Comparison of Techniques for Forest Change Mapping Using Landsat Data in Karnataka, India

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Abstract

The potential for forest change monitoring in the state of Karnataka, India using Landsat imagery was evaluated. Imagery from 1986 and 2003 was analyzed using two change detection techniques: (1) image differencing of the Normalized Difference Vegetation Index (NDVI), the second principal component (PC2), and the Kauth-Thomas greenness index (KT-G), and (2) post-classification comparison (PCC). As field validation data did not exist for 1986, extensive visual assessment was conducted to locate and identify errors of commission and omission in the change maps. The image difference vegetation maps did not display obvious errors of omission, but the NDVI difference performed better than KT-G and PC2 differences in terms of errors of commission. It was therefore classified into a deforestation/reforestation map and evaluated against the PCC forest change map. PCC was able to more accurately detect changes over the 17-year period. Analysis of the literature and the forest change maps showed that deforestation was primarily a result of submergence by reservoirs created in hydroelectric developments, whereas reforestation was mainly due to significant increases in forest plantations, as a result of various social forestry projects.

Introduction

Forests are vital and important global resources that need to be monitored for sustainable management and conservation. In India, there are large and diverse forest resources (Figure 1), which are the result of highly varied climate, topography, and soils. The forest types include tropical rainforest in north-eastern India, desert and thorn forests in the west (for example in Gujarat and Rajasthan states), mangrove forests in West Bengal, Orissa and other coastal areas, and the alpine pastures of Ladakh (Jammu and Kashmir area) in the north. Forests are generally used as sources of timber for defence, communications, and industries such as plywood, as well as for fuel and timber by local populations (Negi 1998).

Despite amendments made in forest policies to conserve and manage these resources, Indian forests are still undergoing significant change. The main causes of forest depletion are overgrazing, conversion to non-forestry uses such as infrastructural development (energy, roadways, etc.) (Reddy 1988), shifting cultivation (practised mainly in north-eastern India) (Unni 1975; Kushwaha *et al*. 1993), unsustainable extraction of fuel and fodder from forests, forest fires, over-cutting beyond permitted limits and illegal encroachment into forestland due to land shortages or insecure land tenure (Rangan 1996; Gadgil 1989; Sekhsaria 1999; Kant 2001; MOEF 1999). For example, approximately 1.5 x 10^6 ha of forestland was estimated to be illegally occupied in the 1990s for agriculture and other uses (Ministry of Environment and Forests (MOEF) 1999). Reforestation has also resulted in significant changes to the extent and types of forests. It consists mostly of industrial monoculture plantations and social forestry projects carried out under the supervision of the Joint Forest Management (JFM) programme.

As a consequence of the high regional diversity of forest types and causes of forest change, it is not possible to map and do evaluation of forest resources for the whole of India using conventional field survey methods. The Forest Survey of India (FSI), as an associated institution of the Ministry of Environment and Forests, is responsible for preparing the state of the forest reports and the national vegetation map of India every two years. Since 1987, remote sensing has been the primary data source used to produce these maps. The FSI also prepares forest inventories and carries out growing stock and volume assessments. Hence, it is a key organization in India for the generation of primary forest cover and resources data. The first FSI assessment on the forest cover of the country, published in 1987 (FSI 1999) used Landsat

Multi-Spectral Scanner (MSS) data and visual interpretation at 1:1,000,000 scale. From the second assessment, the resolution of the sensor improved to 30 m x 30 m and scale of interpretation to 1:250,000 (FSI 1999). Transparent false colour composite images were manually overlaid on topographic base maps and forest classes were directly delineated. Comparison of two maps was conducted to assess change in these classes. Following this initial period of visually based forest mapping, digital analysis has been conducted to map forests and detect changes. The non-forested areas are first masked out using forests defined on the Survey of India (SOI) topographic maps. Then, forest cover is classified using supervised maximum likelihood (Lillesand and Kiefer 2000) techniques with NDVI (Normalized Difference Vegetation Index = {(NIR-R) / (NIR +R)}, where NIR is the near infrared spectral band, and R is the red spectral band) as the input data (FSI 1999).

Since 1995, Indian Remote Sensing (IRS) data have been used. For the 1999 report, FSI classified 13 states digitally, while the rest of the country's forest cover was mapped visually. Data for most of the digitally classified states were acquired from October to December 1998, and for rest of the states, from October to December 1996 (FSI 1999). The lack of a consistent sensor, spectral bands, spatial resolution, and data processing methods hinders accurate analysis of vegetation change over time periods longer than a few years using the FSI maps. From previous studies in other locations, it was found that Landsat TM is very well suited to temporal analysis of forest change over medium to long time periods (Klankamsoran 1987; May *et al*. 1997; Oliver 2000; Wang *et al*. 2004; Asner *et al*. 2002; Alves 2002). It provides broad spatial coverage, moderate resolution (pixel size of approximately 30m), seven high quality spectral bands ranging from the blue to the thermal IR, and frequent acquisition throughout the year (every 16 days) (Tole 2000). These characteristics make it well suited for mapping temporal changes in various compositional and structural forest groups at landscape and regional scales.

Change detection is the process in which temporal differences in the state of an object or phenomenon are identified (Singh 1989). It is important in monitoring natural resources as it can quantify the spatial distribution of land cover change in the area of interest. During the past 20 years, it has become a major application in remote sensing because of increasingly consistent image quality and repetitive coverage at short intervals (Mas 1999). Singh (1984; 1986) used image differencing to monitor change due to shifting cultivation in a tropical forest environment. Prakash and Gupta (1998) used spectral band differences, ratios, and NDVI to detect change in land use in the Jharia coalfield of India, and found that all the methods were equally good in detecting the changes in the study area. Young and Wang (2001) analyzed differences in NDVI in China from 1982-1992 and found them to indicate declines in productivity in forest regions and increases in agricultural regions.

In this research, Landsat TM data were used to compare temporal change methods for detection of deforestation and reforestation over 17 years in the southwest region of India.

Objective

The primary objective of this research was to evaluate the potential for monitoring forest change in India at regional to state scales using Landsat TM data by comparing two temporal analysis methods: image differencing and post-classification comparison. The maximum time period during which Landsat TM data were available for the study area (see description below) was selected to be able to assess subtle to severe deforestation as well as reforestation.

The research was conducted in two phases. The first compared image differencing of NDVI, principal components and Kauth-Thomas transformations for detection of overall vegetation change (i.e., of all vegetation types). Then, results from the best of these methods were classified as forest gain or loss and evaluated against the post classification comparison method.

Methodology

Study Area Selection

After reviewing forest characteristics and Landsat data for several regions of India, a study area was selected in the state of Karnataka (Figure 1). Karnataka is approximately 760 km N-S and 420 km E-W, covering an area of 191,791 km^2. The Western Ghats mountains run through the state roughly parallel to the west coast. Land cover and land use include forest, urban and built-up land, rivers and reservoirs, agricultural and barren land. Karnataka was selected as the study area because of its abundance of natural and plantation forest cover, high rates of forest change (deforestation and reforestation) (Menon and Bawa 1997), and its status as a bio-diversity hot-spot region (Menon and Bawa 1997; Shi 2003). In addition, Landsat data were available for the state for 1986 and 2003. Other areas experiencing rapid forest change in NE India were also considered, but data were not available or were not accessible due to the area's sensitive political nature.

Satellite Data

Landsat 5 (TM) data from April 1, 1986 and Landsat 7 Enhanced Thematic Mapper (ETM+) data from February 19, 2003 were acquired for an area covering much of the Western Ghats in several districts within the state of Karnataka.

A subscene (Figure 1b, red rectangular area) covering approximately 102 km x 157 km was clipped out to reduce data size for the many tests of image processing and analysis methods that were implemented.

Image pre-processing

The 1986 scene was aligned to the 2003 scene, which had been acquired in UTM projection. A second-order polynomial transformation was derived from eleven high contrast control points that had not changed between the two dates. Nearest neighbour re-sampling was applied when assigning pixel values to the aligned raster for the 1986 scene. The root mean square (RMS) error of the transformation was 0.23 and 0.32 pixels for the 'x' and 'y' directions, respectively.

For temporal analysis, image calibration was necessary to reduce or eliminate differences due to atmospheric or sensor variations between the two dates. Two types of calibration may be conducted: 'absolute', using atmospheric corrections and sensor drift calibration, or 'relative', where one scene's image brightness distribution is matched to the other. The latter was applied to each band pair using regression of a given 1986 band (x) against the corresponding 2003 band (y, selected as the reference because of its superior image quality). Strong regression functions were obtained because most pixels had not changed between the two dates. In contrast, it was felt that a coarse scale atmospheric model (such as available in common atmospheric correction procedures) would not provide as reliable a correction for such a hilly region next to a large ocean. Table 1 shows the 1986 original and relatively calibrated spectral band mean and standard deviations beside the 2003 values. The thermal band was excluded from further use because of its lower resolution and because principal component analysis (PCA) showed that it did not contribute significantly to the data variance in any of the components.

The band means were matched very well after calibration, while the standard deviations of the 1986 calibrated data were slightly lower than those for the 2003 data. The Blue band in 1986 and 2003 had a noticeably higher mean brightness of 74 DN than the other bands, which may be due to the proximity of the study area to the Arabian Sea, the presence of other water bodies, such as rivers, reservoirs etc., and atmospheric haze.

Change detection analysis

Two commonly applied methods of temporal analysis, image differencing and post-classification comparison, were selected to provide capability for comparison with results presented in other studies.

Image Differencing

Image differencing was applied to vegetation enhanced images that were derived using three transforms: NDVI (Mas 1999), Principal component analysis (PCA), and the Kauth-Thomas Tasselled Cap transformation (KT) (Roy *et al*. 1991). In all cases, the (calibrated) 1986 transformed data were subtracted from 2003 transformed data. Standardized PCA was conducted (as opposed to unstandardized) as it generally produces more useful components for analysis of land cover change using multi-temporal datasets (Young and Wang 2001). The first principal component (PC1) accounted for 76% and 68% of the data variance of the 1986 and 2003 scenes, respectively. The factor loadings were almost equal for each band indicating that PC1 represented overall scene brightness. The second component (PC2) accounted for 18% and 28% of the 1986 and 2003 scene variances, respectively. It exhibited the strongest vegetation gradient, having high positive factor loadings for the NIR band for both dates (0.74 and 0.78, respectively) and negative factor loadings for the visible bands (ranging from -0.92 for the 2003 blue band to -0.12 for the 1986 red band). PC3 accounted for less than 4% of the data variance in both scenes. Based on these results, PC2 was selected for use in image difference analysis of vegetation change. The KT transformation (Roy *et al*. 1991; Guild *et al*. 2004) was applied to both scenes to produce brightness, greenness and moistness indices. The greenness index (KT-G, Equations 1 and 2 (Mather 1989; Huang *et al*. 2002, as cited in IDRISI Kilimanjaro 2004 help guide) was used in image differencing analysis. B1-B7 are the band numbers of the TM and ETM+ sensors.

$$\text{KT-G (TM)} = -0.2848B1 - 0.2435B2 - 0.5436B3 + 0.7243B4 + 0.0840B5 - 0.1800B7 \quad (1)$$

$$\text{KT-G (ETM+)} = -0.3344B1 - 0.3544B2 - 0.4556B3 + 0.6966B4 - 0.0242B5 - 0.2630B7 \quad (2)$$

Hereafter the difference images for these data types are referred to as $NDVI_d$, $PC2_d$, and $KT\text{-}G_d$, respectively. From the distribution of values in the $NDVI_d$, $PC2_d$ and $KT\text{-}G_d$ images, z-scores were calculated and classified into six categories of standard deviation (s) from the mean difference: < -2s; -2 to -1s; -1s to mean; mean to +1s; +1 to +2s; and > +2s. Here, the classes < -2s and > +2s were the pixels in the

Table 1 Means and standard deviations of the Landsat spectral bands for the 1986 original and calibrated data, and the 2003 reference data.

Band	Mean (DN)			Std. dev. (DN)		
	1986 (original)	1986 (calibrated)	2003	1986 (original)	1986(calibrated)	2003
Blue	83.69	74.25	74.26	8.63	4.56	6.72
Green	37.69	54.44	54.44	8.00	7.24	8.63
Red	41.56	48.72	48.77	17.22	15.04	17.20
NIR	59.01	47.40	47.36	29.74	22.08	23.34
Mid-infrared 1	80.09	64.20	64.23	54.32	39.14	42.64
Mid-infrared 2	37.54	39.48	39.51	29.66	26.41	29.40

change data distribution that fell within the distribution tails. For a normal change distribution, they comprise 5% of the total scene pixels and represent significant vegetation loss and gain, respectively. Between the two thresholds, pixels were assumed to have not changed significantly. Use of two standard deviations as a threshold indicating significant change in a difference image was selected because: a. visual analysis of difference images created from tests of several thresholds showed that it represented the best compromise between errors of commission (forest change detected where there obviously was not change) and errors of omission (forest change that was not detected); b. it represents a commonly applied statistical significance threshold, and c. it was in the middle of the range of values used in other studies (e.g. from 1.5 (Rogan *et al*. 2002) for moderate change to 3 (Young and Wang 2001) for extreme change). Here, the resulting six classes were colour coded to visually compare with raw image colour composites for identification of the types of vegetation change detected as well as possible errors. Further, to show the significantly changed areas only, binary images were created displaying only those pixels representing change of < -2s and > +2s.

Post classification comparison (PCC)

PCC consisted of cross tabulation of forest / non-forest maps to determine the pixels that had changed from one class to the other. Supervised maximum likelihood classification of the 1986 and 2003 Landsat scenes was conducted to create the maps. Training data were selected in easily identifiable areas of the following three classes: water; natural and plantation forest; and non-forest including bare soil, urban and agriculture. A 1:1,000,000 map from the Water Resource Development Atlas (Water Resources Development Atlas of India 1996) also aided in this process. A standard deviation threshold value of 2.0 for the training data distributions was selected following tests of thresholds ranging from 1.0 to 3.0 because it produced the maximum Transformed Divergence (Jensen 2003) between the classes. These separability tests, as well as visual analysis, were performed on several data sets including: all spectral bands, a dataset consisting of NDVI, PC2 and KT-G, as well as other arbitrary combinations of bands and transformed data. The best data set consisted of NDVI, PC2, KT-G and the blue, green and red spectral bands. Hence, it was used for both the dates to perform the supervised classification. Following classification, the water and non-forest classes were merged to one class and assigned a grey level of zero.

Conversion of image difference 'vegetation' change to 'forest' change for evaluation against PCC

From the above analysis of image differencing to produce vegetation change maps, the best result was further evaluated against the PCC method. As the vegetation loss and gain maps derived from image differencing included all types of vegetation (e.g. agricultural, shrubland, forest), they had to be converted to maps showing only forest change. Using the maximum likelihood classification of forest (DN = 1) and non-forest (DN = 0) for each date as described above, an overlay procedure was implemented as follows. For deforestation, areas that were classified as forest in the 1986 imagery AND which exhibited vegetation loss were taken to be 'deforested' during the 1986-2003 period. For reforestation, areas that were classified as forest in the 2003 imagery AND which exhibited vegetation gain over the 17-year period were taken to be 'reforested'.

Analysis of errors in image differencing and PCC

At the outset of this project, it was known that accurate field or remote sensing based validation data for 1986 would be unavailable. As an alternative, validation was conducted by visually identifying areas of change or no-change in magnified displays of the CIR composites. This analysis was conducted for the vegetation difference images to determine the best data transform and for the forest change maps to evaluate image differencing against PCC. To accomplish this, the change images were searched extensively for evidence of errors of omission (no-change detected when change had occurred) and errors of commission (detection of change when no change had occurred). In addition, for visually interpreted areas of change, each method was assessed for its completeness in spatially detecting that change. It was quite evident when a given method detected only the most severe change, as the area of visible change was mapped as a mix of change and no-change pixels.

Results and Discussion

Following the methodology described above, first image differencing to determine overall vegetation change was assessed using three different data transforms. The best results from this were then evaluated against PCC in an analysis of forest change.

Comparison of NDVI, PC2 and KT-G image difference images for vegetation change detection

Figure 2 is an example image difference binary change detection map showing significant vegetation gain (> +2s) and loss (< -2s) for the study area. All the transform differences detected the presence of change in a given local area equally well, but $NDVI_d$ and $KT\text{-}G_d$ had fewer errors of omission in detecting vegetation loss than $PC2_d$. They therefore mapped vegetation loss in a more spatially complete and accurate manner than $PC2_d$.

An example is shown in Figure 3 where significant vegetation loss has occurred due to flooding by a hydroelectric reservoir. The $PC2_d$ change map does not show change in the upper extent of the valley (at the white arrow) as well $NDVI_d$ and $KT\text{-}G_d$. At this location, the type of change is not from vegetation to water, but vegetation to bare ground. Both $NDVI_d$ and $KT\text{-}G_d$ correctly show the change as one of significant vegetation loss. Note that all subsequent figures showing gradations in change use the same legend as Figure 3, while all figures of binary change / no-change use the legend of Figure 2.

Table 2 Total area detected as deforested, reforested, and unchanged by NDVI difference analysis and post classification comparison.

Analysis Method	Deforestation (ha)	Reforestation (ha)	Unchanged Forest (ha)	Unchanged Non-Forest (ha)
NDVI Difference	23,200	53,400	555,470	848,450
Post Classification Comparison	11,030	51,296	566,500	851,694

In terms of errors of commission, Figure 4 shows an example where KT-G_d falsely detected change in the coastline (i.e., change from water to bare ground or sand at the black arrow in Figure 4b) as a change in greenness while $NDVI_d$ and $PC2_d$ were correct in not identifying this area as vegetation change. The other vegetation loss areas such as those near the coast towards the lower right of the image were well detected by all three methods.

Errors in vegetation gain were more difficult to visually identify, because spectrally, vegetation gain varied from subtle to moderate, but was never as significant as vegetation loss by activities such as clear cutting or reservoir flooding. However, it was evident in several locations that the three methods did not spatially map vegetation gain equally well. For example, Figure 5 shows a valley with a river cutting across the image from top to bottom that has become enlarged due to reservoir flooding. To the left of the river, forest gain is mapped as positive change from the mean to > +2s. $NDVI_d$ and KT-G_d more completely mapped the significant forest gain (> +2s) from pink (low density vegetation) to red (high density vegetation) in the CIR image than did $PC2_d$. To the right of the river, vegetation gain appears to be almost as strong as on the left side of the river, but all the methods detected it as slight (mean to +1s) to moderate (1-2s). This could be due to shaded slopes reducing the dynamic range of image brightness and thus the range of image differences or to vegetation gain that was not actually as strong as on the left side of the river.

From the above examples, and from many other local areas evaluated in a similar manner, differences between the data types were more evident for vegetation loss because examples of severe loss could be easily found whereas very few existed for vegetation gain. Over the 17-year period, vegetation gain was generally slight to moderate. It was therefore concluded that image differencing of all the data types identified the occurrence of change quite well but that there were differences in the spatial completeness with which the changes were mapped and in the susceptibility to errors of omission and commission for the significant classes. In this context, $NDVI_d$ was slightly better than KT-G_d, and both were much better than $PC2_d$ at detecting significant vegetation change. The $NDVI_d$ maps were therefore used in subsequent analysis against the PCC method. Although the context and location of this study is different from others, these results agree with those of Tole (2002) and Guild *et al.* (2004) but they contrast with Rogan and Yool (2001) who found KT components to be best for mapping fire-induced vegetation depletion.

Ev0aluation of NDVI difference against PCC

The $NDVI_d$ vegetation change map (Figure 2) was reclassified to two binary maps showing deforestation and reforestation, respectively, using the overlay method described above. These maps were then compared to their PCC counterparts that were produced directly from cross tabulation of classified forest / non-forest maps for each date. Table 2 shows the areas detected as deforested, reforested and unchanged for each method.

The areas detected as deforested differ for the two methods by a factor of greater than two while the other estimates are all within 4% of each other. To investigate further, cross tabulation of the two deforestation maps and of the two reforestation maps was conducted. For deforestation, 12,100 ha (134,769 pixels) that had been identified as deforested by $NDVI_d$ were identified as unchanged by PCC, while no pixels identified as deforestation by PCC were identified as unchanged by $NDVI_d$. The additional pixels identified as deforested by $NDVI_d$ were found to include significant errors of commission related to reduced agriculture and aquaculture in areas where water levels were higher in 2003. Figure 6 shows an example of such errors.

Similarly, in the reforestation cross tabulation, $NDVI_d$ found an additional 2,122 ha (23,575 pixels) that had been identified as unchanged by PCC while there were no pixels identified as reforested by PCC and unchanged by $NDVI_d$.

Figure 7 shows example errors of commission in the $NDVI_d$ reforestation map. Lower water levels have resulted in added exposed land surface along the shoreline and where a river has replaced a bay. The light pink tones indicate that the added area is not forest cover but has had some vegetation re-growth probably consisting of shrubs and other ground vegetation. The $NDVI_d$ reforestation map is therefore confusing regrowth in ground vegetation with significant forest growth. This sensitivity to subtler vegetation change may be useful for some applications but here only forest growth and deforestation were desired.

For both cases above, the $NDVI_d$ errors of commission may be reduced by using a higher standard deviation threshold of change in the $NDVI_d$ analysis (e.g. s > 2.0) and/or by re-training the forest change classification of the $NDVI_d$ vegetation change image. However, associated errors of omission may result if these restrictions are applied.

From the above analysis, it was concluded that for these data, PCC provides more accurate representation of significant forest change, whether deforestation or reforestation. These results agree with Mas (1999) who found PCC to be more accurate than raw image and

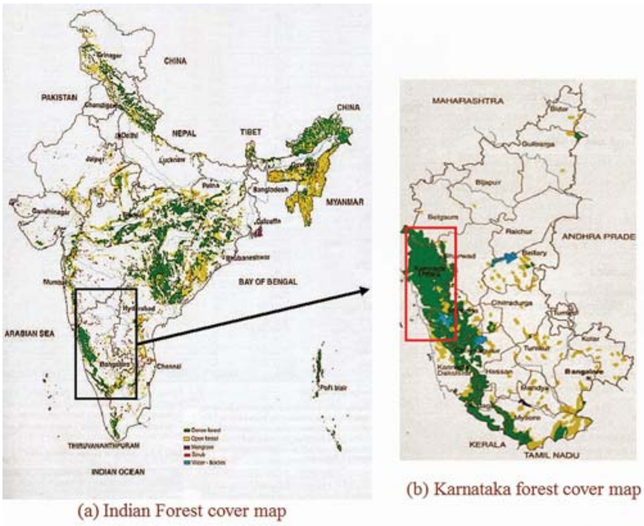

Figure 1 Location of the study area (Karnataka, Southern India). Black rectangle on left encompasses the state of Karnataka. The red rectangle on the right shows the subscene area used in this research. (Forest Survey of India, 1999)

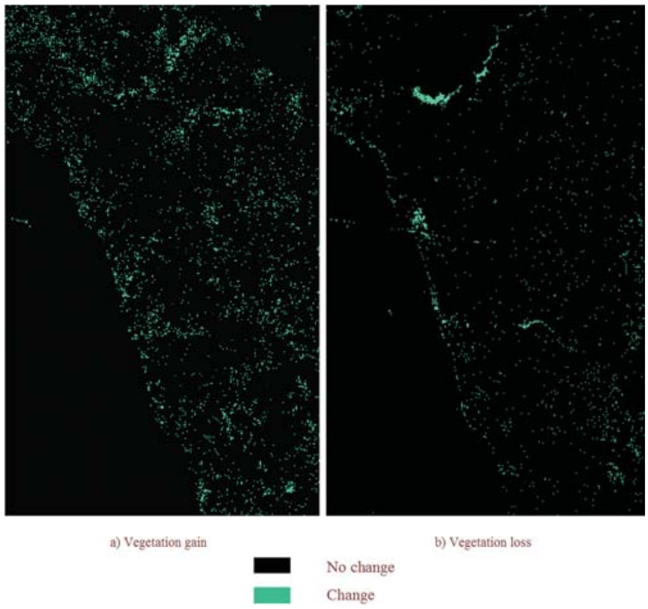

Figure 2 Example binary vegetation change maps for the study area derived from image differencing of NDVI.

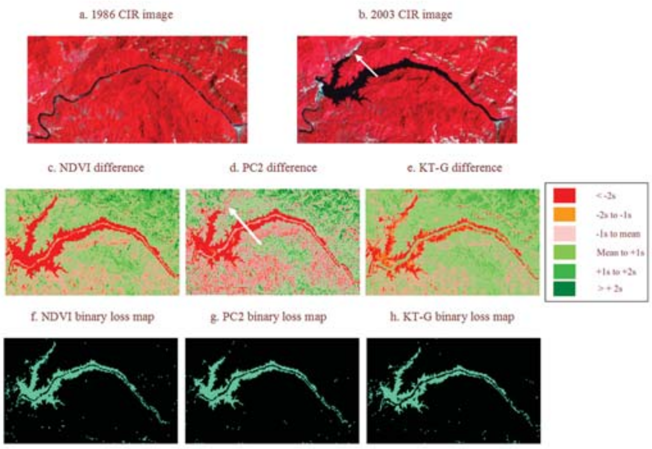

Figure 3 Example full resolution CIR composite, graded vegetation gain (+) and loss (-) maps, and binary vegetation loss maps produced by image differencing of the three data transforms. The white arrows point to an example error of omission in vegetation change of the PC2 difference map.

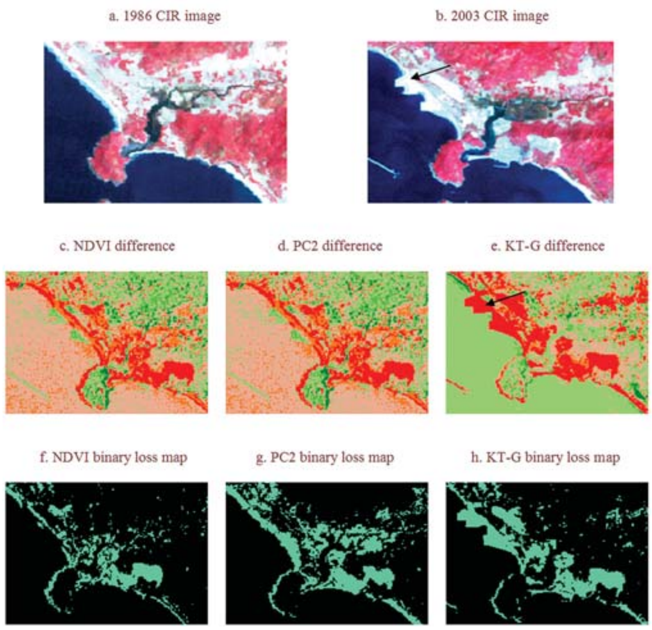

Figure 4 Example full resolution CIR composite, graded vegetation gain (+) and loss (-) maps (see legend in Figure 3), and binary vegetation loss maps produced by image differencing of the three data transforms. The black arrow points to an example error of commission in vegetation change of the KT-G difference map.

vegetative index differencing, selective PCA, and direct multi-date unsupervised classification for monitoring land-cover changes in a coastal region of Mexico. Sunar (1998) also found PCC, along with PCA to be best for detection of land cover changes in Turkey. However, Foody (2001) applied PCC to detect land cover change around the southern limits of the Sahara desert and found that it underestimated the areas of land cover change, and where change was detected; the magnitude of change was overestimated.

Conclusions

The results of this research show that Landsat data are very useful in monitoring changes in forest cover over moderate time intervals (17 years in this study) at a broad level of classification such as forest / non-forest for a regional area or state. For image differencing, the three data transforms tested all detected areas of visible vegetation change. However, the NDVI difference produced fewer visually identifiable errors of omission and commission than the

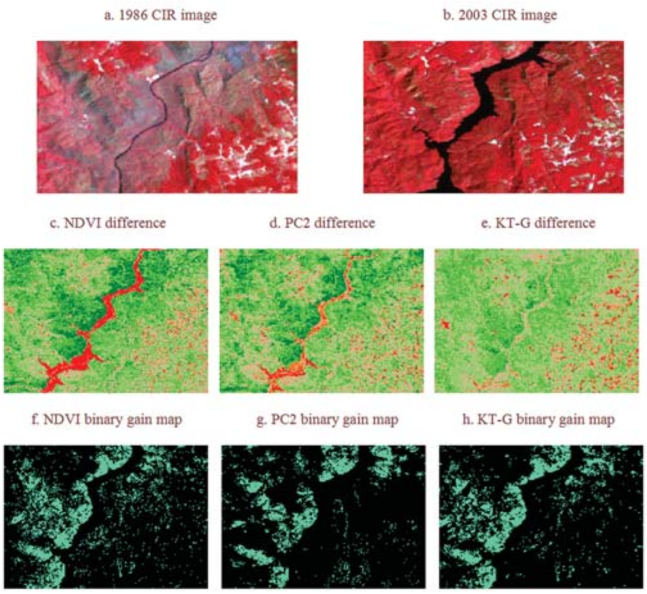

Figure 5 Example full resolution CIR composite, graded vegetation gain (+) and loss (-) maps (see legend in Figure 3), and binary vegetation gain maps produced by image differencing of the three data transforms. Errors in spatial completeness of vegetation gain mapping are visible on the left side of the river valley, particularly in the PC2 difference maps (Figure 5d, g).

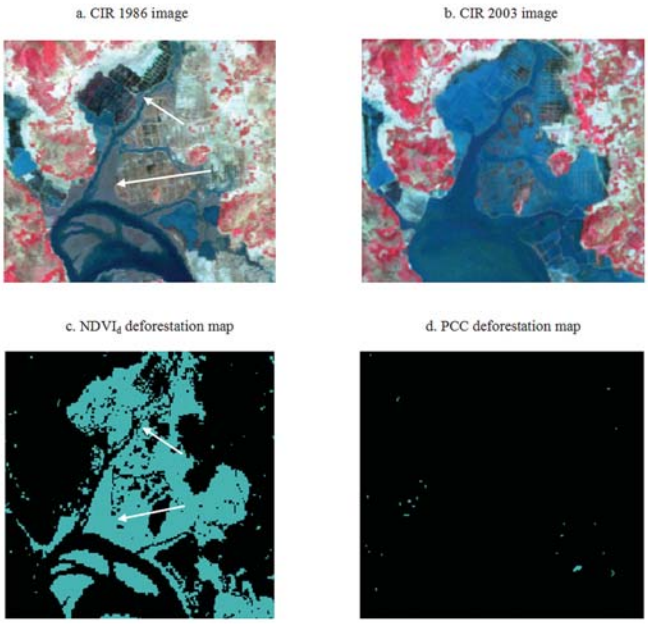

Figure 6 Example of errors of commission from the NDVI difference analyses that were related to changes in water levels and reduced agricultural / aquacultural activities.

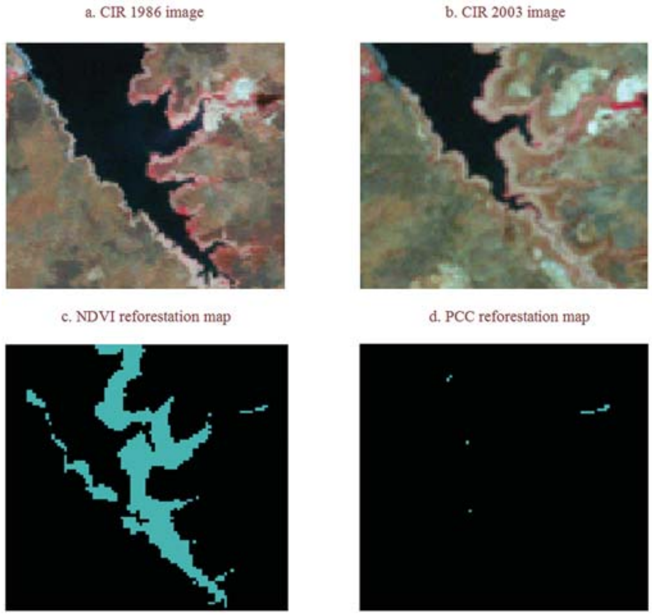

Figure 7 Example reforestation error of commission for the NDVI difference method.

second principal component and the Kauth-Thomas greenness index. It was therefore used in an evaluation against post classification comparison (PCC) but was found to be more susceptible to errors of commission. NDVI differencing requires little user input other than the threshold at which ‘change’ is considered to be significant. However, to produce maps of deforestation and reforestation, classification of the vegetation change map into forest change is required. In post classification comparison, only classification of forest and non-forest is necessary for each date, but errors can propagate when the maps are cross-tabulated to determine forest change.

Extensive visual interpretation of areas of forest change in association with literature analysis revealed that the main reasons for deforestation were submergence by reservoirs for development projects and pressure from increased human and livestock populations. As most of the rural population of India is dependent on forests for their livelihood, the forests are subject to degradation from uncontrolled logging, illegal cutting beyond silviculturally permissible limits, over-grazing, extraction of fuel wood and unsustainable forest management policies that exclude local communities. Therefore, eco-development planning for sustainable forest use is critical in these areas.

During the 1986-2003 period, this research has also shown that reforestation has been significant and greater in total area than deforestation, resulting in an overall increase in forest cover. The primary reforestation types were monoculture and mixed plantations established under the JFM programme as well as other social forestry projects funded by the World Bank and the state government. These industrial forests do not have high biodiversity as did the original forests, but they are often planted on degraded lands and therefore represent an improvement in vegetation cover over what has existed for the past few decades.

Although this study provides evidence that favours certain forest change detection methods over others, further work is needed to: (1) establish long-term validation programs for such monitoring, (2) compare these methods against more recent change detection methods such as linear spectral mixture analysis (Adams *et al*. 1995; Roberts *et al*. 1998) and fuzzy classification (Lee 2002), and (3) spatially extend the analysis to the full state level using multiple Landsat scenes.

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