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ORIGINAL ARTICLE

Mangrove forest distributions and dynamics (1975–2005) of the tsunami-affected region of Asia†

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ABSTRACT

Aim We aimed to estimate the present extent of tsunami-affected mangrove forests and determine the rates and causes of deforestation from 1975 to 2005.

Location Our study region covers the tsunami-affected coastal areas of Indonesia, Malaysia, Thailand, Burma (Myanmar), Bangladesh, India and Sri Lanka in Asia.

Methods We interpreted time-series Landsat data using a hybrid supervised and unsupervised classification approach. Landsat data were geometrically corrected to an accuracy of plus-or-minus half a pixel, an accuracy necessary for change analysis. Each image was normalized for solar irradiance by converting digital number values to the top-of-the atmosphere reflectance. Ground truth data and existing maps and data bases were used to select training samples and also for iterative labelling. We used a post-classification change detection approach. Results were validated with the help of local experts and/or high-resolution commercial satellite data.

Results The region lost 12% of its mangrove forests from 1975 to 2005, to a present extent of *c.* 1,670,000 ha. Rates and causes of deforestation varied both spatially and temporally. Annual deforestation was highest in Burma (*c.* 1%) and lowest in Sri Lanka (0.1%). In contrast, mangrove forests in India and Bangladesh remained unchanged or gained a small percentage. Net deforestation peaked at 137,000 ha during 1990–2000, increasing from 97,000 ha during 1975–90, and declining to 14,000 ha during 2000–05. The major causes of deforestation were agricultural expansion (81%), aquaculture (12%) and urban development (2%).

Main conclusions We assessed and monitored mangrove forests in the tsunami-affected region of Asia using the historical archive of Landsat data. We also measured the rates of change and determined possible causes. The results of our study can be used to better understand the role of mangrove forests in saving lives and property from natural disasters such as the Indian Ocean tsunami, and to identify possible areas for conservation, restoration and rehabilitation.

Keywords
Change analysis, deforestation, image processing, Indian Ocean tsunami, Landsat, mangrove forests.

INTRODUCTION

Mangroves forests, distributed circumtropically in the intertidal region between sea and land in the tropical and subtropical latitudes, provide important ecosystem goods and services. The forests help stabilize shorelines and reduce the devastating impact of natural disasters, such as tsunamis and hurricanes. They also serve as breeding and nursing grounds for marine species and are sources of food, medicine, fuel and building materials for local communities. However, the forests have been declining at an alarming rate – perhaps even more rapidly than inland tropical forests (Aizpuru *et al.*, 2000) – and much of what remains is in degraded condition (Valiela *et al.*, 2001; Wilkie *et al.*, 2003). Conversion of

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mangrove forests to aquaculture is on the rise in many countries of the region without considering the fact that the total economic value of intact mangrove forests is often higher than that of shrimp farming (Balmford *et al.*, 2002). The remaining mangrove forests are under immense pressure from clearcutting, encroachment, hydrological alterations, chemical spills, storms and climate change (Blasco *et al.*, 2001; McKee, 2005).

The Indian Ocean tsunami of December 2004 and other natural disasters have highlighted the importance of mangrove forests as a 'bio-shield' that protects vulnerable coastal communities. Mangrove forests attenuated the Indian Ocean tsunami waves and protected coastal communities in Indonesia, Thailand, India and Sri Lanka (Danielsen *et al.*, 2005; IUCN, 2005; Kathiresan & Rajendran, 2005). In some areas, mangrove forests hit by the Indian Ocean tsunami suffered severe damage from breaking and uprooting. Recent findings suggest that the continued destruction and degradation of many mangrove forests throughout the tropics over the past few decades has decreased the protective capacity of mangrove forest ecosystems and reduced their ability to rebound from natural disasters (Dahdouh-Guebas *et al.*, 2005; Nigel, 2005; Weiner, 2005). However, accurate and reliable information on the present extent of mangrove forests and the rate and causes of deforestation in the tsunami-affected region of Asia has not been available (Adeel & Pomeroy, 2002; Danielsen *et al.*, 2005; UNEP, 2004). Such information is needed to better understand the protective role of mangrove forests and to learn more about deforestation dynamics, carbon fluxes, forest fragmentation and the provision of ecosystem goods and services.

Remote sensing is an indispensable tool for assessing and monitoring mangrove forests, primarily because many mangrove swamps are inaccessible or difficult to field survey. Remote sensing provides synoptic coverage, and historical satellite data dating back to the 1960s are available. Global mapping initiatives have failed to map the extent and rate of deforestation with sufficient detail because these studies have been based on satellite data with coarse spatial resolution (1 km or coarser). For example, only extensive mangrove areas were mapped as part of the Global Land Cover 2000 survey (Stibig *et al.*, 2007). At local scales, several studies have used moderate-resolution satellite data [e.g. Landsat, SPOT and the India Remote Sensing Linear Imaging Self-scanning Sensor (IRS LISS III)] to characterize and map mangrove forests (Silapong & Blasco, 1992; Ramsey & Jansen, 1996; Blasco *et al.*, 2001; Selvam *et al.*, 2003; Ramasubramanian *et al.*, 2006; Vaiphasa *et al.*, 2006). Synergistic use of optical and radar data has been particularly useful in cloud-covered tropical mangrove areas (Aschbacher *et al.*, 1994; Giri & Delsol, 1995). However, large areas of the tsunami-affected countries of Asia (Indonesia, Malaysia, Thailand, Burma, Bangladesh, India and Sri Lanka) remain unmapped. As a result, the present extent of mangrove forests, and the rate and causes of deforestation, are unknown.

We determined the extent and distribution of mangrove forests in the tsunami-affected countries and identified the rates and causes of change using multi-temporal satellite data and field observations. Our analysis sought to answer the following research questions: how much mangrove forest remains; where are the remaining mangrove forests located; what is the rate of change; what are the main reasons for the change?

Study area

Our study area covers the coastal areas of Indonesia, Malaysia, Thailand, Burma (Myanmar), Bangladesh, India and Sri Lanka. We chose this area for a number of reasons. First, this area was the most devastated during the Indian Ocean tsunami of December 2004; as a result, many national governments and international organizations are now implementing ambitious conservation and rehabilitation programmes. Second, the region contains approximately 10% of the total mangrove forests of the world, including the largest remaining contiguous mangrove forest in the world, the Sundarbans. Third, strong demographic pressure and diverse climatic conditions in the region have created a mosaic of mangrove diversity that is changing constantly. Fourth, the region is the epicentre of mangrove biodiversity and consists of many existing and planned national parks, biosphere reserves and world heritage sties.

The forest is under severe threat from both anthropogenic and natural forces. Anthropogenic threats include encroachment from expansion of agriculture (e.g. rice farming, coconut and oil palm), aquaculture, urban development (e.g. resorts), mining, salt pan development and overexploitation of resources. Natural threats include erosion, sedimentation and sea level rise. Because of these threats, mangrove forest is the most threatened habitat in the region. Only sporadic patches of mangrove forests are left in India and Sri Lanka, and they have been depleted in Burma, Thailand, Malaysia and Indonesia.

In addition to deforestation, mangrove forests have been declining in biological diversity and economic value. Many flora and fauna are vulnerable, near-threatened, threatened, endangered or critically endangered. Economic activities such as extraction of timber and fuel wood, fishing and the collection of honey and other forest products have also diminished.

DATA AND METHODOLOGY

Data acquisition

We used Landsat GeoCover and recently acquired Enhanced Thematic Mapper Plus (ETM+) data, made available through the US Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) (http://eros.usgs.gov). GeoCover is a collection of Landsat data with global coverage and generally cloud-free images. Data were collected for three epochs: (1) the '1975' imagery from 1973 to 1983, (2) the '1990' imagery from 1989 to 1993, and (3) the '2000' imagery from 1997 to 2000. Detailed descriptions of GeoCover data can be found at https://zulu.ssc.nasa.gov/mrsid/. Additional

Multispectral Scanner (MSS) and Thematic Mapper (TM) data were acquired to supplement cloud-covered areas. The '2005' Enhanced Thematic Mapper Plus (ETM+) data collected from 2005 to 2006 were acquired from EROS. Approximately 216 Landsat TM or ETM+ scenes each for 1990, 2000 or 2005, and 57 MSS scenes for 1975 were acquired for the study. Same-year and same-season data are best for this kind of study, but cloud-free images of the region were not available for all time periods, prompting us to augment them with multi-season and multi-year data. Twenty-four QuickBird scenes and eight IKONOS scenes, all collected in 2005 and 2006, were also acquired.

Field survey

We conducted a 4-week field survey in Malaysia, Thailand, Sri Lanka and India during June and July 2006. A total of 182 calibration/validation points were collected. We used a Global Positioning System (GPS) to record the exact location of the survey site, and we took a photograph at every location. All the photos were georeferenced using GPS-Photo Link (http://www.geospatialexperts.com/) and were used in tandem with satellite imagery within Google Earth to verify mangrove locations and conditions. Data on presence or absence of mangrove forests, and their condition, density, crown cover and management regimes were collected during the field survey. Density and crown cover were estimated visually. The extent of damage caused by the Indian Ocean tsunami and any recovery measures taken were also noted. The field data served as training data, a portion of which served as independent reference data for the verification of classification results.

We visited the national mapping agencies of the countries in the region to collect ancillary data such as forest classification maps, topographic maps and tsunami reports (Table 1). The team also visited local forestry departments to discuss various aspects of mangrove management. With their help, mangrove and non-mangrove areas were delineated on hard-copy maps. Local officials provided field data and information on mangrove damage due to tsunami and afforestation/reforestation status. They also guided the research team during the field visit.

Pre-processing

The use of multi-temporal satellite data (MSS, TM and ETM+) at a subcontinent scale poses a number of challenges: geometric correction error, noise arising from atmospheric effects, errors arising from changing illumination geometry and instrument errors (Homer *et al.*, 2004). Such errors are likely to introduce biases and/or noise into mangrove forest classification and change analyses. Pre-processing is necessary to remove or minimize such errors.

Landsat images acquired in the Universal Transverse Mercator (UTM) projection and coordinate system were re-registered to the Albers equal area projection. To improve the root mean square (RMS) error to ± 1/2 pixel, we used additional ground control points (GCPs) collected from 1:50,000-scale topographic maps. Images were resampled with cubic convolution, which has a better spatial accuracy than the commonly used nearest neighbour resampling technique (Shlien, 1979; Park & Schowengerdt, 1982).

Removing or minimizing the presence of 'noisy' pixels is also important. Noise in image data can be caused by several factors: (1) differences in atmospheric scattering in the visible bands, (2) differences in water and/or dust particles in the atmosphere, (3) temporal variations in the solar zenith and/or azimuth angles, and (4) inconsistencies in sensor calibration for separate images (Homer *et al.*, 2004). To reduce the noise caused by atmospheric effects and illumination geometry, we applied the techniques developed by Homer *et al.* (2004) for the US National Land Cover Database 2001. Each image was normalized for solar irradiance by converting digital number values to the top-of-the atmosphere reflectance (Chander & Markham, 2003). This conversion algorithm is 'physically based, automated, and does not introduce significant errors to the data' (Huang & Townshend, 2003). A test of this technique on mangrove areas in the Sundarbans (Giri *et al.*, 2007) showed it to be a reasonable pre-processing method for a large data base covering several countries in Asia. Owing to the unavailability of data on atmospheric conditions for the region, atmospheric correction was not performed. Cloud-covered areas were replaced by additional Landsat scenes obtained during the same period.

Classification

Many image classification and change detection techniques have been described in the literature (Singh, 1989; Civco *et al.*, 2002). For change analysis, Civco *et al.* (2002) compared four techniques – traditional post-classification, cross-correlation analysis, neural networks and object-oriented classification

Table 1 Secondary data collected and used during the study.

Secondary data	Country
Mangrove forest maps prepared using Landsat data	Thailand, India
Forest classification maps 1 : 250,000 using field inventory data	Sri Lanka, Malaysia, Indonesia
Land use/land cover maps at 1 : 1,000,000 scale	Bangladesh, Malaysia
Topographic maps, 1 : 100,000 scale	Sri Lanka, Thailand
QuickBird, IKONOS	Selected areas in Thailand, Bangladesh, India and Sri Lanka
Atlas of Mangrove Wetlands of India	India

Table 2 Class definitions.

Classes	Supervised classification class definitions
Mangrove	Areas covered by both closed and open mangrove forests
Non-mangrove	Areas covered by croplands and other land uses
Barren lands	Areas devoid of vegetation, e.g. sand dunes, sediments or exposed soil
Water bodies	Areas of open water with no emergent vegetation, e.g. channels and waterways

– and concluded that each method has advantages and disadvantages, and there is no single best way. Considering the large volume of data acquired from different time intervals, we adopted the traditional post-classification approach.

For image classification, we used a hybrid supervised and unsupervised classification approach because there was insufficient ground truth for a purely supervised classification. The images were not enhanced prior to unsupervised classification and the thermal band (band 6) was excluded from the classification. Water bodies were mapped with a supervised classification. We then used an ISODATA clustering algorithm within ERDAS Imagine to generate 50 spectral clusters at the 99% convergence level. Through iterative labelling, mangrove classes were identified and labelled with reference to field data and high-resolution QuickBird and IKONOS imagery, and then merged into a single mangrove category. Four land cover classes were generated: mangrove, non-mangrove, barren lands and water bodies (Table 2). Post-classification editing such as 'recoding' was performed to remove obvious errors. Each classified image was resampled to 50 m to be consistent with MSS data. However, this resampling did not improve the spatial details of MSS data. Finally, four classification images were produced, one each for 1975, 1990, 2000 and 2005.

Change analysis

We used a post-classification change analysis technique to compare classification results from the four epochs of imagery. This approach is probably the most common and intuitive change detection method, because it provides 'from–to' change information. However, our approach may have three sources of uncertainty: (1) semantic differences in class definitions between maps, (2) positional errors, and (3) classification errors. To minimize the semantic differences in class definitions, we specified the same number of classes for all four dates. To minimize positional errors, additional GCPs were selected and RMS error was reduced to ± 1/2 pixel as explained in the pre-processing section. Post-classification editing (i.e. recoding) using secondary data helped to correct classification errors. In doing so, problematic areas were identified visually and using area of interest (AOI) in ERDAS Imagine followed by recoding. However, some positional and classification errors might still remain.

Change maps were generated by subtracting the classification maps between six periods: 1975–90, 1975–2000, 1975–2005, 1990–2000, 1990–2005 and 2000–05. The change areas were visually interpreted to identify the factors (e.g. agriculture, aquaculture, urban development) responsible for the change. Each of the change areas was checked individually during the workshop by at least two experts to identify the causes of change. Published maps and high-resolution satellite data such as QuickBird and IKONOS were used for the purpose. A 3-pixel by 3-pixel window was used to identify the dominant land-cover types in the high-resolution satellite data. Once the mangrove/non-mangrove areas were calculated for each period, the rate of deforestation was calculated by using the following equation suggested by Puyravaud (2003):

$$R = \left(\frac{1}{t_2 - t_1}\right) \ln\left(\frac{A_2}{A_1}\right) \quad (1)$$

where R is the rate of deforestation, A_1 is the area at an initial time t_1 and A_2 is the area at a later time t_2. Maps and photographs collected during the field visit, along with high-resolution IKONOS and QuickBird satellite data, were analysed visually to discover the causes of deforestation. This involved visual analysis of change maps and reference data.

Validation

Qualitative validation was performed with the help of local experts and high-resolution satellite data such as QuickBird and IKONOS. We divided the entire area into 500 × 500 grids and checked each grid visually to identify and correct 'gross' errors inherent in the classified maps. Quantitative accuracy assessment was not performed because sufficient ground truth data for historical dates are not easily available. A workshop was held at which local experts validated the change areas and the causes of change. The experts provided ground truth data and photographs for a number of sites throughout the study area.

RESULTS AND DISCUSSION

To meet the need for accurate and reliable information on the present extent of mangrove forests of the region, our study prepared a geospatial data base of mangrove distribution for the year 2005 using Landsat data. The data base provides an up-to-date and consistent overview of the extent and distribution of mangrove forests with better spatial and thematic details than previous data sets.

We estimate that in 2005 there were approximately 1.67 million ha of mangrove forest remaining in the region. This estimate is higher than previous estimates by Spalding *et al.* (1997), probably because it is based on moderate-resolution Landsat data on which we were able to identify many small (0.81 ha), previously unidentified, mangrove areas. However, we did not map mangrove patches smaller than the 1 ha, which was the minimum mapping unit (MMU) used for the analysis. We assumed that mangrove areas smaller than our MMU have no significance on the total mangrove area of the region.

The largest percentage of the remaining mangrove forest areas in our study area in 2005 is located in Burma (551,361 ha; 33%), followed by Bangladesh (438,764 ha; 27%), India (337,727 ha; 21%), Thailand (168,910 ha; 10%), Malaysia (70,560 ha; 4%), Indonesia (68,194 ha; 4%) and Sri Lanka (10,379 ha; 1%). The largest expanse of mangrove forests is located in the Sundarbans (along the border between Bangladesh and India); the Ayeyarwady Delta, Rakhine, and Tahinthayi (Burma); Phang Nga and Krabi (Thailand); and Matang (Malaysia).

The largest tracts of the remaining forests of the region are in different states and conditions owing to different threats and management interventions. Despite having the highest population density in the world in its immediate vicinity, the areal extent of the mangrove forest in the Sundarbans has not changed significantly in the last 25 to 30 years (Giri *et al.*, 2007). A strong commitment from the governments of India and Bangladesh, in the form of various protection measures, such as forest reserves, wildlife sanctuaries, national parks and international designations, is responsible for keeping the Sundarbans mangrove forest relatively intact. This is an excellent example of the coexistence of human, terrestrial and aquatic plant and animal life. In Phang Nga, mangrove forests are found all along the coast and on some larger islands, including Ao Thalane and Ao Luk. Many areas in Phang Nga and Krabi are protected under the conservation areas network. The Ao Phang Nga National Park covers an area of 4000 ha and represents the largest tract of remaining original primary mangrove forests of Thailand. All three mangrove areas in Burma are under immense pressure from human exploitation. Forests that are not protected represent some of the most degraded or destroyed mangrove forests of the region. Matang forest in Malaysia is intensely managed and is considered to be one of the best managed mangrove forests in the world. The forest, consisting mainly of *Rhizophora apiculata*, is the largest tract of mangrove forest in Peninsular Malaysia (*c.* 40,000 ha). Approximately 80% of the area is managed through a sustainable-yield production system with a 30-year rotation cycle. Smaller patches of mangrove forests are found in all seven countries with many isolated patches in Sri Lanka and India. Many of these smaller patches are under immediate threat from human exploitation. Unfortunately, the majority of these forests are not protected under the existing protected areas network. In some cases, these small patches of forests are managed by local communities.

Time-series analysis of MSS, TM and ETM+ data has revealed a net loss of 12% of mangrove forests in the region from 1975 to 2005 (Fig. 1). The net deforestation resulted because the deforestation rate outpaced the afforestation/reforestation rate (Fig. 2). The overall net loss is lower than the country average for Thailand, Malaysia and Indonesia, because other parts of these countries are undergoing massive changes. For example, in Thailand, the Andaman coast experienced much less development pressure than the Gulf of Thailand (outside of our study area). Approximately 80–90% of mangrove forests along the Gulf of Thailand have disappeared in the last 30 years (Thampanya *et al.*, 2006).

This rate of deforestation was not uniform through space and time. The annual rate of deforestation during 1975–2005 was highest (*c.* 1%) in Burma compared with Thailand (−0.73%), Indonesia (−0.33%), Malaysia (−0.2%) and Sri Lanka (−0.08%). In contrast, mangrove forests in Bangladesh (+0.14%) and India (+0.04%) remained essentially unchanged or slightly expanded during this period. The increase in mangrove area in India that we found is consistent with reports from the Forest Survey of India which stated that mangrove forest cover has increased or remained unchanged since 1995. However, almost all the mangrove areas in India are severely degraded with reduced or negligible vegetation cover (Wilkie & Fortuna, 2003). Bangladesh has started ambitious mangrove rehabilitation programmes, and mangrove forest areas have also increased by aggradation (Giri *et al.*, 2006). The reforestation programmes in both India and Bangladesh were initiated by the government and local communities.

Net deforestation peaked at 137,000 ha (approximately 1% year^{-1}) during 1990–2000, increasing from 97,000 ha (0.2% year^{-1}) during 1975–90, and declining to 14,000 ha (0.06% year^{-1}) during 2000–05. The main reason for the decline in the rate of deforestation is that the intensity of aquaculture expansion appears to have levelled off in all the countries except Burma and Indonesia. The highest rate of deforestation during 1976–90 occurred in Thailand (1.8%). The rate of deforestation in other countries was relatively low during this period. However, during 1990–2000, the rate of deforestation was highest in Burma (2.9%) and Malaysia (1.3%). Similarly, the deforestation rate during 2000–05 was highest in Indonesia (0.75%), mainly because of the expansion of aquaculture.

At the local level, both deforestation and forest regeneration occurred with varying intensities, with localized hotspots of rapid change. We identified the major deforestation fronts that are located in the Ayeyarwady Delta, and Rakhine and Tahinthayi provinces of Burma; Sweetenham and Bagan in Malaysia; Belawan, Pangkalanbrandan, and Langsa in Indonesia; and Southern Krabi and Ranong in Thailand (Fig. 1). Major reforestation and afforestation areas are located on the south-eastern coast of Bangladesh, and in Pichavaram, Devi Mouth, and Godavari in India.

The major causes of deforestation were agricultural expansion (81%), aquaculture (12%) and urban development (2%). As expected, causes of deforestation also varied with space and time (Fig. 3 & Table 3). In Thailand, 41% (16,815 ha) of mangrove forests have been converted to aquaculture and another 2% (710 ha) have been converted to urban development. However, the largest factor was agricultural expansion (50%, 20,300 ha). Other factors, such as mining, are also responsible for deforestation in Thailand. These land conversions are particularly evident in Phuket, Ranong and southern Krabi. In Indonesia, 63% (20,960 ha) of the mangrove forests have been cleared for shrimp ponds and another 32%

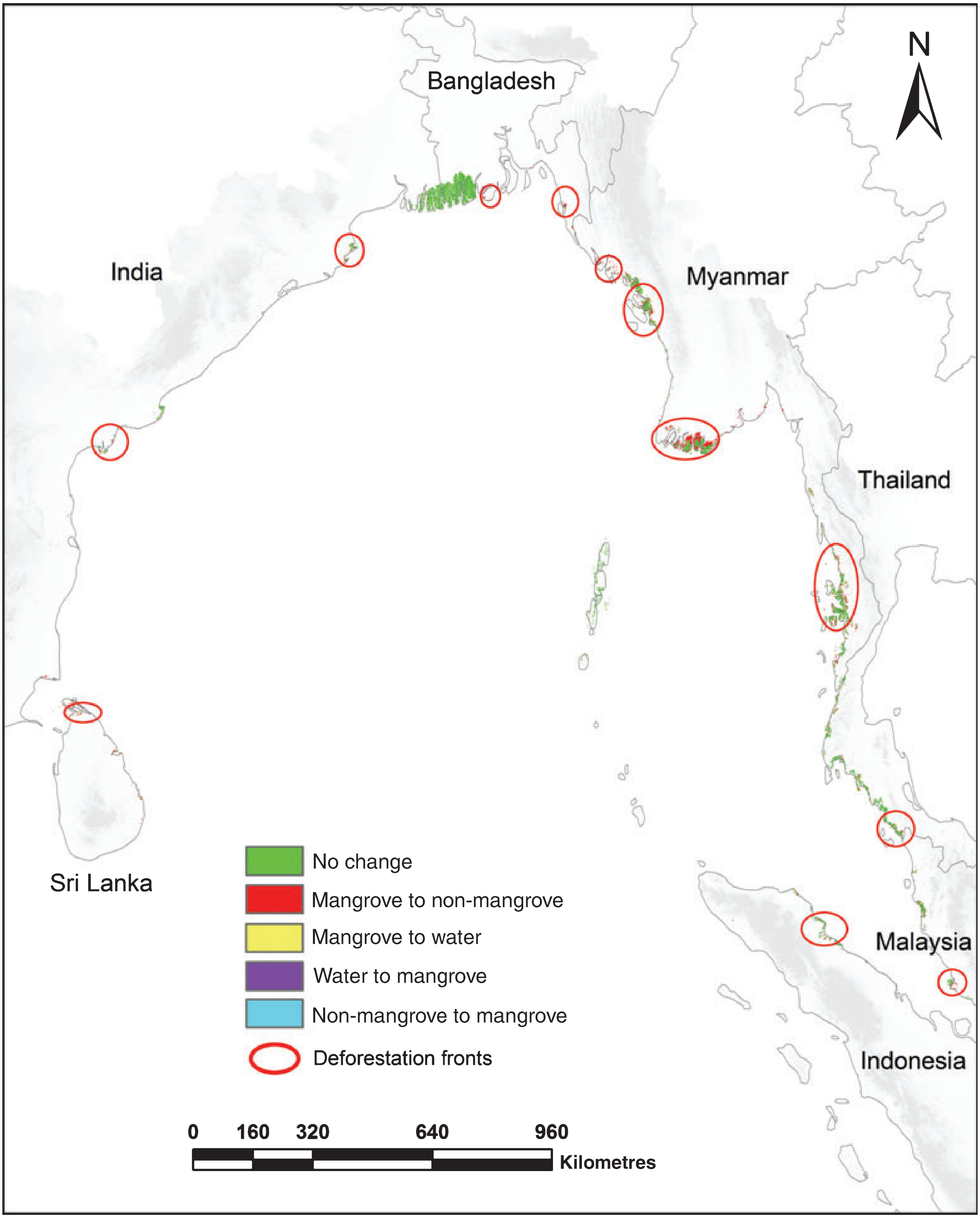
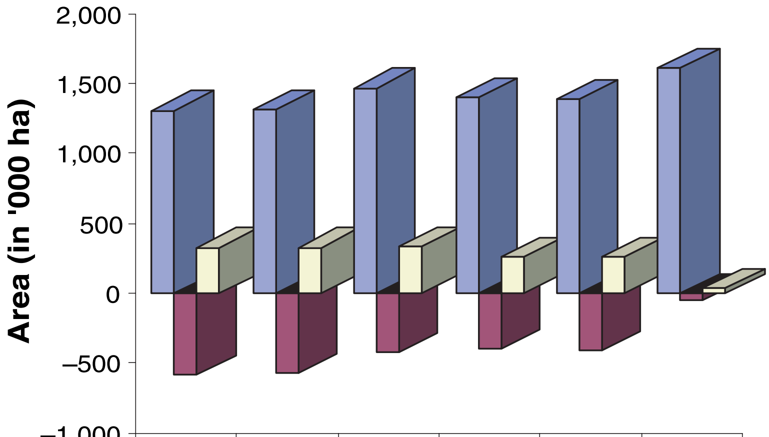


Figure 1 Change in mangrove forest cover change from 1975 to 2005.



	1975–2005	1975–2000	1975–1990	1990–2000	1990–2005	2000–2005
No change (ha)	1,305,542	1,312,760	1,469,005	1,397,608	1,387,924	1,607,716
Deforestation (ha)	–584,363	–577,884	–426,432	–398,695	–407,601	–50,212
Afforestation (ha)	327,600	326,488	328,844	261,339	256,279	36,348

Figure 2 Areal estimate of deforestation and afforestation from 1975 to 2005.

(10,625 ha) for agricultural lands. Conversion to urban development accounted for approximately 4% (1420 ha). The large percentage of change in Malaysia is primarily associated with the 30-year rotation cycle of clearcutting mangrove forests in Matang Mangrove Reserve. The forests are also being converted to urban areas.

The deforestation in Burma is due to the overexploitation of mangrove forests for fuel wood collection, charcoal production and illegal logging, followed by encroachment for paddy cultivation. We estimated that 98% (293,035 ha) of mangrove deforestation in Burma during the period 1975–2005 was due to agricultural expansion (Fig. 4). During the same period, approximately 2% (6870 ha) of forests were converted to aquaculture. In the Ayeyarwady Delta, forests are also being destroyed or degraded by erosion and sedimentation (Barbier, 2006); the delta has the fifth largest sedimentation in the world.

CONCLUSIONS

The results of our study will be useful in several ways. First, we improved our understanding of the distribution of mangrove forests in the region, and assessed the rates and causes of deforestation. The geo-spatiotemporal data base generated by this study provides an up-to-date, consistent and unbiased account of the extent, distribution and dynamics of mangrove forests of the region, and has better spatial and temporal detail than the information previously available. Second, an unbiased

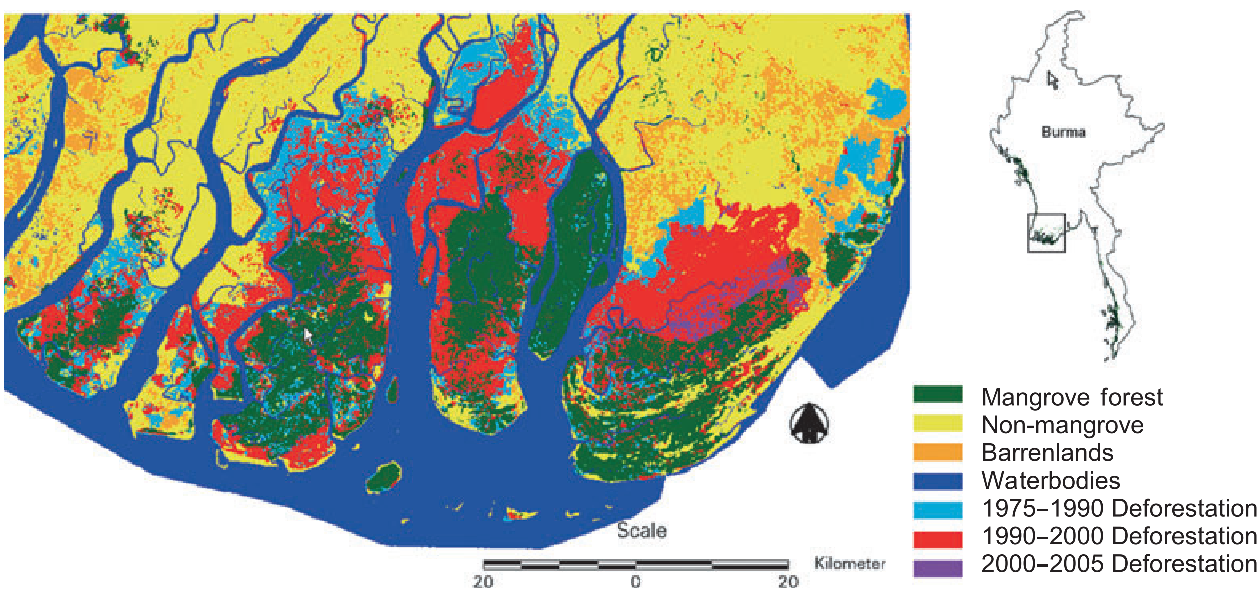


Figure 3 Spatial distribution of mangrove deforestation in Ayeyarwady Delta, Burma, during 1975–90, 1990–2000 and 2000–05.

Table 3 Conversion of mangrove forest to other land use/cover categories.

	Area converted [ha (%)]								
	To aquaculture		To agriculture		To urban		To other		
Country	Area	± Error estimate	Area	± Error estimate	Area	± Error estimate	Area	± Error estimate	Total
Thailand	16,816 (41)	1009 (3)	20,296 (50)	1826 (5)	710 (2.1)	15 (2)	2745 (7)	220 (1)	40,567
Malaysia	1605 (7)	96 (0)	9605 (43)	864 (4)	4532 (20)	615 (14)	6557 (29)	525 (2)	22,299
Indonesia	20,956 (63)	1257 (4)	10,628 (32)	956 (3)	1420 (4)	60 (4)	0 (0)	0 (0)	33,004
Burma	6868 (2)	412 (0)	293,035 (98)	26,373 (9)	66 (0)	0 (0)	122 (0)	10 (0)	300,091
Bangladesh	1070 (11)	64 (1)	7193 (77)	647 (7)	0 (0)	0 (0)	1046 (11)	84 (1)	9309
India	7554 (22)	453 (1)	17,179 (50)	1546 (4)	168 (0)	1 (0)	9178 (27)	734 (2)	34,079
Sri Lanka	134 (1)	8 (0)	12,558 (92)	1130 (8)	26 (0)	0 (0)	901 (7)	72 (1)	13,619
Total	55,004 (12)	3300 (1)	370,495 (82)	33,344 (7)	6921 (2)	1437 (20)	20,549 (5)	1644 (0)	452,969

account of the status and trends of mangrove forest areas can support region-wide decision-making on the distribution of resources for the conservation and rehabilitation of mangrove forests. Third, our regional analysis is a starting point from which to assess the role of mangrove forests in saving lives and property from natural disasters such as the Indian Ocean tsunami of 2004.

Monitoring deforestation at a regional scale using moderate-resolution satellite images over a long period of time requires the processing of large volumes of data. We used simple but efficient methods to analyse these data. This approach applied semi-automated image analysis techniques to assess present status and to monitor the rates and causes of change, and it does so over a large area covering tsunami-affected regions of Asia. Our analyses show the potential of producing consistent and timely mangrove forest data bases of the region using the historical archive of Landsat data.

Unlike many other areas in Asia, conversion to aquaculture is not the major cause of mangrove deforestation in the region. At the regional level, conversion to agriculture is the dominant factor, followed by conversion to aquaculture and urban development. However, the degree to which these factors play a role varies according to space and time. For example, agriculture is the major factor in all the countries except in Indonesia, where aquaculture is the dominant factor. In Thailand, aquaculture accounts for 40% of mangrove deforestation, which is much higher than the regional average of 12%. Similarly, urban development is more dominant in Malaysia.

Deforested and degraded mangrove areas can be rehabilitated and restored in some cases (Fig. 5). The identified deforestation areas can be used to select potential rehabilitation sites together with a matrix of criteria such as extent, accessibility and socio-economic factors. Not all deforested areas can be restored back to mangrove forests. For example, urban areas are very unlikely to revert back to mangrove forest. The majority of agricultural areas and some of the aquaculture areas can be reforested. Other abandoned aquaculture areas are very difficult to rehabilitate or regenerate, mainly because these sites are highly degraded by pollution and pesticides. Delineations of degraded mangrove forests are needed to promote regrowth and enrichment planting.

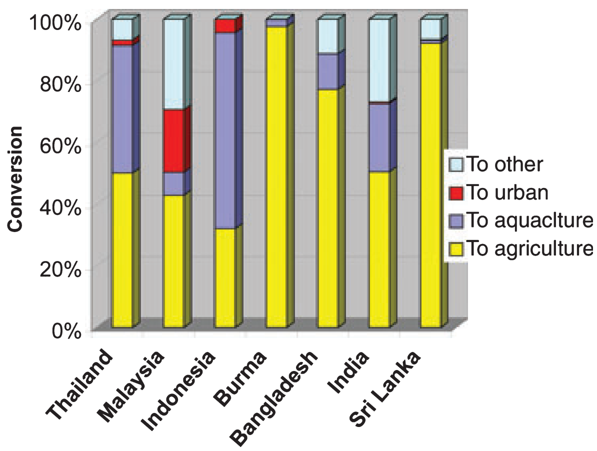


Figure 4 Major causes of mangrove deforestation, by country.

Figure 5 With some management intervention, this abandoned shrimp pond can be rehabilitated (photo Chandra Giri).

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