Analysis of Land Cover Change and Misregistration Bias in North District of Sikkim, India

MD Behera, Neeti, A Jeyaram and V Jayaraman[1]
RRSSC-ISRO, IIT Campus, Kharagpur; 1NNRRMS-RRSSCs, ISRO Hqs. Bangalore, India.
E-mail : mukundbehera@yahoo.co.uk
Tel : 91-3222-255466, Fax. : 91 3222 277210

Abstract

Satellite remote sensing provides an important basis for studying routine land cover dynamics, especially in difficult and inaccessible terrain with complex physiography. Land cover change and patch analysis was done for the hilly terrain of North District, Sikkim state between the period of January 1997 and November 2002. 10-land cover classes were derived using unsupervised classification technique and change analysis was done following post-classification comparison method. Majority of the land cover changes were attributed to seasonal snow cover, agricultural activities and deforestation. Analysis of mean patch size and mean patch shape indicates spatial heterogeneity of the landscape. The mean patch shape of forest cover was observed to be higher than rest of the land cover categories. Patch size distribution revealed that snow cover, dense forests and forest blanks occur with higher degree of contiguity. In North district, the altitude ranges between ca 350m and 8588m (height of Mount Kanchenjunga) in a small area of about 4295 km^2, where image-to-image misregistration is imminent in absence of an accurate digital terrain model. This became the basis for calculating the misregistration bias in land cover changes. An estimation using PAR (perimeter area ratio) as an index revealed that highly dispersed and adjacent patches have higher misregistration bias and vice versa. The land cover change accuracy has dropped to a maximum of 11% within 1.04 (~1) pixel of misregistration as revealed by the study. This method of PAR provides one of the simplest and definite methodologies in calculating misregistration bias in post-classification based change detection exercise.

Introduction

Land cover change plays a pivotal role in socio-economic development and contributes significantly to Earth atmospheric interactions and biodiversity loss. Satellite remote sensing over various spatial and temporal scales offers the most reliable, time & cost-effective means of assessing land cover change. Land cover change is regarded as the single most important variable of global change affecting ecological systems (Vitousek, 1994) with an impact on the environment that is at least as large as that associated with climate change (Skole, 1994). It is well established that land cover change has significant effects on basic processes including biogeochemical cycling and thereby on global warming (Penner, 1994). Change detection and monitoring involve the use of multi--date images to evaluate differences in land cover (Singh, 1989) from time varying image sequences (Coppin and Bauer, 1996). Various methods of change detection exist; of which post-classification comparison is the most common one (Jensen, 1996). Patch size and shape allow a general

ISSN 1686-6576/© Geoinformatics International

characterization of the landscape structure. Total amount of energy or nutrients in a patch is directly proportional to the patch area. Patch size also affects interior to edge ratio and therefore have a bearing on functional properties of ecosystem. Large area will have more species than smaller one as it provides core environment for sensitive species (Behera *et al.,* 2005). Landscape ecologists have been using this PAR relationship with map and image data to characterize the complexity of landscape patterns (Krummel *et al.,* 1987). This is an important measurement as it determines the level of edge effect and indicates the "core area". The core is the portion of the patch that is not influenced by the edge effect. It is a measurement of the complexity of shapes of the patches and is an expression of the spatial heterogeneity of a landscape mosaic.

The usefulness of remotely sensed data in change detection is dependant not only on radiometric and spatial resolution of the data but also on subsequent processing and quality of the preprocessed data (Anuta *et al.,* 1984). *Image–to-Image* registration is the translation and rotation alignment process by which two images of like geometry and of the same geographic area are positioned coincident with respect to one another so that corresponding elements of the same ground area appear in the same place on the registered images (Chen and Lee, 1992). This type of geometric correction is more useful when it is not necessary to have each pixel assigned a unique x y coordinate in any map projection *i.e.,* if the goal is to compare two images obtained on different dates to see whether any change has taken place in them (Jensen, 1996). While it is possible to first rectify both of the images to a standard map projection and then evaluate them, this may not be necessary to simply identify the change between the two images. In an *image-to -image* registration exercise, the geometric errors are inherited from the reference image. However, when conducting rigorous change detection between two and more dates of the remotely sensed data, it may be useful to select a hybrid approach (image to map rectification of the first image and image to image registration of subsequent ones) (Jensen *et.al.,* 1993). Moreover, it is very difficult to locate ground control points (GCPs) in remotely sensed data especially in mountainous/rugged terrain covered with dense vegetation cover. So *image-to-image* type of geometric registration is preferred in such a scenario. Accurate and widely spread GCPs are essential for better accuracy. GCPs are utilized to compute transformation matrix consisting of coefficients that are used in polynomial equations to convert the coordinates. Polynomial equation is used to transform the pixel coordinates of raw image into real world coordinates. The size of the matrix depends upon the order of transformation. Polynomial transformation with second order or higher is suitable for hilly and complex terrain. A 1st order transformation called linear transformation is good to correct linear distortion that shifts (scale, offset, rotate, reflect) the image up, down, right, or left, stretches the image larger or smaller, or rotates the entire image. The 2nd and higher order transformation fit higher order polynomial equations to the data and allow points to be shifted in non-uniform manner and thus suitable to correct non-linear distortion (Anon., 2003).

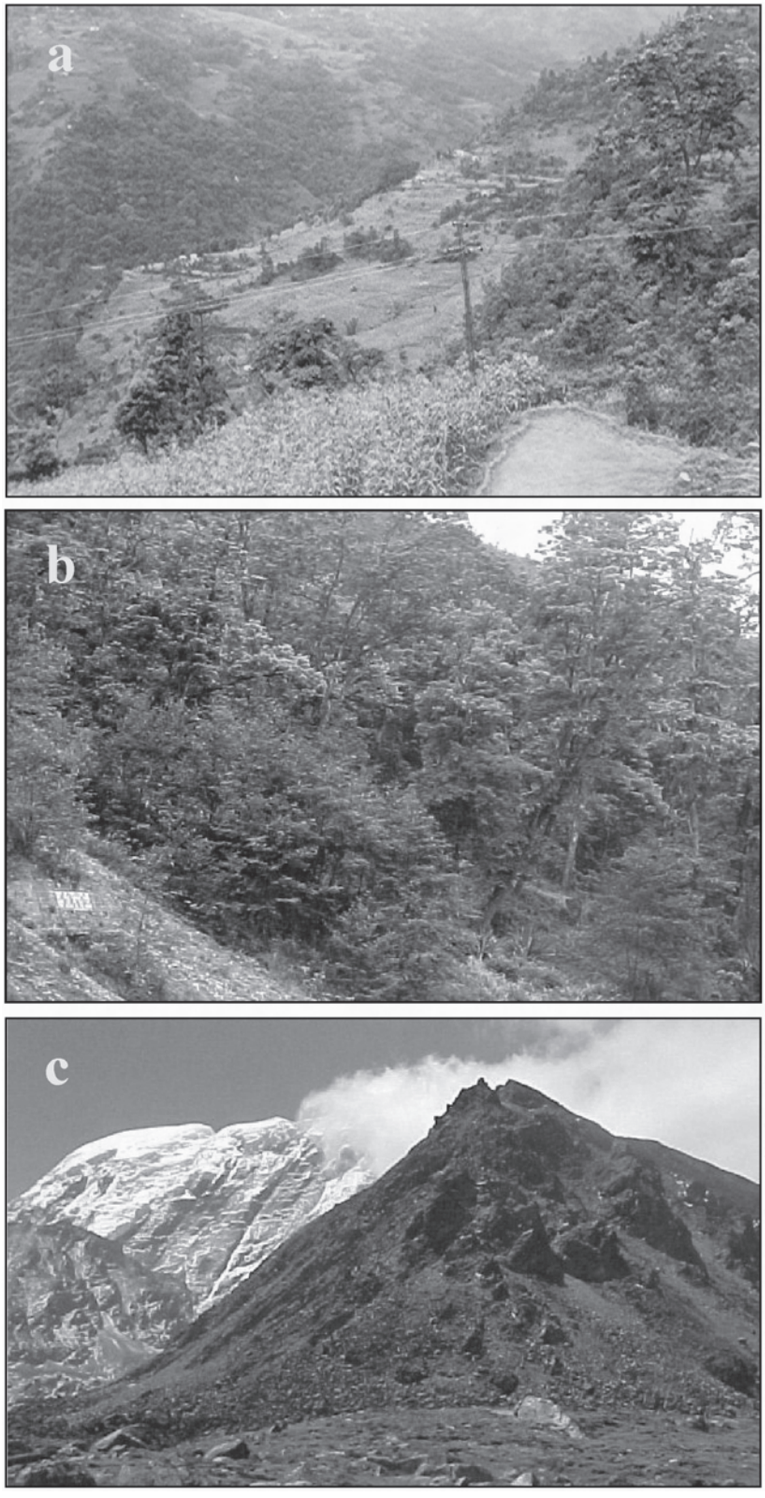
Land cover change may be overestimated due to positional error in multi-temporal images, even with sub-pixel co-registration (Verbyla and Boles, 2000). It is important to quantify the degree of error and determine the error sources and their propagation processes. If accurate registration between images is not achieved, then spurious differences will be detected, arising merely because different locations are compared instead of differences in properties at the same location between one time and another. However, perfect co-registration of multi-temporal images is impossible as there is always residual error in rectification models (Labovitz and Marvin, 1986). Co-registration (positional) errors have been recognized as a significant source of land cover

overestimation (Townshend *et al.,* 1992, Stow, 1999). Values of 0.5 to 1 pixel are normally regarded as being satisfactory and visually the results of overlying two images with this level of misregistration appear acceptable (Townshend *et al.,* 1992). Verbyla and Boles (2000) introduced a bootstrap resampling method to estimate false land cover change due to positional error and observed that the precision of the estimates may be too low to be of practical value in some land cover change applications. PAR (Perimeter Area Ratio) is a simple landscape index that quantifies the amount of false changes that are potentially attributed to co-registration errors between the two images (Salas *et al.,* 2003). The PAR of a clump determines the shape of the feature. The higher the ratio, more complex the shape is or greater departure from simple euclidean geometry (*e.g.,* circle or square) and *vice versa* (Frohn, 1998). Individual clumps PAR values provide an indication of shape of the changed area. Higher PAR values represent change areas with a shape closer to linear. False changes due to co-registration errors are likely to have a non-linear shape. Salas *et al.* (2003) have opined that PAR is an easily derived method for determining potential areas of linear *false* change caused by misregistration in change detection analysis.

It is well-known that the accuracy of single image analysis would contribute to change detection accuracy. Additionally positional miss correspondence of two images will significantly affect the change detection accuracy. Misregistration introduces both additional false-positive errors (commission errors) and false-negative errors (omission errors). More importantly, misregistration reduces the ability of any change detector to detect the true changes and increase the probabilities to pick additional false changes since the wrong locations are compared. The true changes removed by misregistration are spatially distributed away from the edges. Townshend *et al.,* (1992), in a semivariance study of misregistration effects on false change detection, spatially degraded Landsat MSS NDVI data to simulate Terra MODIS NDVI data at pixel sizes of 250 and 500m. Using a constant positional error shift, they found for densely vegetated areas, that an error of over 40% of the actual difference in NDVI could be induced by misregistration of one pixel. The authors recommended that to achieve NDVI change errors of less than 10%, image co-registration accuracies of less than 0.2 pixel may be required. Dai and Khorram (1997) used a similar semivariogram approach with Landsat TM bands 2-4 and concluded that to detect 90% of true change, a co-registration accuracy of <0.2 pixels may be required. It is generally expected that the finer the spatial frequencies present within the image, the greater the consequences of misregistration would be. In ecological applications, the type of land cover change is important and therefore image differencing of classified images is often used. The present study involves analysis of (i) land cover for the periods 1997 and 2002 (ii) patch shape and size for the same period, (iii) change in area over the 6-years and (iv) biasness in area estimation due to misregistration using PAR methodology.

North District, the Study Area

North district is located in the eastern Himalayas between 27° 19' & 28° 08' N latitude and 88° 05' & 88° 51' E longitude. This district accommodates India's tallest mountain peak on Mount Kanchenjunga (8588m height). The mountains, lush valleys, fast-flowing rivers, terraced hills and incredible floral wealth accounts to land cover structures of the district (Figure 1a-c). With dissected hills and mountains, the district provides a highly complex terrain and varied topographic conditions. The altitude varies between 350m to above 8580m in an area of 4295 km^2. The district receives heavy rainfall. The perennial river Teesta and its tributaries water the district, those are in turn fed by snowmelt and rainfall. Seasonal snow



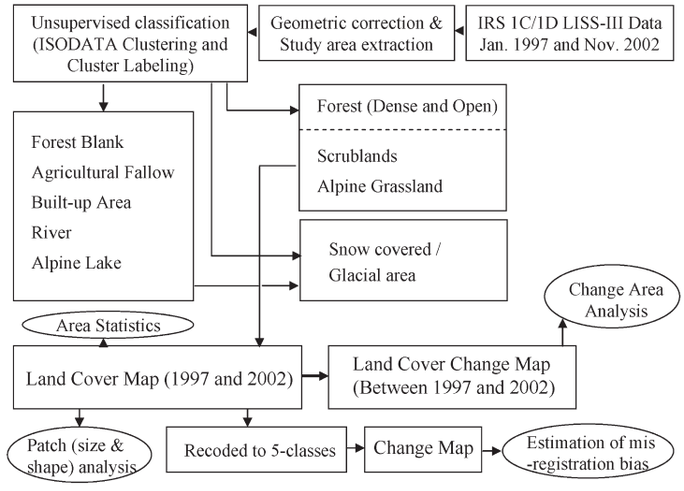
Figute 1: a. Anthropogenically modified forested landscape of North district;
b. Dense evergreen forests and c. Snow-claded mountains and alpine grasslands

cover and human activities are two important factors that regulate the land cover dynamics of the district. Landslide and debris flow are common phenomena in the district. The land use change mainly occurs due to agricultural and developmental activities. Cardamom is a major cash crop of the local inhabitants that is grown as undergrowth along forests. Due to population growth and increase in demands of various products, the natural resources exploitation has reached to an unprecedented level triggering land cover change (Sundriyal and Sundriyal, 2003).

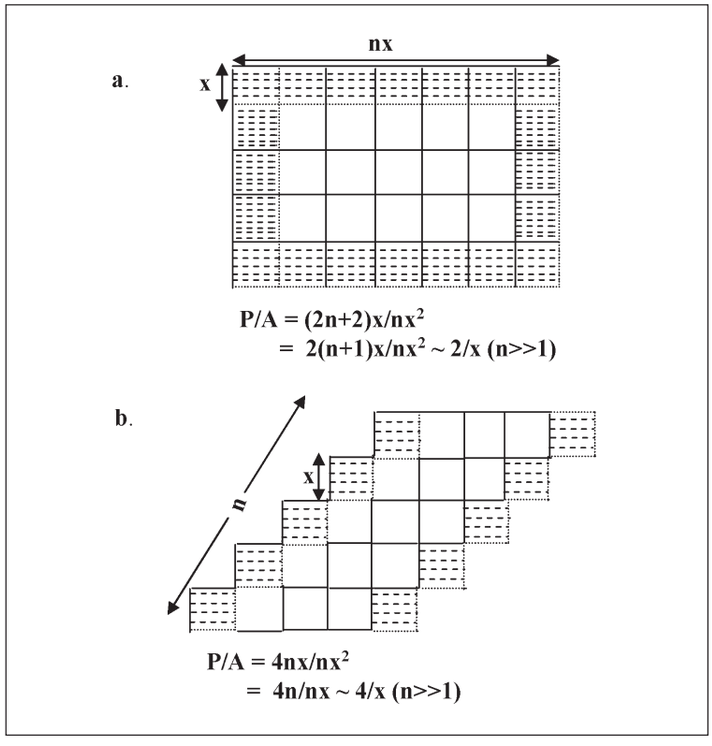
Methodology

A cloud free 02 January (winter season) 1997 IRS-1C LISS-III (path 107, row 52) and a 09 November (spring season) 2002 IRS-1D LISS-III (path 107, row 51; 80% south shift) scene were acquired for the study. Cloud-free data availability has always been a problem in the eastern Himalaya of which North district of Sikkim forms a part. Moreover, since the vegetation present here are evergreen in nature *i.e.,* both coniferous and broad-leaved, these two near-anniversary datasets were utilized for the change detection study. Both IRS 1C &1D have the same spatial (23.5m), spectral (operates in green, red, near infrared and short wave infra red (SWIR) portions of electromagnetic spectrum), radiometric (8-bits) and temporal (21-days) resolutions. These near-anniversary image dates were used to ensure a minimum number of exogenous effects *i.e.,* low cloud cover, low soil moisture content and a minimum sun angle effects. Though the spectral characteristics of IRS 1C and 1D LISS-III data are the same, atmospheric correction was applied to normalize any differences in spectral responses because of various controlling parameters.

The 1997 image was registered to available reference map with 2nd order polynomial statistics using nearest neighborhood resampling algorithm at 23m pixel size, which further acted as reference image for image-to-image registration with 2002 image. *Image-to-Image* registration was done using 50-GCPs uniformly distributed over the image plane. It was difficult to collect GCPs as the study area is dominated with forest vegetation and snow cover. Tie points were mostly located across river/water body cross sections and intersections of small stream segments. Using the control and check point options available in ERDAS *Imagine* software, the minimum possible r.m.s. error of 1.04 (~1) pixels was achieved. Reconnaissance survey was done for all representative classes with respect to their occurrence and spectral response on satellite images. The images were classified using ISODATA (Iterative Self-Organizing DATa Analysis) algorithm following a classification scheme. The classification scheme has 3 classes in level-I *i.e.,* forest, non-forest and others (snow covered/ glacial area). Further, in level-II, the forest is classified into scrub, alpine grassland and dense and open forests; whereas non-forest is categorized into forest blank, agricultural area, built-up area-rural, river and lake classes. Level-I separation between forest and non-forest classes was done following cluster-labeling approach (Figure 2). Then the images pertaining to forest and non-forest classes were taken separately for further levels of classification. Zeroing of the masked in and masked out areas alternately did this. Spectral and texture based judgement of the clusters allowed separation between dense and open forests. Scrubland and alpine grassland classes were separated with appropriate cluster labeling. Controlled cluster technique was used for further separation within other land cover classes. Purely separated clusters were deducted from the image and again the binary FCC was subjected to ISODATA unsupervised classification. All the classes were then combined to obtain the final land cover map of North district (Figure 2). The final classified image was smoothened with a 3 x 3 median filter to eliminate speckles that occurred during the classification. Post-classification comparison approach of change detection was done and the area statistics



Figute 2: Methodology for land cover classification and change assessment, Patch analysis and estimation of Misregistration bias. Unsupervised classification technique followed by cluster labeling approach was used for land cover classification (Classification scheme is given in Table 1). The study objectives anr mentioned inside elliptical circles.



Figute 3: Schematic diagram of PAR (Perimeter/Area Ratio) utilized to quantify the amount of false changes due to misregistration where x represents the spatial resolution of sensor and n represents the number of pixels along edge. Shaded region shows the false land cover change **a.** Depicts the false changes across row and columns and **b.** Depicts the flase changes across diagonals (the individual box denoteds one pixel) [Modified from Salas *et al.,* 2003)

Table 1: Land cover distribution and change area statistics between 1997 and 2002 for North district, Sikkim state

Sl.	Land use/ land cover class	1997 (in km^2)	2002 (in km^2)	Change in Area (km^2)	Change in area (%)
1	Built up area (Rural)	0.59	0.59	—	—
2	Dense forest (> 40%)	850.17	848.37	-1.80	-0.21
3	Open forest (10-40%)	443.70	440.84	-2.86	-0.64
4	Scrubland	394.20	387.69	-6.51	-1.65
5	Forest blank	1252.09	1048.63	-203.45	-16.25
6	Alpine grassland	710.29	595.14	-115.15	-16.21
7	Agriculture area	18.84	20.45	1.61	8.56
8	River	17.84	16.98	-0.86	-4.82
9	Lake	20.83	10.94	9.89	-47.48
10	Snow covered / Glacial area	586.21	925.22	339.01	57.8

('-' indicates decrease in land cover area)

Table 2: Distribution of mean patch size (km^2) and mean patch shape (PAR; Perimeter/ Area) for the land cover classes between 1997 and 2002.

Sl. No.	Land Cover Classes	Mean Patch size (km^2)		Mean Patch shape	
		1997	2002	1997	2002
1	Built-Up area (Rural)	0.03	0.03	4.5	4.5
2	Dense forest	1.27	1.41	4.55	4.5
3	Open forest	0.12	0.11	5.46	5.3
4	Scrubland	0.1	0.11	5.5	5.15
5	Forest blank	0.26	0.28	5.69	5.06
6	Alpine Grassland	0.09	0.08	4.79	6.34
7	Agricultural area	0.03	0.03	4.65	4.6
8	Lake	0.16	0.1	1.92	2.97
9	River	—	—	—	—
10	Snow covered/ Glacial area	0.34	0.63	3.65	3.74

for various land cover changes is shown in Table 1. The mean patch size and mean patch shape were calculated for each class for both the periods (Table 2). Also the patch size distribution was calculated and presented in Table 3.

Biasness in land cover change area due to mis-registration was analyzed for the forest vegetation classes *i.e.,* forest, scrubland and alpine grassland (Table 4, Figure 4a-i). A simple landscape index *i.e.* PAR was used to quantify the amount of false changes and the details are given in Figure 3. PAR is measured in terms of the boundary length of the patch divided by its area at a particular location in the reference unit Alternatively, in remote sensing concept it can be described as total edge divided by total area of the patch *i.e.* the length of all borders between different patch types (classes) in a reference area divided by the total area of the reference unit. Clump analysis was performed for the above nine land cover change

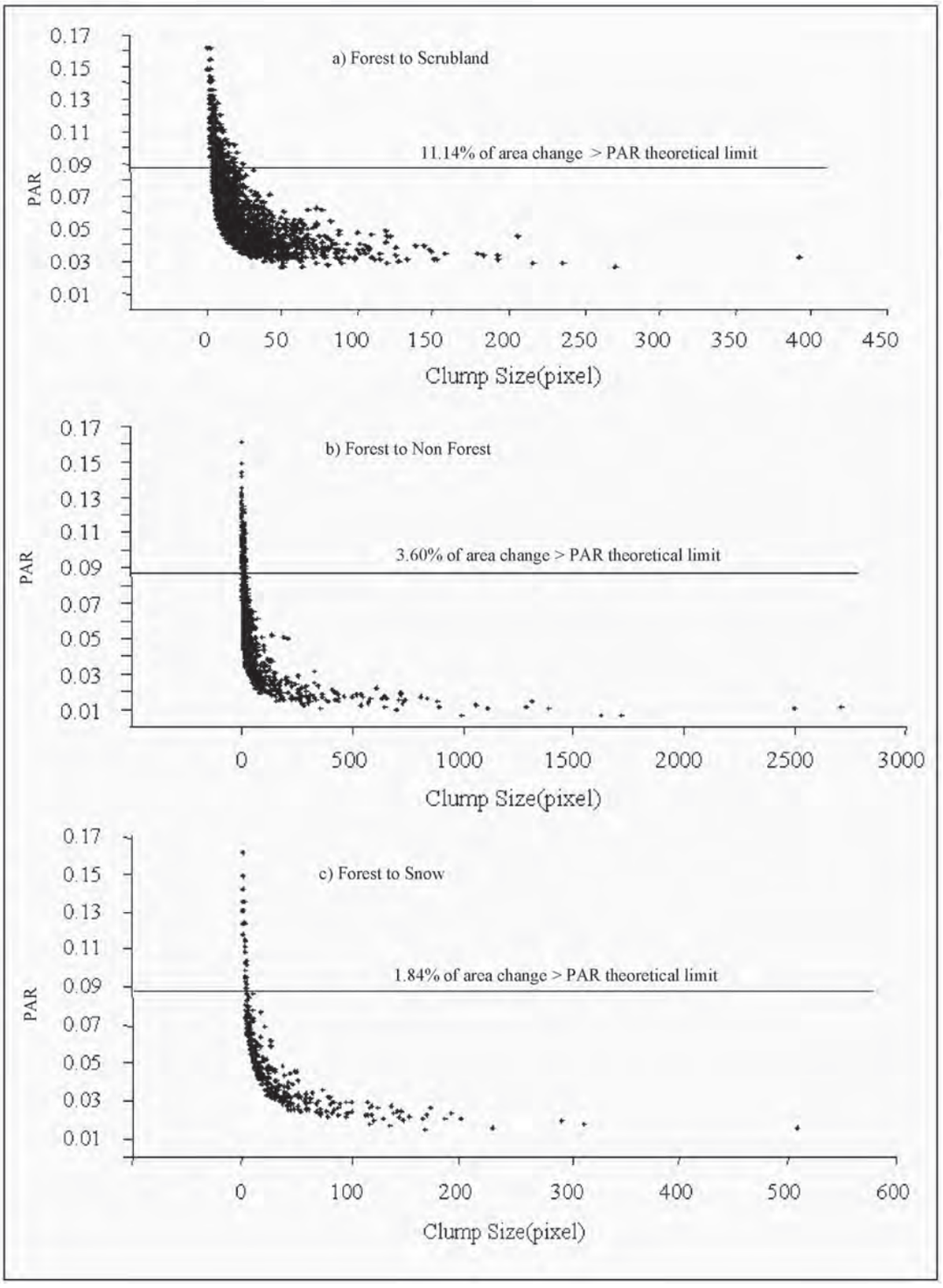
Table 3: Patch size (in km^2) distribution of various land cover classes in North district of Sikkim for 1997 and 2002

a. Patch size distribution for the year 1997

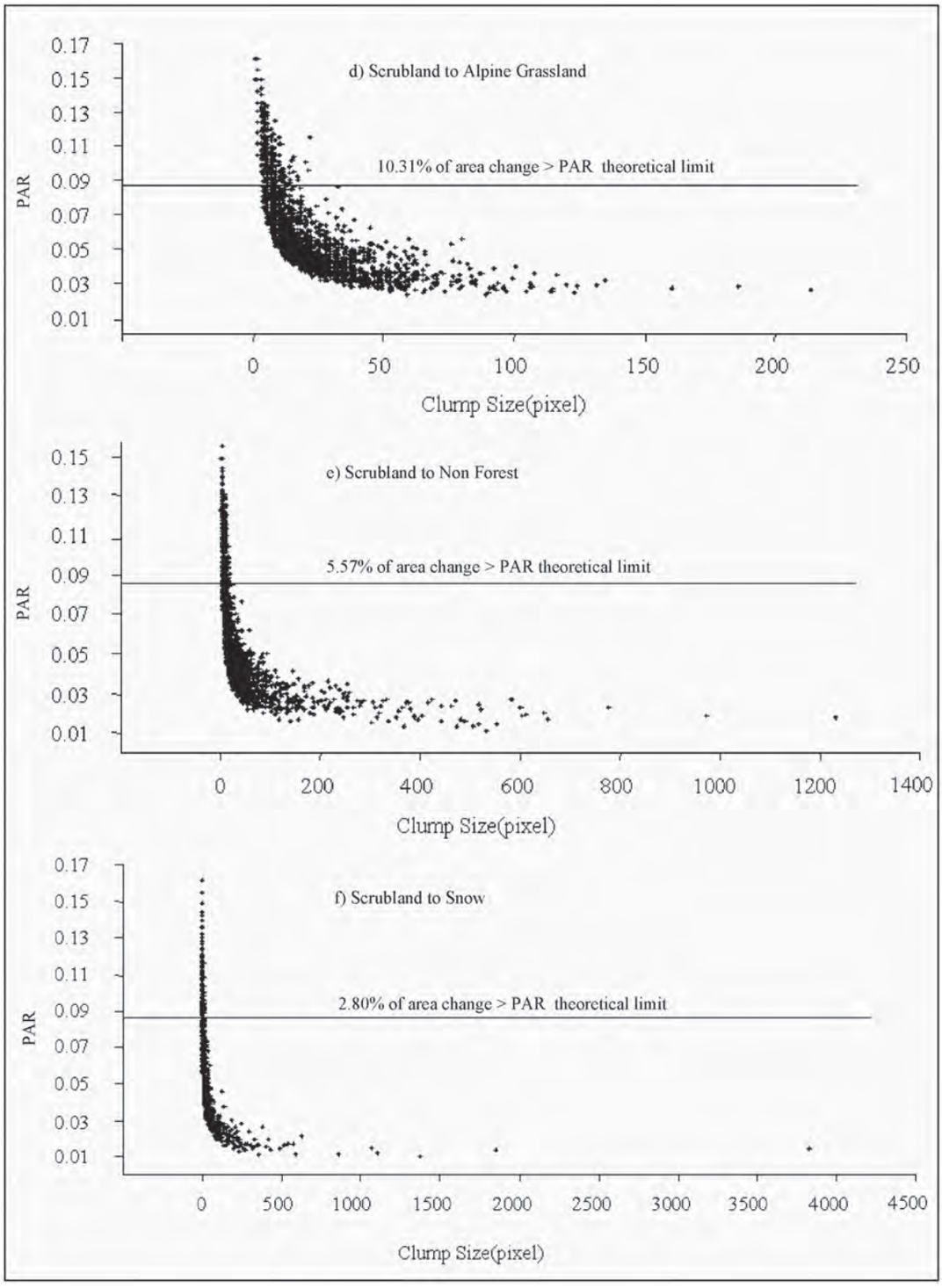
Size (km^2)	Built-up	Dense forest	Open forest	Scrub land	Forest blank	Alpine grassland	Agri- culture	Lake	Snow cover
< 1	0.59	15.92	131.43	135.56	129.67	264.3	18.84	16.22	87.6
1-5	—	5.68	94.63	82.21	54.79	161.66	—	4.54	46.71
5-10	—	9.11	36.98	38.6	28.81	73.69	—	—	16.61
10-50	—	—	129.11	77.75	87.08	146.18	—	—	210.7
>50	—	819.47	51.51	60.04	952.19	64.73	—	—	224.68

b. Patch size distribution for the year 2002

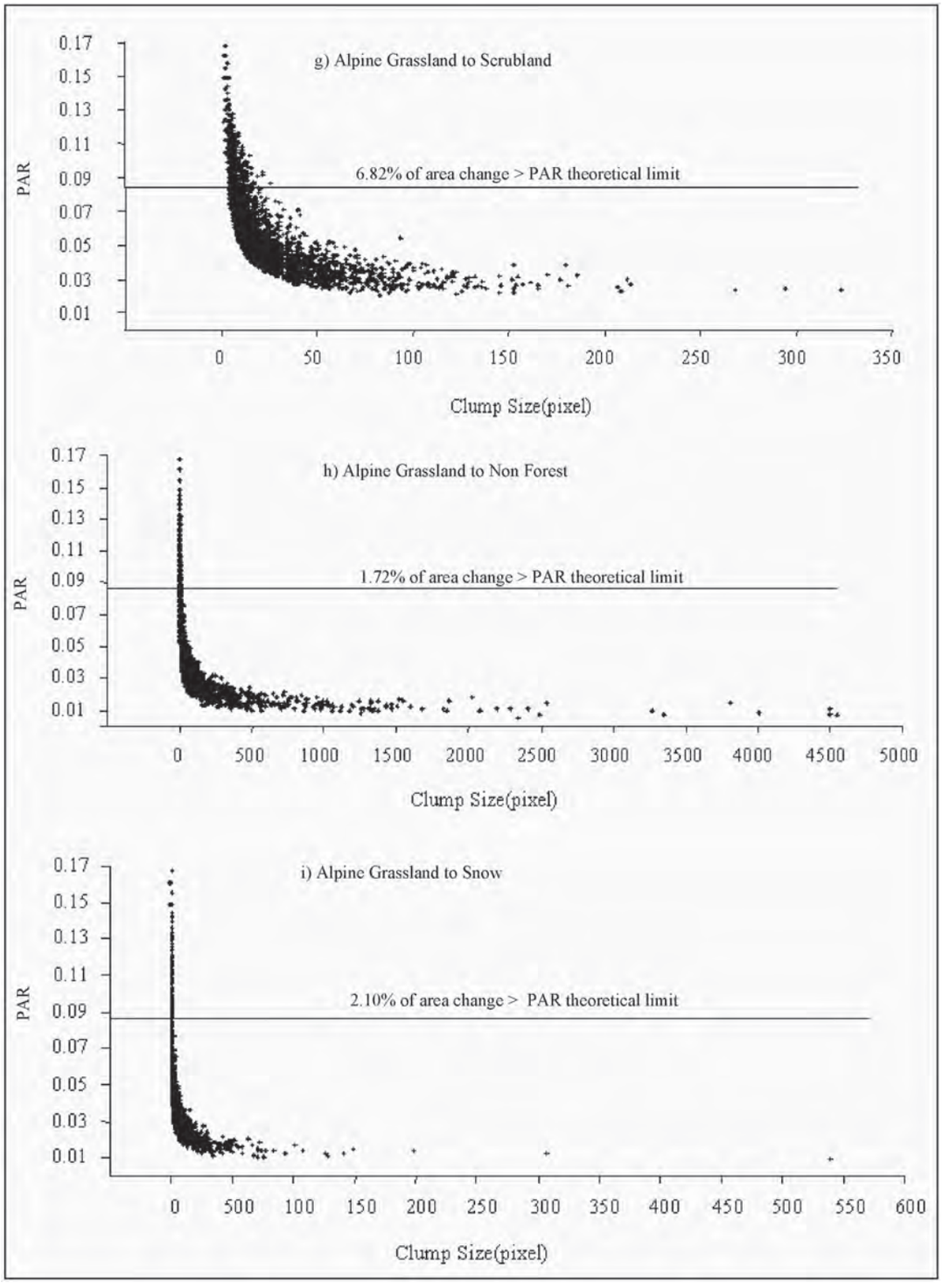
Size (km^2)	Built-up	Dense forest	Open forest	Scrub land	Forest blank	Alpine grassland	Agri- culture	Lake	Snow cover
< 1	0.59	12.25	133.82	136.73	145.45	219.94	15.12	9.54	76.37
1-5	—	3.03	93.93	64.49	161.07	72.57	5.34	1.42	60.71
5-10	—	9.17	36.83	43.6	91.88	24.88	—	—	50.17
10-50	—	—	123.11	80.37	130.36	81.8	—	—	143.31
>50	—	823.91	53.18	62.69	519.87	195.82	—	—	594.61



Figute 4 (a-c) : PAR by clump size for land cover changes as an indicatorr of misregistration bias



Figute 4 (d-f) : PAR by clump size for land cover changes as an indicatorr of misregistration bias



Figute 4 (g-i) : PAR by clump size for land cover changes as an indicatorr of misregistration bias

Table 4: PAR by clump size for land cover changes as an indicator of misregistration error

Land Cover Change		Change > PAR Theoretical Limit		Total Area (in km^2)
From	To	in %age	in km^2	
Forest	Scrubland	11.14	3.99	35.86
	Non-forest	3.6	1.7	47.45
	Snow	1.84	0.14	7.52
Scrubland	Alpine grassland	10.31	3.16	30.65
	Non forest	5.57	2.62	47.09
	Snow cover	2.80	0.72	25.57
Alpine grassland	Scrubland	6.82	3.40	49.87
	Non-forest	1.72	3.50	203.34
	Snow	2.10	1.64	78.16

classes pertaining to forest and non-forest/ snow covered/ glacial areas (Figure 4a-i). Clumping of groups of contiguous pixels using neighborhood from all eight directions were done for analysis of change in area. Higher PAR values represent change areas with a shape closer to linear. PAR of individual clump was determined from the change image. False changes due to co-registration errors are likely to have a non-linear shape (Salas *et al.,* 2003). The theoretical limit of the PAR for a single pixel offset was calculated. For purely diagonal single pixel offsets, the PAR = $4/x$, regardless of the size of the diagonal strip, with x being the spatial resolution (*i.e.,* 23 m). This is the upper limit of PAR for all single pixel offsets; for 23 m spatial resolution of IRS 1C/1D LISS-III data, this value is 0.087 m^{-1} (Figure 3). For single pixel offsets for either the row or column directions, the PAR = $2/x\,(1+1/n)$, where n is the number of pixels along offset edge. This is the lower limit of PAR for all single pixel offsets; for 23m LISS-III data this value approaches 0.17 m^{-1} for very large values of n (Figure 3). The PAR values of the clumps were compared with the theoretical limits in order to estimate the potential biasness in land cover changes due to misregistration.

Results

4295 km^2 area of North district was classified into ten land cover categories for both the periods. Four forest classes (*viz.,* dense forest (> 40%), open forest (10-40%), scrubland and alpine grassland), five non-forest classes (*viz.,* built up area (rural), forest blank, agriculture area, river, and lake) and other (snow covered / glacial area) classes were mapped (Table 1).

The dense forests are generally distributed throughout the district and are constituted of both broadleaved and coniferous species (Figure 1b). They depict red to dark red color on FCC image and occupy 850.17 km^2 in 1997 and 848.37 km^2 in 2002 (Table 1). The open forests primarily occur in lower hill slopes. They show brighter red tone on FCC image and occupy 443.7 km^2 in 1997 and 440.84 km^2 in 2002 (Table 1). The scrublands are distributed all over the district in the agriculture areas in lower altitudes and above the tree-line in higher altitudes. Rhododendron is the single dominant species found abundantly distributed in high-altitude scrublands. They depict brackish-red tone on FCC image and occupy 394.2 km^2 in 1997 and 387.69 km^2 in 2002

(Table 1). Alpine grasslands were found beyond the tree-line, above 4000m altitudes (Figure 1c). These grasslands are seasonally covered with snow and thus remain in a dormant state during winter season. They occupy 710.29 km^2 and 595.14 km^2 in 2002 (Table 1). Major forest blanks were mapped in alpine and sub-alpine zones. The forest blanks are natural and occur due to excessive cold environmental conditions unfavorable for vegetation growth. The other anthropogenically-derived forest blanks were found mainly across the settlement areas (Figure 1a). They occupy 1252.09 km^2 in 1997 and 1048.63 km^2 in 2002 (Table 1). Agriculture areas found distributed in 18.84 km^2 and 20.45 km^2 areas in 1997 and 2002 respectively, indicating an increasing trend during the period (Table 1). Mangan, the district head-quarter could only be mapped owing to its larger spatial dimension. It occupies 0.59 km^2 area for both the periods (Table 1). The river *Teesta* and some of its major tributaries could be mapped despite some confusion due to hill shadows that occupied 17.84 km^2 and 16.98 km^2 in 1997 and 2002 respectively. Lakes were found distributed in higher reaches on the alpine zones that gets partially or fully-frozen during winter. Their spread was 20.83 km^2 in 1997 and 10.94 km^2 in 2002. According to 1997 assessment, the snow-covered glacial area was 586.21 km^2 whereas 925.22 km^2 in 2002 (Table 1).

There was no change in the built up areas over the period. A marginal decrease of 1.8 km^2 (0.21%) dense forest was reported (Table 1). This can be attributed to clearing of some forest for agricultural purposes and degradation of some dense forest to open forest. Similarly, a decrease of 2.86 km^2 (0.64%) open forest could be due to similar reason. A decrease of 6.51 km^2 (1.65%) scrubland could be because of seasonal conversions to agricultural lands and the buried high-altitude scrubs under seasonal snow cover. A large decrease in forest blanks (203.45, 16.25%) and alpine grasslands (115.15, 16.21%) can definitely be attributed to seasonal snow cover. An increase of 1.61 km^2 of agricultural area was reported over the period. A seasonal decrease of 0.86 km^2 river area was noticed over the period, which is accountable to seasonal snow cover. Lakes demonstrated a decrease of 9.89 km^2 (47.48%) area that is also attributed to seasonal snow cover. The snow covered/ glacial area was increased by 57.8% over the period which can also be a seasonal effect (Table 1).

The mean patch size and shape were determined for each class for both the images (Table 2). Highest mean patch size was observed for dense forests both in 1997 (1.27 km^2) and 2002 (1.41 km^2), whereas lowest mean patch size was observed for built-up areas and agriculture lands *i.e.,* 0.03 km^2 and 0.03 km^2 respectively (Table 2). Forest blanks have the highest mean patch shape (5.69) and lakes (1.92) have lowest mean patch shape for 1997; whereas Alpine grasslands have the highest mean patch shape (6.34) and lakes (2.97) have lowest mean patch shape for 2002. The clump size distribution for various land cover patches revealed similar pattern of distribution (Table 3). For dense forests, forest blanks and snow covered/ glacial areas, higher clumps account to maximum areas whereas open forests, scrublands and alpine grasslands have smaller clumps contributing to maximum area (Table 3). Built-up areas, agriculture areas, rivers and lakes do have all the clumps less than 1 km^2 size (Table 3).

Maximum bias due to misregistration was observed for forest to scrubland change (3.99 km^2; 11.14%) followed by Scrub to Alpine grassland change (3.16 km^2; 10.31%) (Table 4); whereas as the minimum misregistration error was estimated for forest to snow covered/ glacial area change *i.e.,* 0.14 km^2 (1.84%; Figure 3a-i). Comparison of the observed value and theoretical limits of P/A indicated that 3.6 % (1.7 km^2) biasness in area change from forest to non-forest was found due to such error. About 16.6% of the total change *i.e.,* 0.85% in forest area between 1997 and 2002 was due to misregistration bias

(Table 4). Similarly 81.32% of the total change in scrub between the five years period could be the true change; whereas 18.68% (10.31% to alpine grassland, 5.57% to non-forest and 2.80% to snow) of the total change in scrubland could be due to misregistration bias. The misregistration bias in change area from alpine grassland to scrub, non-forest and snow were 6.82% (3.4 km^2), 1.72% (3.5 km^2) and 2.1% (1.64 km^2) respectively (Figure 4a-i).

Discussion and Conclusions

Satellite remote sensing and GIS are beyond doubt the most relevant technology for change detection analysis especially in complex terrain conditions. Multi-date assessment of the natural resources provides the opportunity to monitor the changes over a period of time, thereby leading to decision-making. The map-to-map comparison was chosen for the study as it detected a full change matrix useful for detailed analysis (Jensen *et. al.,* 1996). However, the effectiveness of map-to-map technique is highly dependent upon the assumptions and used to produce maps of the same area at different times. Ten land cover categories mapped for the district provides the spatial pattern and distribution of the landscape. The major changes in the study area are due to seasonal snow cover, which could be attributed to the satellite data used (Table 1). Large decrease in forest blanks and alpine grasslands was observed that can also be due to seasonal snow cover. The decrease in scrubland could also be due to seasonal snow cover. Consequently, it is worth noting that the observed changes in forest vegetation occupied relatively small aerial extent. The increase in agricultural areas of 8.5% (1.16 km^2) over the period is beyond doubt a significant anthropogenic change, which is a reflection of increased population pressure and associated causes thereof. The agricultural areas are not believed to be atypical; particularly, human induced convergence of land cover tends to be characterized by high spatial frequencies, because of the relatively local scale of human activities. The mean patch size of few agricultural patches seems to have increased over the period (Table 3). Likewise, changes due to seasonal snow cover are characterized by higher spatial frequencies. Both increase and decrease in mean patch size was noticed indicating dynamism over the period. An overall decrease in mean patch shape was observed for all land cover classes except lakes and snow covered/ glacial areas over the five year's period (Table 2).

Patch size and patch shape allowed characterizing the structural component of the landscape. Higher mean patch size of dense forests indicates higher stability and high energy and nutrient content, whereas Built-up areas having lowest mean patch size are relatively unstable (Table 2). Only three classes *i.e.,* dense forest, forest blank and snow/ glacier covered areas have greater percentage of clumps over 10 km^2 for both the periods (Table 3). The decrease in dense forest area and increase in clump counts over the period implicates invasion of other land cover units, whereas the decrease of clump counts for open forest and grassland over the period may be attributed to the seasonal snow cover that would have provided a continuum. The open forest and grasslands though occur in larger clumps, also do have many smaller clumps distributed over varied dimensions. This distribution of clumps of different sizes has a significant bearing on conservation and planning. The dense forests were observed to occur on high altitudes and highly complex terrain, whereas open forests occur in relatively accessible areas and in low hill slopes leading to different clumps (Table 3). Alpine grasslands do occur in varied patches beyond the tree line, but their occurrence depends on seasonal snow cover spread and occurrence duration. The estimation of false changes considering the shape (PAR) factor provides a fair idea about misregistration bias. Except the land cover change from forest to scrubland and scrubland to alpine grasslands,

misregistration bias was below 10%. This implies that for these two land cover classes the potential linear changes are more (Table 4). For scrubland to non-forest and alpine grassland to scrubland, the misregistration bias is more than 5% *i.e.,* 5.57% (2.62 km^2) and alpine grassland to scrubland *i.e.,* 6.82% (3.4 km^2), indicating that the potential changes are close to linear (Fig. 4a-i). This result also indicates that the land cover classes having highly dispersed and boundary (adjacent) patches are more likely possesses higher misregistration bias and *vice versa.*

The accuracy assessment of change image is more complex than single image accuracy assessment. The study shows that change detection is dependent critically on the accuracy of geometric registration of two images since the change analysis is generally performed on pixel-by-pixel basis. The study also describes the general trends and combined effects of real changes on the ground and changes caused by misregistration. The percentage of false changes added by misregistration is slightly greater or slightly less than the corresponding percentage of true changes removed (omission error). While making change estimates the spurious positive and negative changes in detected values caused by misregistration would have counter balanced each other. Thus, increases in misregistration would lead to progressively greater over estimates of either positive and negative changes or any other major spectral properties. The change accuracy has been dropped to a maximum of 11% within one pixel of misregistration as revealed by the study. Therefore, it is needed to consider the specification of registration accuracy in the design of any remote sensing system, if reliable detection of land cover change is a major objective.

Acknowledgements

This investigation carried out against 'Natural Resources Census Mission (prototype) study for North district, Sikkim' was supported by National Natural Resources Management Systems (NNRMS) and National Remote Sensing Agency (NRSA) of Indian Space Research Organization (ISRO), Bangalore, India. We are very much thankful to two anonymous Referees who have provided very useful comments to the earlier version of this manuscript.

References

Anon., 2003, Erdas Imagine Field Guide, *Ver., 8.7.,* ERDAS Inc., Atlanta, Georgia.

Anuta, P. E., Bartlucci, L. A., Dean, M. E., Lozano, D. F., Malaret, E., McGillem, C. D., Valdes, J. A. and Valenzuela, C. R., 1984, Landsat-4 MSS and thematic mapper data quality and information content analysis. *IEEE Transactions on Geoscience and Remote Sensing,* GE-20, 222-236.

Behera, M. D., Kushwaha, S. P. S. and Roy, P. S., 2005, Geo-spatial modeling for rapid biodiversity assessment in Eastern Himalayan region. *Forest Ecology and Management.* 207, 363-384.

Chen, L., and L. Lee, 1992, Progressive generation of control frameworks for image registration. *Photogrammetric Engineering & Remote Sensing,* 58(9):1321-1328.

Coppin P. R. and Bauer, M. E., 1996, Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Review,* 13, 207-234.

Dai, X and Khorram, S., 1998, The effects of Image Misregistration on the accuracy of remotely sensed change detection. *IEEE Transactions on Remote Sensing and Geoscience,* 36(5), 1566-1577.

Frohn, R. C., 1998, Remote sensing for landscape ecology (Eds.), Lewis Publishers, New York.

Jensen, J. R., 1996, Introductory Digital Image Processing: a remote sensing perspective (New Jersey: Prentice-Hall).

Jensen, J. R., Cowen, D., Narumalani, S., Weatherbee, O. and Althausen, J., 1993, Evaluation

of coastwatch change detection protocol in south Carolina. *Photogrammetric Engineering & Remote Sensing,* 59(6):1039-1046.

Krummel, J. R., Gardner, R. H., Sugihara, G., O' Neill, R. V. and Coleman, P. R., 1987, Landscape patterns in a disturbed environment. *Oikos,* 48, 321-324.

Labovitz, M. L. and Marvin, J. W., 1986, Precision in geodetic correction of TM data as a function of the number, spatial distribution, and success in matching of control points: a simulation. *Remote Sensing of Environment,* 20, 237-252.

Penner, J. E., 1994, Atmospheric chemistry and air quality: In: W. B. Meyer, B. L. Turner II (Eds.), *Changes in land use and land cover: a global perspective,* 437-471, Cambridge: Cambridge University Press.

Salas, W. A., Boles, S. H., Frolking, S., Xiao, X. and Li, C., 2003, The perimeter/area ratio as an index of misregistration bias in land cover change estimates. *International Journal of Remote Sensing,* 24(5), 1165-1170.

Singh, A., 1989, Review Article-digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing,* 10, 989-1003.

Skole, D. L., 1994, Data on global land cover change: acquisition, assessment and analysis. In: W. B. Meyer, B. L. Turner II (Eds.), *Changes in land use and land cover: a global perspective,* 437-471, Cambridge: Cambridge University Press.

Stow, D.A., 1999, Reducing the effect of misregistration on pixel-level change detection. *International Journal of Remote Sensing,* 21, 2477-2483.

Sundriyal, M. and Sundriyal, R. C., 2003, Underutilized edible plants of the Sikkim Himalaya: Need for domestication. *Current Science,* 85(6), 631-636.

Townshend, J. R. G., Justice, C. O., Gurney, C. and McManus, J., 1992, The impact of misregistration on change detection. *IEEE Transactions on Remote Sensing and Geoscience,* 30(5), 1054-1060.

Verbyla, D. L. and Boles, S. H., 2000, Bias in land cover change estimates due to misregistration. *International Journal of Remote Sensing,* 21, 3553-3560.

Vitousek, P. M., 1994, Beyond global warming: ecology & global change. *Ecology,* 75, 1861-1876.