map geometry and data classification. Aspinall and Hill (1997) regard theses errors to be mainly related to misidentification of classes, positional accuracy in boundary location and failure to recognise internal polygon heterogeneity. Chrisman (1987) described the factors as resulting in errors of identification (error in assigning the correct attribute) and discrimination (errors in separating adjacent classes). Lanter and Veregin (1992) considered error as to comprise the multiple dimensions of positional accuracy, thematic accuracy, lineage, logical consistency and completeness. This study only highlighted the aspect of errors related to positional and thematic accuracy, which influence the results of change detection. Understanding the nature of error in spatial data is necessary to ensure the development of relevant analysis techniques and provide confidence in the quality of outcomes (Chrisman 1991).

<u>Thematic error</u>

Thematic errors occur when there is mislabelling of areas observed on a map during the classification process. This error for a map can be assumed by the assessment of classification accuracy. Guidelines for the mapping accuracy of thematic classes have been proposed by Anderson et al. (1976) and vary between 80 and 90 percent accuracy. The Coast Watch Change Analysis Project (C-CAP) of USA established guidelines of 90 percent for thematic accuracy of all categories. However investigations by Jensen et al. (1993) recommended setting a value of 85 percent as better accuracies cannot be achieved when using Landsat TM data.

No clear standard for values of thematic accuracy may be universally determined due to variation in the separability of different combinations of targets, even though they may be located on the same level of the classification scheme. The study achieved 81 percent overall classification accuracy for the Landsat ETM and 79 percent for the Landsat TM imagery. Assessment of the thematic errors has been made and the factors influencing accuracy have been discussed in subchapters 4.5 and 4.6 respectively.

Positional error

The positional error is the difference of position (coordinates) between the ground location and map location is related to the process of image rectification. Welch (1985) provides specifications of ± 0.5 pixel for geodetic rectification. This value for georeferencing is also often reported as the standard (Labovitz and Marvin 1986). Hill and Aifadopoulou (1990) achieved similar result, but indicate that local misregistration may reach 1.0 – 1.5 pixel. Positional accuracy in change detection is a crucial concern (Ferguson et al. 1992, 1993). Townshend et al. (1992) indicate that geometric rectification for change assessment within 0.5 – 1.0 pixel accuracy is acceptable. Change data produced by postclassification comparison will conspicuously record positional errors of one pixel or more. This compounds the problem of recognising real changes in the extent of land cover classes, which furthermore tend to occur at class boundaries (Dobson et al. 1995, Anon 2005). In a study by Aspinall and Hill (1997) 20 percent of all changes that were observed between two land cover data were identified to be due to geometric limitations. Martin (1989) indicates that displacements between images of only 0.5 pixel can introduce unacceptable levels of error in change assessment.

Landsat TM and ETM imagery collected for this study was already processed for geometric and radiometric correction. Positional error of Landsat ETM imagery was checked using GPS coordinates of ground locations, which were identified in the Landsat ETM imagery as well as in the study area. The positional error was determined as ± 0.6 pixel. This issue is addressed in chapter 3 of this study. Assessing the location error between the two images was not possible to measure as ponds is the only detectable features available for comparison identified in the Landsat ETM image were absent in the historical TM image. They had been constructed after 1989.

As accuracy of the postclassification comparison is totally dependent on the accuracy of the individual classifications any changes reported must be considered in the context of thematic and positional accuracy as described in this section.

5.5 Causes of change of forest cover

During field visits a focus was laid on the identification of land cover classes as represented in the Landsat ETM imagery. Attention was also given to find out if there have been changes of forest cover in the study area and the reasons behind the changes. Various references have also been consulted in order to update interpretations on possible reasons for the changes of forest (Canonizado and Hossain 1998, Chaffey et al. 1985, FAO 1998a, Ravila et al. 1998). Discussions were held with officials and staff members of the Sundarban Forest Division of Bangladesh Forest Department and to some extent with local inhabitants/people in the study area for exploring the reasons for changes of forest cover. The opinions/ideas and experience about the changes of forest in the study area have been gathered and integrated in this study. The causes identified as being responsible for changes of forest cover can be classified into two major groups – natural causes and man made causes (figure 5.4). Man made causes is tremendously affecting the sustainability of the use of forest products. The reasons that have been found responsible for changes are interlinked with each other and several interest groups are involved. The natural causes are also affecting the study area during the whole year. Flooding causes erosion along the banks of the courses of the river almost every year. From the records it is proven that cyclones also destroy a considerable amount of forest periodically. The loss of considerable amount of Sundri trees has also been reported due to the die back disease in some compartments of the study area.

Most people living in the surrounding of the forest territory are mainly engaged with fishing. Some are involved in cultivation or shrimp farming. Seasonal collection of non-timber forest products like grass and honey also supplies a considerable amount of people. They frequently depend on the forest for their daily necessities. People have to collect regularly fuel wood, poles, posts for house construction and fencing, fish traps as well as boat building materials for their needs. They fulfil their needs through obtaining these materials from the forest illegally. Legal extraction of the non-timber forest products is possible with the permission of Bangladesh Forest Department, but extraction of timber products is prohibited due to the existing moratorium. Some organised groups are involved in illegal extraction of timber from the forest and in supplying the local markets. These groups are continuously being supported or backed by the patrons (e.g. local politicians, businessmen, government officials etc.) of the area in their efforts of continuous removal of forest resources from SRF illegally. Due to patronising these illegal removals of forest resources by local influential persons, law enforcement agencies are reluctant to act against them. This indicates that corruption plays an important part in continuous illegal removal of forest products from SRF. Application of laws against the illegal removal of forest products is also inadequate. Huge population pressure coupled with a considerable number of unemployed population forces people to extract forest products illegally from SRF, which is negatively affecting the ecological and economical sustainability of the resources.

There has been considerable and continuous reduction in freshwater inflow from the upstream catchments especially from the Ganges-Gorai drainage due to the construction of the farakka dam in India. Widespread increase in sedimentation and resultant silting of waterways are the results. Drying out of the Bhola river and Kharma khal (canal) between the forest and adjacent settlements have accelerated the process of forest change in the study area. Reduction of fresh water in-flow induced inundation of more forested land by saltwater. Thus soils are affected by an increasing level of salinity which in turn negatively influences the natural regeneration of the forest.

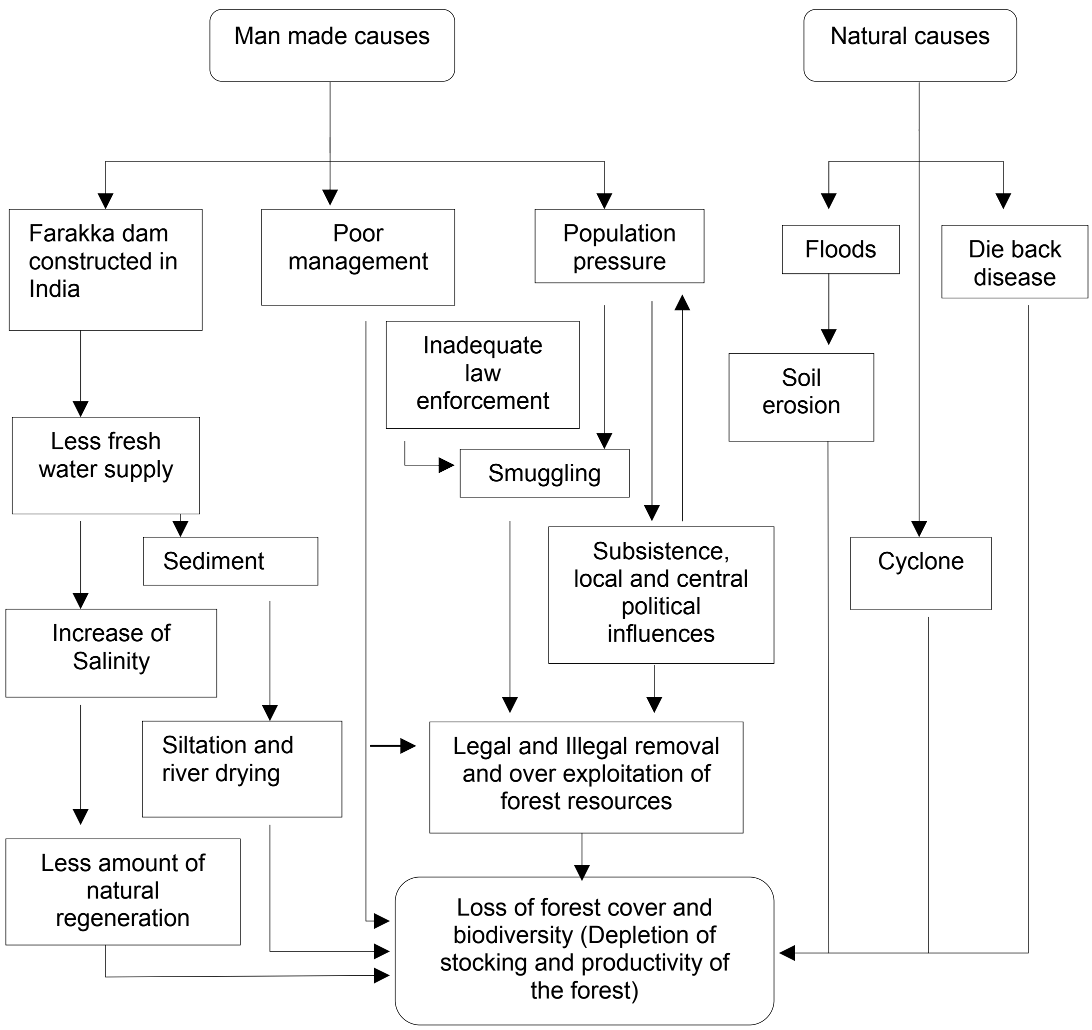


Figure 5.4: Causes of changes of forest in the study area of SRF

During field visits it was observed that areas near the forest boundary at Dhansagar and Kalamteji station of the study area already have lost the typical ecological characteristics of mangrove ecosystem due to the drying of the Bhola river and the Kharma khal. This problem became more prominent by the plantation of exotic species (such as *Acacia* spp.) at Dhansagar, which is threatening the insitu-biodiversity of the mangrove forest. These plantations should be removed from the forest immediately. The Government of Bangladesh had raised a project to excavate the two water flows for about 16 km to restore the ecological condition for mangroves in the area, but the project has been stopped since the new government came to power in 2001. It was expected that the excavated rivers would increase high tide inflow of water in the forest areas. In order to restore the mangrove environments in the study area it is very much necessary to restart this project work. These activities would then help to protect the forest against illegal extraction by prohibiting frequent invasion of people inside the forest.

Any disturbances like depletion of trees from the forest induce changes of forest structure and composition in local to landscape scales (Forman and Gordron 1989, Morrison and Swanson 1990). As a consequence changes in composition, structure and landscape pattern can influence ecological processes and functions, which indicate direct changes in biological diversity (Spies and Franklin 1996, Hemstrom et al. 1998). The existing management plan for SRF was formulated in 1998 after completion of a detailed inventory during 1996. Due to the moratorium the Forest Department could not follow the existing management plan and thus no management operations are executed in the forest. By now bringing the forest under planning and management is to some extent necessary for conservation of the biodiversity as well as of the sustainability of resources.

As global warming and the green house effect causes climatic change which results in a rise of sea water level, the SRF will be seriously affected. It is urgent to protect the forest and around a million people settling in the region from probably upcoming natural disasters like tsunamis, cyclones or tornados. Lack of proper management of the mangrove forest resources results in serious consequences not only locally but also concerns Bangladesh as a whole.

Among the causes of change natural ones cannot be controlled fully, while man made causes may be controlled more effectively. This would result in a decrease of change in forest in the course of time. The study proves that a significant activity of extraction of the tree resources continues although the moratorium exists. Efforts of

Bangladesh Forest Department have to be increased in order to reduce the rate of unauthorised/illegal extraction of forest resources from SRF for protect its resources. For the conservation of biological diversity and protection of the forest it is important to consider these factors in order to optimise the efforts for settling sustainable management, which supports production, income, employment and provides ecological service and safeguard to the coastal settlements.

In order to effectively address and handle the problem of reduction of forest resources and changes of forest covers, Bangladesh Forest Department needs appropriate tools for periodical monitoring of the forest. Such a monitoring would assist detecting the specific causes for gradual changes of forest cover timely and in taking appropriate measures to control the causes of changes. Remote sensing provides a great potential to monitor the forest and has been applied to many management issues in tropical coastal environments. It also offers the possibility to monitor large regions and to study changes in the entire ecosystem over space and time. This study in chapter 6, attempts to formulate/illustrate a monitoring scheme for SRF, which would facilitate Bangladesh Forest Department in performing the needed tasks of monitoring of the forest.

5.6 Summary

Monitoring of the study area of SRF provides spatial information on its status in and in terms of the factor of change. Detection of change patterns of forest cover by means of remote sensing can be achieved in various ways depending on the characteristics of data sources and targets as well as the facilities of data processing. However this research analysed the trend of change over time and has been directed towards establishing an effective approach to detect change by postclassification comparison of multitemporal satellite data as well as by appropriate evaluation and presentation techniques.

The interval for change assessment of 11 years allowed for the detection of significant change, which is related to increasing human intervention in the study area. Several techniques have been used to provide in-depth details on the extent and the spatial distribution of change identified by classifying Landsat satellite data. These include area-based change summaries, maps of the distribution of change classes and the analysis of a detailed change matrix, which provide information on areas of change and on transition sequences. The study also tries to comment on the causes of change of forest cover by highlighting the factors of impact and the relations between these factors. It is also highlighted that human activities in the mangrove ecosystem of SRF increase the complexity of changes.

Studying the patterns of error within the classifications and the process of change assessment provides an important diagnostic capability for understanding the influences of data quality on the achieved results of change detection. Identifying the sources of error facilitates the sound design of data collection and data analysis in order to minimise error. Analyses of thematic and positional errors are needed to highlight their influences in the classified and change assessment data.

Chapter 6

Monitoring scheme using satellite imagery

6.1 Introduction

The SRF has been more and more threatened in the past decades. From the previous inventories it is clear that huge extraction of timber resources is affecting SRF although there is a moratorium existing since 1989. This study proves for a significant loss of trees from this forest. All the results indicate that the forest is under a gradual process of change since a long time. More over it can easily be realised that the dependency of the people on timber and non-timber forest products is also increasing and their interventions into this valuable mangrove ecosystem make the situation more critical day by day. The loss and degradation of this natural ecosystem will impact heavily on coastal communities - in economic, livelihood and social terms as well as the indigenous people will lose natural safeguard against future tidal waves like tsunami. Therefore it shows the importance to protect the mangrove forest. The Bangladesh Forest Department has to be more active in developing and implementing sustainable management of the mangrove forest resources for the use of the people and also for protecting the heritage site.

Meeting the goals of sustainable forest and ecosystem management requires increasing monitoring efforts. Realising the importance of this forest at local and national level the Bangladesh Forest Department needs to convey the importance of monitoring to the Ministry of Environment and Forest (MOEF) or Implementation Monitoring and Evaluation Division (IMED) of Planning Commission via MOEF for policy decision and budget allocation, in so periodical monitoring could be ensured as a basis for decision making for the sustainable management of SRF.

Remote sensing can effectively provide assessment and monitoring of forest cover change thus help in developing ecologically as well as economically sound forest planning. Consistent methodology and cost effectiveness could be enhanced by the development of a proper monitoring scheme using satellite remote sensing. Several studies revealed a widespread application of remote sensing in mapping and monitoring mangrove ecosystems along coastal regions of the world (Hurd et al. 1992, Scavia et al. 1995, Green et al. 1996, Perez et al. 2002). The presented study provides the outlines of a monitoring scheme as a preliminary guide to derive suitable and reliable spatial information on the mangrove forest cover periodically. There are several important aspects which have to consider by the responsible authorities of Bangladesh Forest Department, which needed to implement the monitoring scheme based on satellite remotely sensed data as discussed in the following sections.

6.2 Scope and limitation in Bangladesh Forest Department for monitoring the SRF

The Bangladesh Forest Department recognised remote sensing as a tool in obtaining data at the occasion of the Forest Resources Management Project (FRMP), funded by World Bank and hosted in the Resource Information Management System (RIMS) unit at Dhaka. This unit used aerial photography of the year 1995 for mapping and assessing the forest cover and prepared a detail database of the vegetation types, growing stocks, rivers, office locations, compartment boundaries etc. of SRF. In order to strengthen the spatial database for mapping of SRF, the Sundarban Biodiversity Conservation Project (SBCP) of the Forest Department established a GIS unit in the Sundarban Forest Division office at Khulna in 1999. Both units are equipped with remote sensing and GIS hardware and software, but these tools are not properly used due to lack of trained personnel.

Some members of the Forest Department have undergone training to perform GIS related work and to maintain the software. But dealing with remotely sensed imagery is more or less unknown to the personnel. There is availability of GPS in all range offices of SRF and the staff knows GPS functionalities. There are some other factors which also have influence on the application of remote sensing and GIS in SRF, such as lack of financial resources, lack of training opportunities, poor access to data and information as well as to the Internet.

The prescriptions and provisions of the existing management plan are not applied in the SRF due to moratorium. Besides, the Forest Department is not strictly taking into consideration the factors affecting the issue of the sustainability though these factors are clearly visible to all levels of officials. There is no built-in mechanism to monitor the forest resources as well as the impact of removal of timber.

6.3 Forest cover monitoring considerations using remote sensing system

A monitoring program of forest cover change for SRF using satellite remote sensing data needs to come out with several decisions on specific requirements has elaborated in figure 6.1. Meeting properly the requirements prior to monitoring will help to produce acceptable results as described in the previous chapters. The chapters will guide through the presentation of a planning process in forest cover monitoring for SRF while choosing the suitable image classification system or change detection algorithm.

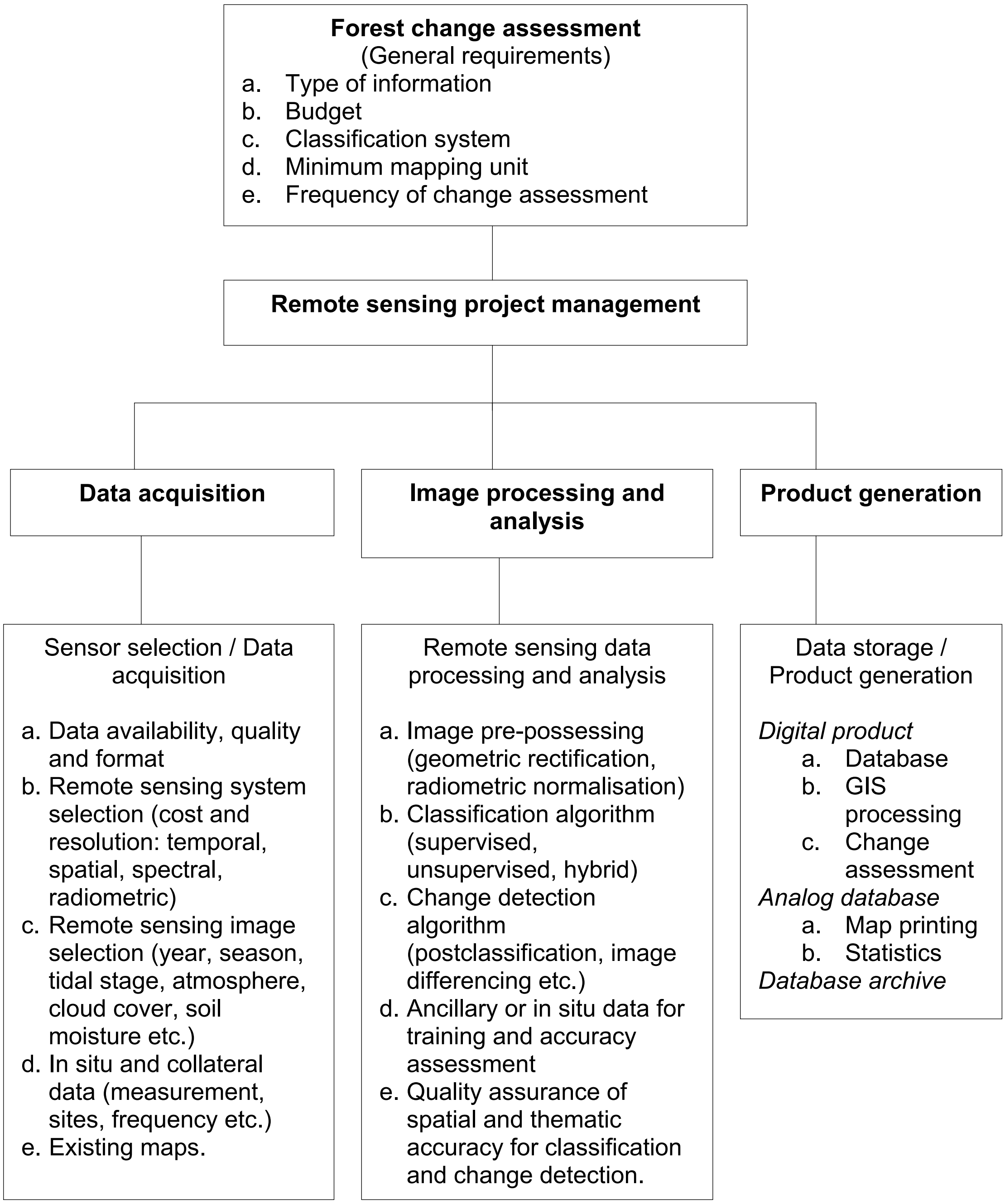


Figure 6.1: Change assessment requirements using satellite remote sensing (adopted from Klemas 2001 and Dobson et al. 1995)

The research found that significant change occurred in the study area of SRF within the 11 years (1989-2000) period. Depending on the real world problem of creating easy to handle and low cost tools for monitoring, limited budgets for data acquisition and limited resources for data analysis, this study intends to being capable a monitoring scheme to track the changes within the forest in space & time. As the needed operational tools for forest assessment and forest monitoring are identified in the study, it is possible to start monitoring efforts from now onwards using a combined method of field observations and satellite image analysis. The periodical monitoring will depend on the availability of funding and the presence of trained experts at local and national level. Data with a slightly higher temporal resolution, such as 5 years, will certainly improve the reliability of analysing gradual process of change of the forest cover. Important aspects to immediately set up measures for protecting the forest as well as its sustainability may be detected more efficiently.

6.4 Costs of monitoring

For the research Landsat ETM and TM imagery of the study area of SRF have been collected from Bangladesh Forest Department and the archive of Global Land Cover Facility for free. But indirect costs associated with image processing and ground fieldwork must be appreciated. In general monitoring costs increase with larger spatial scale, higher level of detail and accuracy, and the frequency of data collection. Careful definition of remote sensing requirements will have a major impact on project cost and product quality (Klemas, 2001).

Image processing and classification of satellite data is critical as being a time consuming step. Taking this study as an initial step to build an operational monitoring system for forest cover classes, thus involve building a sound database and allowing for mapping, running through the change detection process and for identifying and labelling changes. All these processes required 14 months for the study area. For the Bangladesh Forest Department building a database for SRF using remotely sensed data would require not more than 8 months beginning with data acquisition up to the level of planning.

Ground verification is also dues significant costs. Remote sensing provides data about the ‘spectral landscape’, so costly ground verification has to relate the spectral data to land use cover classes. To generate spatial information from remotely sensed data for the SRF, the Forest Department has to conduct an extensive ground survey. Ground sampling of the remotely sensed features is needed to generate a proper classification scheme. The Forest Department already set out ground sampling work for past inventories based on aerial photo interpretation for the forest. Depending on the objectives the Forest Department takes decision about the sampling scheme. During inventory of the forest resources in 1996 sampling plots were established in each one-minute grid interval throughout the SRF. The Forest Department could implement the same sampling approach for field verification of remotely sensed data. Data would then be directly comparable with the previous inventory databases concerning different parameters (e.g. growing stock, height etc.) accumulated from the field sampling. No extensive sampling is needed for generating a classification scheme and for change area calculation related to forest cover classes. Considerable time and financial budget is necessary for the field sampling in SRF, which could easily be realised based on the previous experience of the department. Cost associated with accuracy assessment of the generated results also needs to take into consideration. Allocation of time and budget for a monitoring task is quite variable and also depends upon the specifically formulated objectives.

6.5 Monitoring Scheme for SRF

Monitoring comprises a periodical process of planning, implementation, communication and follow-up activities. To organise the monitoring efforts for the SRF, a monitoring scheme is developed by the study which is illustrated below in figure 6.2. This will assist to the Bangladesh Forest Department to facilitate sustainable use of the limited resources.

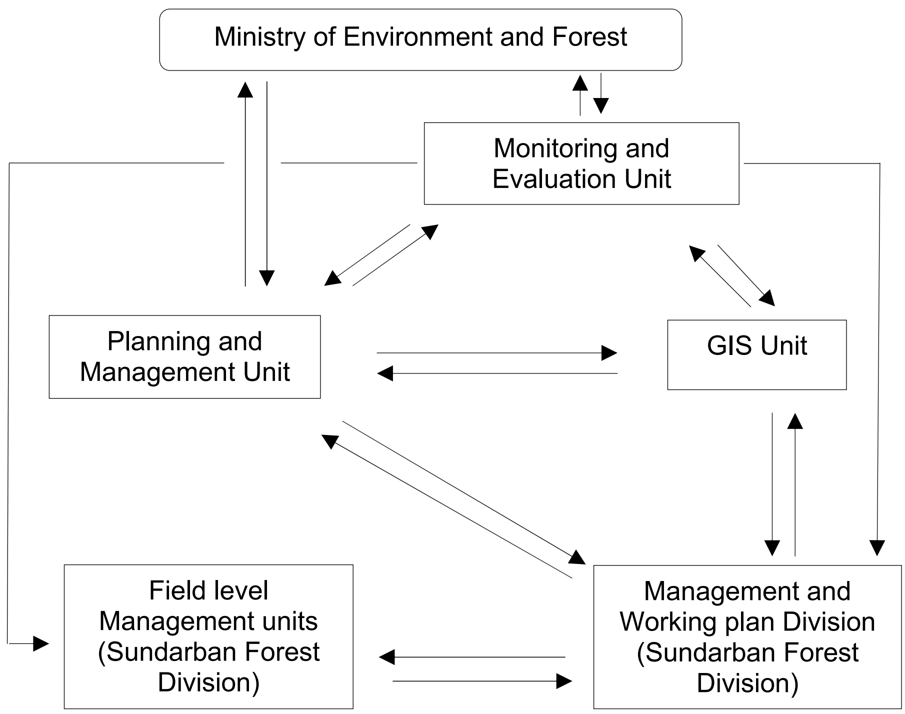


Figure 6.2: Monitoring scheme for the SRF

The goal of setting up this monitoring scheme is to identify and evaluate the changes in forest cover of SRF periodically over time and space. Forest monitoring is often neglected in Bangladesh. Losses in forest cover are not surveyed or mapped and their exact sizes and locations are not conclusively determined, except for a periodic visual observation, which is appearing as the major difficulty for sustainable development of the forest resources (FAO 1998b). Presently the Monitoring and Evaluation Unit of Bangladesh Forest Department is responsible for monitoring the raising of seedlings and distribution, the export and import of forest logs and for evaluating the performances of different components of ongoing projects of the Forest Department. The unit should widely provide main activities of forest monitoring.

The units involved in the scheduled monitoring scheme (figure 6.2) coincide with the existing units of the Bangladesh Forest Department at national and local level. The monitoring and Evaluation unit has given priority to the process of the forest resources assessment and monitoring. The units involved in the monitoring process should be interlinked with each other to organise successful networking under specific responsibilities, in the following way:

Ministry of Environment and Forest

- Decision making on policy level
- Budget allocation for monitoring

Monitoring and Evaluation unit

- Problem identification on field level
- Remote sensing data specification and requirements
- Selection of the remote sensing data classification system
- Frequency of data collection
- Follow up the monitoring process
- Determination of correct implementation management plan of achievement of desired results
- Identification of the local level criteria of indicators of sustainable management and monitoring
- Monitoring, evaluation reports and documentation

Planning and Management unit

- Problem synthesis
- Identification of the information required for planning

- Monitoring project preparation and budget disbursement
- Remote sensing data purchase and handover
- Assistance in preparation of the management plan of the SRF

GIS unit

- Satellite image collection
- Image processing
- Field evaluation and preparation of classification scheme of forest types according to the management plan
- Image analysis and information extraction
- Preparation of map of forest cover classes
- Change assessment of forest according to the planning requirement
- Ground verification of the changes of forest types (area and species)
- Provision of statistics and documents preparation of the for management plan
- Setup and maintenance of an archive of GIS and remote sensing data for multitemporal data comparison (LUCC)

Management and Working Plan Divisions of SRF

- Identification of factors responsible for change of forest types and verification
- Compilation of info/data for mapping and planning
- Updates of the existing management plan with the information provided by the GIS unit after analysis of the satellite data
- Keeping provision for modification or change wherever necessary to adjust with the existing situation
- Identification of the local level criteria and indicators of sustainable management
- Documentation of the archive database and report
- Supervision and technical assistance for implementation of the management plan

Field level management units (range offices and stations) of SRF

- Execution of management plan
- Maintenance of official documents and records
- Observation
- Feed back to the responsible authority

6.6 Potential remote sensing platforms for SRF monitoring

Over the past 25 year, many satellites have been placed in service. They carry sensors with capabilities salient to forest monitoring. These satellite sensors can be categorised following the ground resolution of imagery (pixel size on ground level). They are the coarse resolution (pixel size >80m), medium resolution (pixel size 20 – 80m), high Resolution (pixel size 5 – 20m) and very high resolution (pixel size 1 – 5m). Each satellite sensor has its own characteristics in ground resolution, temporal resolution, spectral resolution, coverage swath and so on. Some of the potential platforms used are listed in table 6.1. Gathering data useful for forest monitoring has to take account the type of sensor, spectral and spatial resolutions and ground coverage. Using satellite imagery in forestry will be competitive in costs and benefit, if coverage of large areas is provided.

Table 6.1: Specification of remote sensing sensors with potentials for use in forestry applications

Sensor/ Platform	Data Provider	Spatial Resolution	Spectral Bands	Temporal resolution	Swath	Purpose
Landsat 5	USGS/ NASA	30-60m (MS)	7 MS bands (vis, NIR, MIR, TIR)	16 days	185km* 185km	Land use/Land cover, global change Studies, large area mapping
Landsat 7	USGS/ NASA	15m (pan) 30-60 m (MS)	1 pan and 7 MS bands (vis, NIR, MIR, TIR)	16 days	183km* 172km	land cover state and change (eg vegetation type), used as multipurpose imagery for land applications
IRS	Euromap	5.8 m (Pan) 23 m (MS)	1 pan and 3 MS bands (Vis, NIR, TIR)	24 days	142km* 142km (MS) 70 km (pan)	Natural resource planning, agriculture monitoring, natural disaster assessment
SPOT vegetatio-n	SPOT Image Corporatio-n	1000 m (MS)	4 MS bands (vis, NIR, SWIR)	1 day	2,250 km	Environmental monitoring, natural resource management
IKONOS	Space Image Corporatio-n	1 m (Pan) 4 m (MS)	1 Pan and 4 MS bands (vis, NIR)	3 days	11 km* 11km	Land use/Land cover, urban planning, agriculture monitoring and analysis, mapping
NOAA AVHRR	USGS/ NASA	1100m (MS)	5 MS bands (vis, NIR, MIR, TIR)	3-4 days	3,000km * 6,000km	Land cover, soil moisture, vegetation indices and vegetation monitoring
TERRA Modis	USGS/ NASA	250-1000m (MS)	7 MS bands (vis, NIR, SWIR)	1-2 days	2,330km *10km	Land use/Land cover, ocean monitoring

Sources: Characteristics listed from the web pages of the respective sensors, February 2006, see reference

6.7 Requirements for successful monitoring of SRF

Bangladesh Forest Department must invest considerable resources to set up its capability of acquiring spatial information on forest cover and changes by means of satellite imagery. Monitoring being a continuous process the Forest Department needs to extend its existing resources. Collecting and publishing data on forest cover on a regional level by mapping and statistics needs responsibilities, such as

- Set up of a GIS
- GIS support for the forest resource framework
- Examination of forest stands by GPS technical support
- Set up of a data archive

The set up with equipments and software for processing geodata (GIS) and remotely sensed data are available in the local office of the Sundarban Forest Division, Khulna as well as in the head office at Dhaka. These needed to provide upgrading in order to meet the upcoming challenges.

The effective application of remote sensing for monitoring the SRF will require capabilities of the Forest Department at national as well as local levels of management. The capabilities at national level for applying remote sensing require the integration of efficient activities for monitoring and mapping, such as

- Training to efficiently perform the GIS and remote sensing tasks
- Evaluation of new technologies
- Development of applications
- Technical support
- Data acquisition

For the development of an operational monitoring scheme based on remote sensing the creation of a network of activities and actors is necessary. This includes experts with the following skills and background:

- Expertise in remote sensing including understanding of the capabilities of all forms of remote sensing of applying analysis is to forest cover classes and knowledge of algorithms, as well as knowledge of GIS, GPS, spatial statistics
- Good navigational skills (mapping)
- Knowledge and understanding of the economy of forest resources and related ecological processes

The GIS unit of Bangladesh Forest Department has to play an essential role in the implementation of activities of forest management. In order to set up a reliable database management for the SRF, training in GIS and remote sensing should be extended to more officials to allow for an accurate utilisation of the remote sensing and GIS for the improvement of management and planning strategies.

Chapter 7

Conclusion and recommendation

7.1 Major findings

Bangladesh Forest Department previously attempted to assess and monitor the Sundarban Reserved Forest using aerial photography and prepared maps at a detailed level for the forest. These maps could not be used on field level as there is no management plan available fitting to the forest cover classes in the maps. Satellite remote sensing data, which are most suitable for mapping and monitoring in terms of benefit and cost relation has been used in this study to build an appropriate classification system of SRF. Based to the existing management plan as well as the spectral properties a level III classification system for the forest, which ensures its applicability for proper planning, was generated.

For mapping land use classes at level III of the USGS classification system, several methods with various band combinations as well as data fusion techniques were examined to identify the most suitable methods of monitoring. Results indicate that IHS imagery with fused PAN data and thus with higher spatial resolution could not increase classification accuracy and showed a wide discrepancy of spectral characteristics of the classes. On the other hand PCA imagery improved the classification accuracy for specific classes. Pure combination of multispectral bands did not offer acceptable accuracies. However the combination of the NDVI layer and the thermal band with the multispectral bands performed well in identifying level III forest cover classes. Classification results were evaluated by field observations and achieved an overall accuracy of 81 and 77.6 percent and a Kappa coefficient of 66.8 and 73.7 percent for eight forest cover classes for the Landsat ETM and TM imagery respectively.

Forest cover changes were assessed during the 11 years period (1989-2000) using the approach of postclassification comparison. Significant change has been observed due to the removal of Sundri (*Heritiara fomes*) and Gewa (*Excocaria agallocha*) in the study area during this period. Human interventions as well as ecological impacts in this valuable mangrove forest were found responsible for the changes. For tracking the changes and trends continuous monitoring is necessary in order to assess spatial parameters of forest ecology and resources periodically and to plan decisions at local and national level. The study has developed a periodical monitoring scheme, which will allow respective authorities to set up sustainable and appropriate monitoring of the Sundarban Reserved Forest with specific regard to the integration of satellite imagery.

7.2 Study limitations

There are some specific limitations in this study, which should be addressed as a means of improvement for further activities. The first limitation of the study is the gap between the date of remote sensing data acquisition and the dates of field visits. The first field visit under the study was conducted 3 years later than the date of image acquisition. This fact obviously created problems during the generation of the classification system as explained in chapter 3. Under reliable conditions of setting up monitoring in the future this limitation can easily be overcome by planning the field visits as close as possible to the image acquisition date.

Training data for supporting the image classification have been acquired during the field visits. The areas visited for data collection have been discussed in chapter 3 and a strong bias with the proximity to river channels was demonstrated. It is due to the presence of anthropophagous tigers in the forest that difficulties arise in walking deeper into the forest without safeguard. For a small group supplied with limited logistics as provided by Bangladesh Forest Department, it was impossible to cover the full area. Nevertheless the respective reference data have not been used against the classified in order to estimate the classification accuracy. The reliability of the reference data is thus weak, as it could not be assessed in combination with ground truthing.

Multispectral mapping by digital remote sensing techniques is characterised but not restricted by inherent limitations. The process of classifying the ground features into specific classes introduces thematic errors during the classification process that are specifically driven by reference data, mixed pixels or spectral confusions. However, these limitations could be addressed by several ways as discussed in chapter 4. It is also possible to overcome them by sound statistical analysis in order to produce accurate land use and land cover maps derived from multispectral satellite data. Strict rectification standards are required for accurate quantification of change detection. Landsat TM and ETM imagery collected for this study was already processed for geometric and radiometric correction. Positional error of Landsat ETM imagery was checked in the field by using GPS coordinates of ground locations of ponds identifiable in the Landsat ETM imagery during field work. The position error was determined as ± 0.6 pixel. Assessing the location error between the two images was not possible as ponds being the only detectable features available for comparison did not yet exist at the time of the acquisition of the historical TM image. The causes are explained in chapter 5. The most important limitation associated with this research is the lack of a quantifiable assessment for change detection.

7.3 Recommendations

The supervised maximum likelihood algorithm was applied for the analysis of the remotely sensed data. The classification results achieved in this study were identified as providing substantial levels of agreement with the reference data, though some forest cover classes exhibit confusion with the spectral properties of other classes. Classification accuracy achieved by the study seems to be adequate for change assessment, but improved results are highly desirable.

In-depth analysing of geometrical and thematic accuracies of classified data for sound analysis is required in order to completely understand the errors occurring within the results. Thus the variations of impacts of errors in classified data arise from image rectification and thematic classification. These errors should be investigated in further in-depth research. A further improvement of understanding quality issues of data and classification could significantly improve the reliability of spatial data management for SRF.

The study has provided a consistent methodology for forest mapping and change assessment by a specifically adopted monitoring scheme. By providing the proper training samples, the findings settled in this research can be further applied in monitoring canopy density classes. Remote sensing can also play an important role in identifying the distribution of settlements around the SRF, which would help to support the forest guards for protection purposes. Identification of areas covered by Sundri trees affected by die back disease in the Sundarban Reserved Forest is possible in order to plan removal from the forest. Assessment of impact of natural disasters such as occurrence of wild fire could easily be identified using remote sensing. The utilisation of the combination of satellite data and ground truth data on silvicultural intervention parameters (e.g. felling of Gewa or diseased Sundri stands) can provide a suitable and cost-efficient inventory concept. Through interpretation of satellite data, a huge information potential on assessing the spatial distribution of felling areas could more or less immediately be provided to the local forest authority.

The whole range of historical imagery data is stored in archives and can be retrieved at specific demand for extended change analysis. The extended implementation of remote sensing and GIS technologies following the presented strategy will allow for a far wider range of alternative stratifications of land cover in general and of forest cover in particular.

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