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Landscape transform and spatial metrics for mapping spatio-temporal land cover dynamics using Earth Observation datasets

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ABSTRACT

Analysis of Earth Observation (EO) data, often combined with Geographical Information Systems (GIS), allows monitoring of land cover dynamics over different ecosystems, including protected or conservation sites. The aim of this study is to use contemporary technologies such as EO and GIS in synergy with fragmentation analysis, to quantify the changes in the landscape of the Rajaji National Park during the period of 19 years (1990-2009). A number of landscape coverage and change detection matrices were computed for analyzing the dynamics of the landscape and unveil the degree of land use change, diversity and fragmentation patterns occurred. Our results suggested that notable changes have taken place in the Rajaji National Park landscape during the studied period, evidencing the requirement of taking appropriate measures to conserve this culturally precious and ecologically natural ecosystem.

Keywords: *Protected Ecosystem; Remote Sensing; Landscape pattern; Fragmentation; Ecological metrics, Geographic Information System*

1. INTRODUCTION

India is one of the 12 mega-biodiversity countries of the world. The total protected area network in India includes 100 National Parks and 515 Wildlife Sanctuaries, 43 Conservation Reserves and four Community Reserves (http://envfor.nic.in/report/report.html). However, after industrial revolution in India, the rapid development of human societies has intensified which caused a continuous and noticeable influence on natural resources (Gadgil and Guha 1995). A rapid growth of human population during last three decades has been noticed in Census of India datasets (censusindia.gov.in/). This expansion in population causes adverse impacts on natural resources and wildlife. The changes that have taken place are especially important and intense, as society is becoming increasingly modernized and urbanized, while natural ecosystems are continuously deteriorated or almost losing their original structure and forms (Islam and Weil 2000, Pandey et al. 2012, Srivastava et al. 2014). This increasing human growth resulted in a shrinkage in the natural habitat (Venture 2005).

Land cover constitutes a key variable of the Earth's system that has in general shown a close correlation with human activities and the physical environment (Bell et al. 2005, Srivastava et al. 2010). The Land cover mostly changes due to its interaction with physical, ecological, geomorphic and anthropogenic processes (Naveh 1987, Paudel et al. 2015). In all the above mentioned driving factors, anthropogenic factors are emerged as a serious factor for changing landscape structure, pattern and dynamics (Naveh and Lieberman 1990, Petropoulos et al. 2015, Srivastava, Han, et al. 2012). Because of high anthropogenic pressure on natural and semi-natural habitats conservation and sustainable practices for land cover has become a priority (De Groot 2006). Hence, quantifying the temporal and spatial patterns of LULC change and its corresponding consequences – particularly so over protected areas - is recognized as a highly significant topic (Fraser and Latifovic 2005). Earth Observation (EO) technology is very well-suited for mapping and monitoring of habitats because of its synoptic repetitive coverage over the same area at various spatial and temporal scales, even available for inaccessible locations (Sanchez-Hernandez et al. 2007). These EO datasets on geospatial platform can provide an effective set of tools for analysing and extracting spatial information to support decision making with more reliable and consistent (Jankowski and Richard 1994).

A large number of landscape change studies in technical literature domain are available employing different EO datasets. The Landsat sensors have shown an excellent promise for synoptic and temporal analysis of the changes (Gupta and Srivastava 2010, Hansen and Loveland 2012) and provide images at high resolution. However, very rare studies are available for developing countries like India. The land cover change studies are very important to understand the exploitation patterns and assessment of area (Banerjee and Srivastava 2014, Srivastava, Kiran, et al. 2012). If landscape changes occurred for prolonged period, it may eliminate species and disturb the ecosystem functioning and services (Martínez et al. 2009, Priess et al. 2007). Yet, most of them considered only forest to agricultural conversions (Singh et al. 2013).

For biodiversity point of view fragmentation, loss and degradation of habitat are widely considered as the most important driving factors (Hanski 2005, Lindenmayer and Fischer 2006) and hence is the topic of research. The term fragmentation has been defined as simultaneous reduction of forest area and subdivision of large forest areas into smaller non-contiguous fragments (Laurance 2000, Midha and Mathur 2010). It is a dynamic development that results in change in pattern of the habitats (Midha and Mathur 2010). The serious impact of fragmentation include loss of habitat, decreased connectivity between ecological entities, reduction in patch size, elevated distance between patches, and an abrupt increase in the edge at the expense of interior habitat (Midha and Mathur 2010). Other causes of fragmentation and habitat loss can be linked to agriculture and infrastructure development, over-exploitation of natural resources, pollution and invasive species (Semwal et al. 2005). At the landscape level, disturbance is related to patch structure, spatial arrangement, their size and duration (McGarigal and Marks 1995) and can be quantified using the spatial landscape metrics. Landscape metrics are the algorithms designed for quantifying landscape pattern depicting the spatial arrangement of land cover patches over a particular geographic area (Herold et al. 2003, McGarigal and Marks 1995, Remmel et al. 2002). These landscape and class level metrics can be used to see the impact of anthropogenic activities on natural cover such as forest. In this context, the present study aim to combine remote sensing and GIS techniques with the landscape transform concept to characterize the dynamics of land cover change and quantifying the fragmentation pattern of Rajaji National Park (RNP). The outputs obtained in this study can be used for sustainable management of this ecologically and economically vital ecosystem.

2. STUDY AREA

The Rajaji National Park (RNP) is located in Shiwalik range of Himalaya of India and lies between coordinates 29°15' N to 30°31' N and 77°52' E to 78°22' E (**Figure 1**). Elevation of the area varies widely from 250 to 1100 m above mean sea level. This entire belt is natural home of Asian elephants (*Elephas maximus*). Besides, many other wild animals like tiger (*Panthera tigris*), leopard (*Panthera pardus*), Sloth bear (*Melursus ursinus*), Hyaena (*Hyaena hyaena*), Barking deer (*Muntiacus muntjak*), Spotted deer (*Axis axis*), Sambhar (*Cervous unicolor*), Wild boar (*Sus scrofa*) and King cobra (*Ophiophagus hannah*) are also common in this region (Joshi 2009). The under-wood is light and often absent, consisting of Rohini (*Malollotus philippinensis*), Amaltas (*Cassia fistula*), Shisham (*Dalbergia sissoo*), Sal (*Shorea robusta*), Palash (*Butea monosperma*), Arjun (*Terminalia arjuna*), Khair (*Acacia catechu*), Baans (*Dendrocalamus strictus*), Semul (*Bombax ceiba*), Sandan (*Ougeinia Oojeinensis*), Chamaror (*Ehretia laevis*), Aonla (*Emblica officinalis*), Kachnar (*Bauhienia variegata*), Ber (*Ziziphus mauritiana*), Chilla (*Casearia tomentosa*), Bel (*Aegle Marmelos*) etc.

In 1983, RNP has been created by amalgamation of three sanctuaries Rajaji sanctuary (estd. 1948), Motichur sanctuary (estd. 1964) and Chilla sanctuary (estd. 1977) and considered as national park to protect Asian elephant's habitat and currently covering an area of ~820.42 km^2. It has been designated as a reserved area for both "Elephant and Tiger" by the Ministry of Environment and Forests, Government of India, with the sole aim for maintaining the viable wildlife population. It comes under International Union for Conservation of Nature and Natural Resources (IUCN) Category II by the World Conservation Union. There are three main seasons at RNP as winter, summer and monsoon. The average temperature during the winter (November to February) varies from 20-15°C while during the summer (May to June) temperature up to 32-40°C are also very common in this area. The annual rainfall over the region ranges from 1200-1500 mm with very high humidity.

Figure 1 Geographical location of the study area

3. DATASETS

In this study, the Landsat datasets are used. A total of eight Survey of India topographical-sheets (53-F/15, F/16, G/13, I/7, J/4, J/8, K/1, and K/5) at 1:50,000 scales. Landsat images were obtained from the United State Geological Survey (USGS) archive (http://glovis.usgs.gov/) at no cost. All satellite images were acquired in different years during the studied period but around the same date to minimize any seasonal and phenological variations (Lillesand et al. 2004).

4. METHODOLOGY

The land use land cover estimation for the studied region was carried out using ENVI (v. 5.0, ITT Visual Solutions) and ArcGIS (v. 10.1, ESRI) software platforms. Further the output product of ENVI and ArcGIS was used in Fragstat (v. 3.3) to compute ecological metrics. An overview of the methodology implemented is depicted in **Figure 2**. A description of the steps taken in evaluating the land cover spatio-temporal dynamics at RNP during the studied period is provided in following subsections.

4.1 Pre-processing

The Landsat images were imported into ENVI and were converted to radiance values (Irons, 2011) and subsequently layer stacking were performed except for the thermal infrared band (i.e. band 6). Image atmospheric calibration was conducted by adopting the procedure as documented by USGS. After layer stacking an empirical line normalisation to all images were implemented using the

Landsat 1990 image as a base (Guide 2008). In order to analyse multi-date satellite imagery stacked layers must be spatially co-registered in the same spatial reference frame (Schmidt and Glaesser 1998), hence an image to image co-registration has been performed in ENVI to a common WGS84 ellipsoid projection.

Figure 2 Flow chart depicting the methodology applied in this study

4.2 Classification of satellite images

In the next step, LULC maps were derived from the Landsat images by following the Maximum Likelihood Classifier (MLC) approach (Richards, 1997). MLC considers not only the mean or average values in assigning classification, but also the variability of brightness values in each class (Banerjee and Srivastava 2013). It is based on Bayes' theorem and the equation used in MLC classification can be represented by equation 1 (Guide 2008).

$$D = \ln(a_c) - [0.5\ln(|\mathrm{cov}_c|)] - [0.5(\mathbf{X} - \mathbf{M}_c)^{\mathrm{T}}(\mathrm{cov}_c^{-1})(\mathbf{X} - \mathbf{M}_c)] \quad (1)$$

where, D is weighted distance; c is a particular class; **X** is the measurement vector of the particular pixel; $\mathbf{M}_c$ is the mean vector of the sample of class; a_c is percent probability that any particular pixel is a member of class c; (Defaults to 1.0); Cov_c is the covariance matrix of the pixels in the sample of class c; $|Cov_c|$ is determinant of Cov_c; Cov_c-1 is inverse of Cov_c; ln is natural logarithm function; T= transposition function.

For ML classification, first the classification key was formulated, consisting of the classes “built-up”, “forest open”, “forest mixed”, “forest dense”, “crop land” and “water bodies” then the training pixels representative of each class were collected from the homogeneous regions. Approximately 30 pixels of each class included in our classification scheme (a total of approximately 180 pixels) were identified as training data. By using the collected training points, the ML classifier was parameterised and implemented on all pre-processed images. Bands 2, 3, and 4 were utilised from both Landsat images with a single probability threshold value of zero for all the LULC classifications using the ML classifier.

4.3 Ecological metrics analysis

The relevant landscape metrics such as area, perimeter, core area, shape and fragmentation at patch and class level were used in this study. The Fragstats 3.3 developed by McGarigal and Marks, 1995 is used in this study for estimation of all the spatial statistics. This software platform is widely implemented nowadays by decision maker, ecologists, wildlife experts and statistician to analyze, characterize and describe the landscape fragmentation (Çakir et al. 2008, Ricketts 2001). The advantage of FRAGSTATS is that the calculations are applied in a GIS environment and thus can be used with satellite images (McGarigal et al. 2002, Rempel et al. 1999). Area provided information to explore the proportion of LULC categories and perimeter-indices helped to understand the role of the edges. The longer the edge of a patch to a given area, the more complex the shape it means patch stability can be judged from ecological perspective. Edge depth was also considered with a buffer zone of 100 m, to calculate the inner undisturbed area, core area, of the patches. Furthermore, distance between the patches belonging to the same LULC class and the fragmentation was determined, too. In the analysis, the following landscape metrics were involved:

- Area and perimeter metrics: area (AREA, ha), perimeter (PERIM, m), and their summarized or averaged quantities (sum of patch areas by LULC classes; mean of patch areas summarized by LULC classes, AREA_MN; mean of edge lengths, PERIM_MN); total edge (TE, m); patch density (ratio of number of patches and the area of investigated, PD, per unit per ha) and largest patch index (ratio of largest patch the area of investigated area).

- Core area metrics: core area (CORE, ha), core area index (core areas expressed as the function of the whole area of the LULC class, CAI, %) and the disjunct core area density (ratio of the number of disjunct core areas within a specified distance and the whole area, DCAD, number per km^2).
- Shape metrics: related circumscribing circle in patch and in class level (CIRCLE and CIRCLE_MN, respectively; ratio of the area of a given patch and the area of the smallest circumscribing circle, CIRCLE, between 0-1).
- Distance metrics: Nearest neighbor Euclidean distance between patches belonging to the same LULC class in patch and class level (ENN and ENN_MN, respectively, m).
- Fragmentation metrics: effective mesh size (MESH, ha) is in high correlation with landscape division which expresses the probability that two randomly placed in the landscape are in the same patch; mesh size is the area of equal sized patches that necessary to be divide the whole area to reach the above probability value (Jaeger, 2000).

4.4 Statistical evaluation

A statistical evaluation was carried to reveal whether there were significant changes between the investigated dates. We applied the Kruskal-Wallis test in hypothesis testing (H_0: the distribution of the data within the dates is the same, H_1: the distribution is different). Besides, we conducted a Principal Component Analysis (PCA) (based on the correlation matrices) with Varimax rotation to reveal the differences in the multivariate space. Highly correlating landscape metrics, accounting for the same information, were omitted; thus, Percentage land (PLAND), PD, Edge density (ED), CIRCLE, DCAD, MESH and ENN metrics were used in the analysis. Biplot diagram showed the correlation structure of the variables; besides, indicated the changes based on the involved metrics.

4.5 Accuracy Assessment

The accuracy of the different thematic maps produced from the classifiers, accuracy assessment was performed based on the computation of the error matrix statistics (Congalton and Green, 1999). As a result, the overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA) and the kappa coefficient (Kc) were computed, as follows (Congalton and Green 2008):

$$\mathrm{OA} = \frac{1}{\mathrm{N}}\sum_{\iota=1}^{r} n_{ii}\,,\ (7), \qquad PA = \frac{n_{ii}}{n_{icol}}\,, \qquad (8)\,, \qquad UA = \frac{n_{ii}}{n_{irow}}\,, \qquad (2)$$

$$K_c = N\sum_{\iota=1}^{r} n_{ii} - \sum_{\iota=1}^{r}\frac{n_{icol}n_{irow}}{N^2} - \sum_{\iota=1}^{r} n_{icol}n_{irow}\ ,\ (10)$$

where n_{ii} is the number of pixels correctly classified in a category; N is the total number of pixels in the confusion matrix; r is the number of rows; and n_{icol} and n_{irow} are the column (reference data) and row (predicted classes) total, respectively.

In computing the above statistic metrics, approximately 30 GPS reference points or ground-truth points (i.e. pixels) from each class were taken from the study area for the accuracy estimation of the classified images. This information was obtained from field visits and previous studies that had been conducted in the area. Validation points were generally selected based on a random distribution in homogeneous regions and away from the locations where the training points had been collected, ensuring non-overlap of pixels between the training data and validation sites.

5. RESULTS AND DISCUSSION

5.1 Accuracy of classified images

The accuracy analysis of the classified maps computed in this study is summarized in **Table 1**. On the basis of the OA, it can be seen that the highest overall classification accuracy was achieved for the year 2009 image (82.05%) followed by that of 1990 (77.78%) and of 2000 (75.00%). In 2009, the least performance of cropland can be attributed to mixed pixel response (Agro-forestry system). Similar lower performances for that particular class were also obtained with the 2000 satellite imagery. The 1990 image classification performance was slightly better and can be linked to less cropland area and dense forest system. For the built-up area, open and mixed forest classes a PA of >75% were obtained, suggesting that all of the collected validation samples also belonged in the same class more number of times. For the same classes, UA was also reported in range 75-100% indicating that all of the points classified as built-up area, open and mixed forest classes could be expected to be the same area when a field survey is performed. The classification of the cropland, dense forest and water bodies' classes indicate a lower PA and UA than the other classes can be attributed to closed resemblance of dense forest with mixed forest and hence complicated the classification procedure. On the other hand, poor classification accuracy of water bodies and cropland can be related to the encroachment of forest canopies over the water body. The low performance of forest class may also be attributed to incapability of classifier to separate the three forest type that is open forest and mixed forest from the dense forest class. Similarly, for water body class, Landsat performance was slightly lower in comparison to the 2009 image.

Table 1: Classification Accuracy of the satellite images

5.2 Spatial changes in LULC

The classification maps produced from the implementation of the MLC are illustrated in **Figure 3.** The classes created and the area under the class provides an insight to the composition of the total area. Based on the results of the classification, it is possible to conclude up to a certain extent the changes that occurred in the area. The analysis of result of water body showed overall change in area from 83.60 to 87.59 km^2 from 1990 to 2000 and after this increment, in the year 2009 the area further decreased to 85.47 km^2. The analysis of result of built-up area showed an increase in area from 6.50 km^2 in 1990 to 7.85 km^2 in 2000 and it further showed an increasing trend to 9.35 km^2 in 2009, this increase in the built-up area may be attributed to the increase in population in this region and dense forest area showed nominal decrease in area from 568.19 km^2 in 1990 to 562.18 km^2 in 2000 which further showed slightly declined to 550.17 km^2 in 2009. This continuous declining trend of dense forest area may be because of developmental activities which have occurred in this region. Open forest has the area 54.44 km^2 to 35.74 km^2 in 1990 to 2000 and increased up to 66.02 km^2 in 2009. However, there is small change in area of mixed forest which increased from 153.95 km^2 in 1990 to 175.03 km^2 in 2000 and then decreased to 155.24 km^2 in 2009. The main reason behind these changes can be attributed to increase in population and encroachment of local people who use this area's forest resources (fuel wood, timber, non timber forest products and fodder) or possibly it may be due to the main industrial area of the state (State Infrastructure and Industrial Development Corporation of Uttarakhand Limited (SIDCUL) at district Hardiwar, Uttrakhand). The SIDCUL is found to be associated with rapid expansion of developmental activities near to the forest area and it requires natural resources like land, water and forest wood as a raw material. The crop land area decreases from 7.77 km^2 in 1990 to 6.29 km^2 in 2000 which further declined up to 6.16 km^2 in 2009 (**Table 2**). Around the RNP, during years (2001-2004), over 900 cases of crop raiding by elephants were recorded which occurred due to illegal encroachment of the park area by the local people.

Table 2: Area of different land use classes in km^2 for the year 1990-2000-2009

Figure 3 Unclassified and classified satellite images of the year 1990, 2000 and 2009 respectively

5.4 Fragmentation analysis

285 The analysis of results showed that forests had the largest relevance in the land cover in the study area, while built-up areas and croplands had only smaller proportion in all dates of the investigation **(Table 3)**. Class of DF had the largest proportion, but in the same time it was consisted of the largest number of patches, too; consequently, however its level of fragmentation was not far-gone due to its large area (MESH was between 902-1886 ha, which was the largest among all classes). An important change was that in 2009 MESH decreased to the half of the area of 2000. For MF, the proportion was between 6-7% related the whole area, but the average patch size was the largest in each year (more than 1000 ha, i.e. twice the average size of other categories). Also, LPI was the highest for this class, too; largest patch covered 6-7% of the class area. OFs had smaller proportion (~2%) in a spatially dispersed pattern and were rather fragmented (see Table 3, MESH). CLs' relevance was very low, and also, their average patch size was the smallest; furthermore, they appearance in the landscape was dispersed.

PCA indicated a large overlap among the dates in the ordinals space **(Figure 4)**. All symbols of the LULC classes were found in the same section of the diagram and can be discriminated well with the help of the involved landscape metrics (PLAND, PD, ED, CIRCLE, DCAD, MESH, ENN); accordingly, in general, the changes were slight. Largest changes were observed in case of MF and DF classes, while, as it can be waited, water bodies changed the smallest. Furthermore, only in case of BU can be identified a trend.

There was overall loss of forest area means loss of dense forest, and open forest which suggest that the population pressure, expansion of city area or other development activities may be responsible for this loss which was further proved by the increased in built-up core area showed the increasing trend from 1990 was 6.51 km^2, in 2000 it was 7.86 km^2 and 9.28 km^2 in 2009 respectively. This increase in built-up area has occurred on the verge of forested area of national park. PLAND for class level metric analysis showed that how much particular land use/cover becomes under fragmentation. Water hyacinth, locally called Jalkumbhi, is choking many wetlands and water bodies in the central part of the landscape, especially near agricultural fields (Semwal, Forests and Programme 2005).

These changes in MPS are further suggesting that the forest was more fragmented in 1990 than in 2000 and again it was more fragmented in 2009. Indeed, between year 1990 to 2000 was the period where natural condition or human activities was having less impact on forest landscape and thus fragmentation was less in 2000 because after the creation of separate state Uttrakhand in year 2000 many new development activities are witnessed in this region. But during the last two decades enhancement of vehicle traffic on national highways (5 nos.), train traffic in Haridwar – Dehradun railway track, rapid construction of motor roads (Joshi and Singh 2010). From 2000 to 2009 either human pressure or a natural condition has played a major role in the decrease of MPS which needs to be further explored. Large–scale habitat loss and human encroachment into the deeper forest regime are responsible for many changes in the park (Joshi and Singh 2010). Just one decade back elephant movement in this track was very common as this forest comprises of rich fodder and perennial water sources. Nevertheless, slowly their movement became restricted in this part primarily due to increasing rate of anthropogenic activities inside the deeper forest regime, ongoing developmental activities, wildfires and shrinking of perennial water sources (Joshi 2009).

Indeed, to our knowledge, from 2002 onwards rapid expansion of developmental activities nearer to the forest area has caused obstruction in frequent movement of elephants besides other wildlife in adjoining forest beats. Tiger movement was frequently recorded before 2002 but after that tiger movement in these forest tracks has got obstructed. As a result of establishment of more than a dozen of industries, demand for water has been increasing and to meet the demand groundwater is being extracted by various stakeholder industries and that has caused the major impact on ground water of adjacent areas.

Table 3 Class level landscape metrics of the LULC classes by dates (MN: mean of patch level metrics)

Figure 4 Biplot diagram of the PCA conducted with landscape metrics of the three dates

6. CONCLUSIONS

The importance of land use/cover pattern using class level metric analysis is to assess the transformation types which affect the spatial pattern of the landscape. The diversity of metrics available and the complexity of habitat loss and fragmentation effects make it difficult to choose an appropriate metric or suite of metrics for a particular situation. The aim of the present study has been to exploit contemporary technologies such as EO and GIS to quantify the changes in the landscape spatio-temporal dynamics occurred in the Rajaji National Park (RNP) during a period of 19 years (1990-2009). Results from this study unveil the degree of land use change, diversity and fragmentation patterns occurred during the periods under study, which indicates that notable changes have taken place in the studied area. Landscape metric and landscape transformation analysis showed that over the time spatial configuration and composition of the landscape has changed drastically, which leads to the degradation of the forest area. The landscape metric analysis showed that from 1990 to 2000 the fragmentation of landscape was slightly low because the natural and climate condition are probably good while, from the year 2000 to 2009 indicates that could be due to human induced disturbance which have increased over this time.

The study demonstrates the immense value of the use of contemporary technologies such as remote sensing and GIS in assessing spatial structure and spatio-temporal changes in landscape dynamics in a cost-effective, semi-automatic and rapid manner. The study provides considerable scientific and practical value to the wider scientific community, which can be used with the present and future open access EO datasets from various other satellites. There are number statistics available in the literatures such as contagion, juxtaposition, evenness and patchiness for the fragmentation analysis. Hence, further exploration of this potentially valuable fragmentation tool by the geospatial community is recommended, so that useful experience and knowledge could be accumulated in the technical literature domain for different geographical locations and environmental conditions.

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Table 1: Classification Accuracy of satellite images

Class	2009		2000		1990	
	Prod. Acc. (%)	User Acc. (%)	Prod. Acc. (%)	User Acc. (%)	Prod. Acc. (%)	User Acc. (%)
WATER BODY	80.00	100.00	66.67	75.00	80.00	57.14
BUILT-UP AREA	85.71	85.71	83.33	83.33	83.33	100.00
CROPLAND	66.67	100.00	66.67	80.00	83.33	71.43
OPEN FOREST	83.33	71.43	83.33	83.33	80.00	100.00
DENSE FOREST	87.50	70.00	66.67	54.55	66.67	57.14
MIXED FOREST	85.71	85.71	87.50	87.50	75.00	100.00
OVERALL ACCURACY (%)	82.05		75.00		77.78	
KAPPA COEFF.	0.78		0.70		0.73	

Table 2: Area of different land use classes in km^2 for the year 1990-2000-2009

Land use Classes	**Land use and Land covers (Area in km^2)**		
	1990	**2000**	**2009**
WATER BODY	83.60	87.59	85.47
BUILT-UP AREA	6.50	7.85	9.35
DENSE FOREST	568.19	562.18	550.17
OPEN FOREST	54.44	35.74	66.02
MIXED FOREST	153.95	175.03	155.24
CROPLAND	7.77	6.29	6.16
Total Area	874.51	874.51	874.51

Table 3: Class level landscape metrics (MN: mean of patch level metrics)

Date	Type	PLAND	NP	PD	LPI	TE	AREA_MN	CIRCLE_MN	CORE_MN	DCAD	CAI_MN	ENN_MN	MESH
1990	BUILT-UP	0.26	21	0.0085	0.15	113400	31.0	0.88	13.5	0.002	6.43	217.9	0.5743
1990	CROPLAND	0.31	10	0.004	0.31	39450	77.9	0.49	52.8	0.001	6.79	3540.6	2.4378
1990	DENSE FOREST	22.87	134	0.0539	3.83	1767725	424.0	0.66	334.2	0.066	26.95	121.2	1028.461
1990	MIXED FOREST	6.20	31	0.0125	5.52	490000	496.7	0.44	383.3	0.010	10.82	1469.4	763.0326
1990	OPEN FOREST	2.19	64	0.0258	0.50	403400	85.1	0.69	45.7	0.037	29.95	281.3	9.1421
1990	WATER	3.36	51	0.0205	1.03	1762575	163.9	0.88	30.7	0.070	5.65	464.3	44.5855
2000	BUILT-UP	0.32	25	0.0101	0.17	122450	31.5	0.81	14.2	0.002	6.58	141.0	0.8145
2000	CROPLAND	0.25	3	0.0012	0.22	46550	210.1	0.60	110.3	0.003	34.46	4011.5	1.1985
2000	DENSE FOREST	22.62	132	0.0531	7.15	1709300	425.9	0.66	338.7	0.053	25.87	112.7	1886.353
2000	MIXED FOREST	7.04	17	0.0068	6.85	427600	1029.6	0.44	848.8	0.004	9.54	2078.7	1168.493
2000	OPEN FOREST	1.44	39	0.0157	0.36	258000	91.7	0.69	50.2	0.025	34.98	383.6	4.4758
2000	WATER	3.53	55	0.0221	1.10	1678525	159.3	0.85	31.7	0.087	6.87	517.6	48.4178
2009	BUILT-UP	0.36	33	0.0128	0.17	132100	28.4	0.74	12.7	0.004	8.37	243.9	0.822
2009	CROPLAND	0.24	12	0.0047	0.17	44000	51.5	0.43	29.2	0.003	12.71	997.6	0.8335
2009	DENSE FOREST	21.39	167	0.0649	3.31	1930550	329.5	0.66	252.5	0.069	26.53	89.9	902.6157
2009	MIXED FOREST	6.04	14	0.0054	3.79	426350	1108.9	0.45	890.8	0.010	17.04	1417.7	475.9615
2009	OPEN FOREST	2.16	73	0.0284	0.32	454100	76.3	0.70	39.0	0.042	26.60	407.6	5.6651
2009	WATER	3.32	70	0.0272	1.02	1775550	122.1	0.85	24.6	0.061	5.16	495.7	35.4496

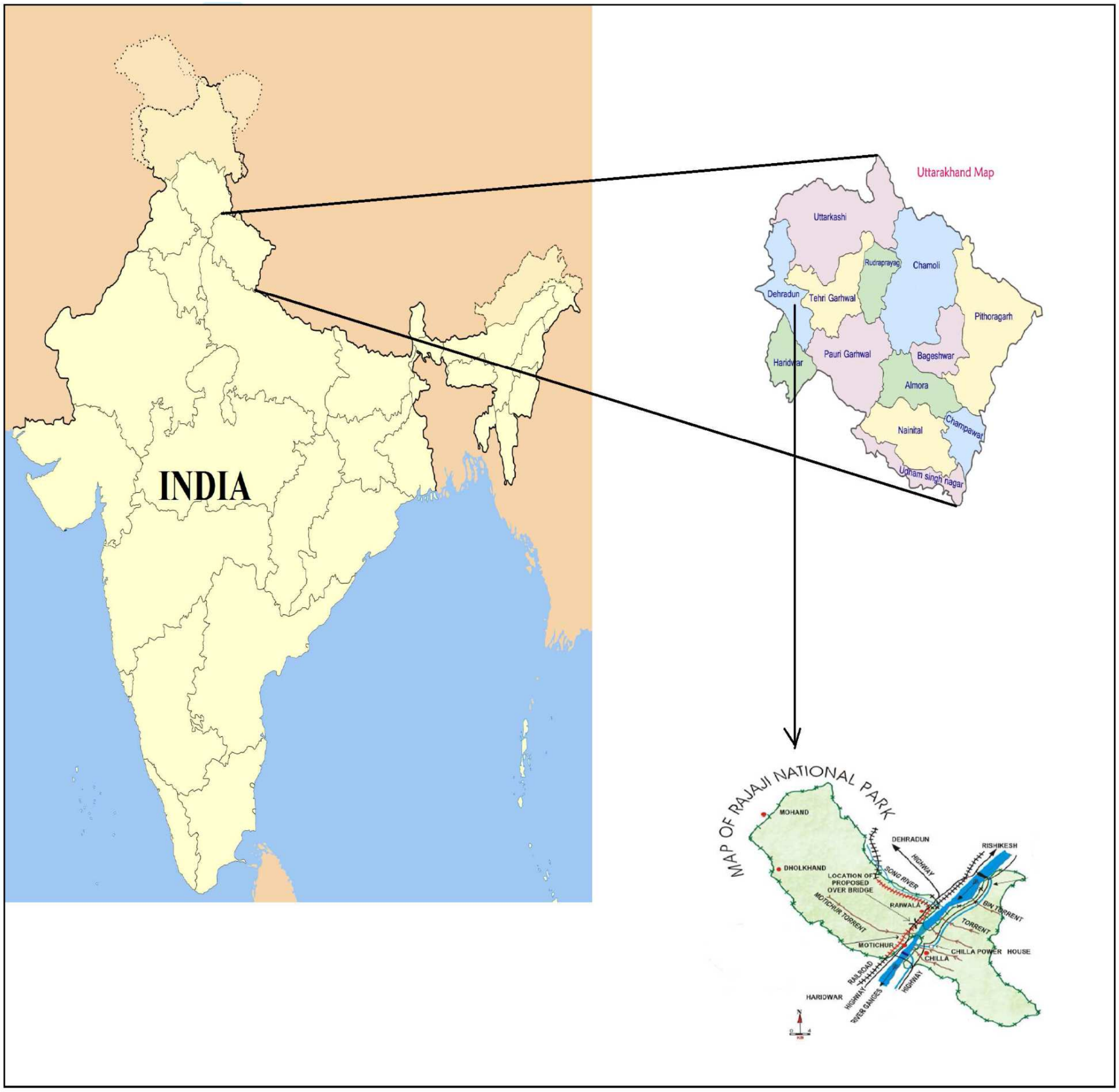

Figure 1 Geographical location of the study area

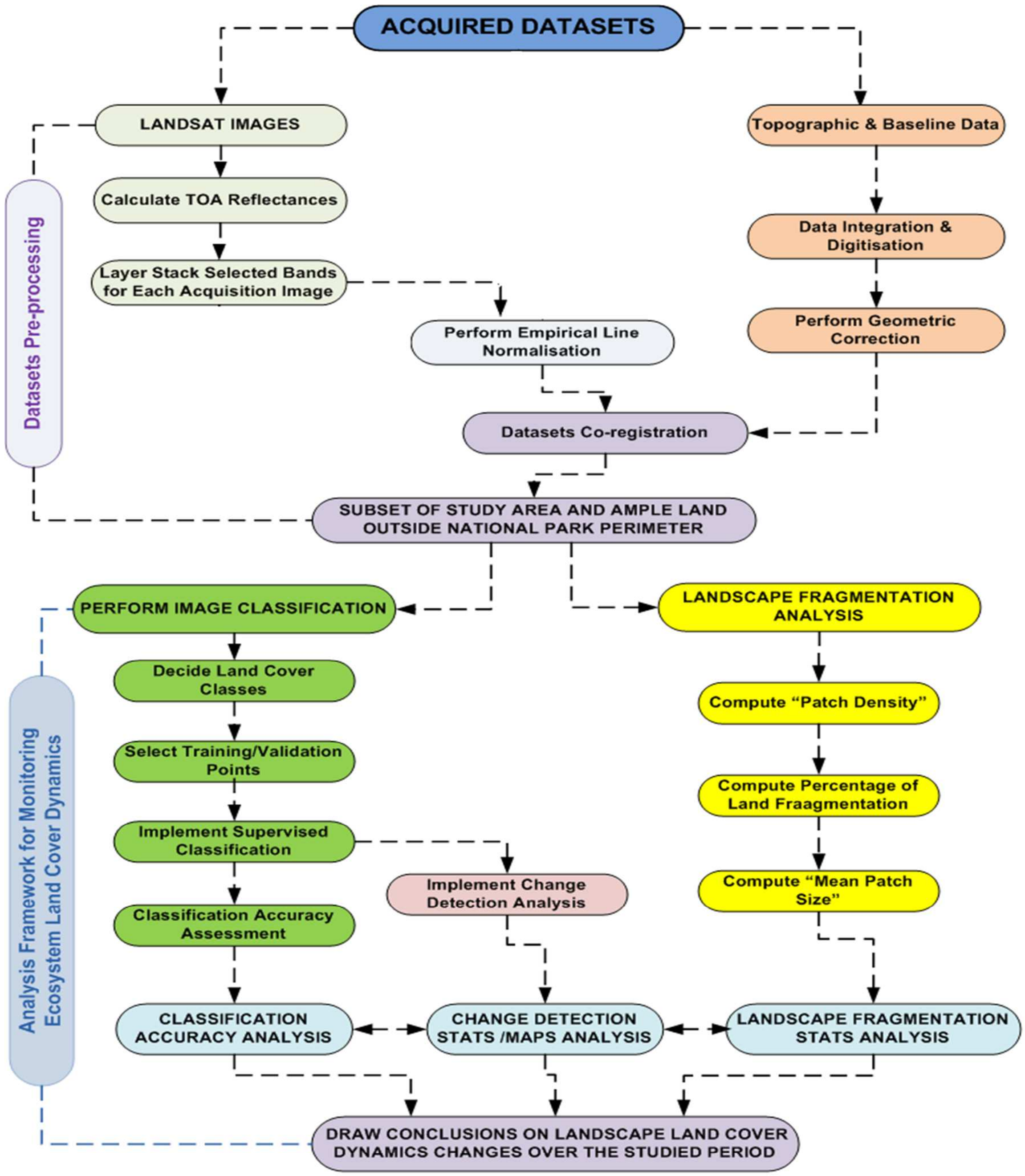

Figure 2 Flow chart of the methodology used in this study

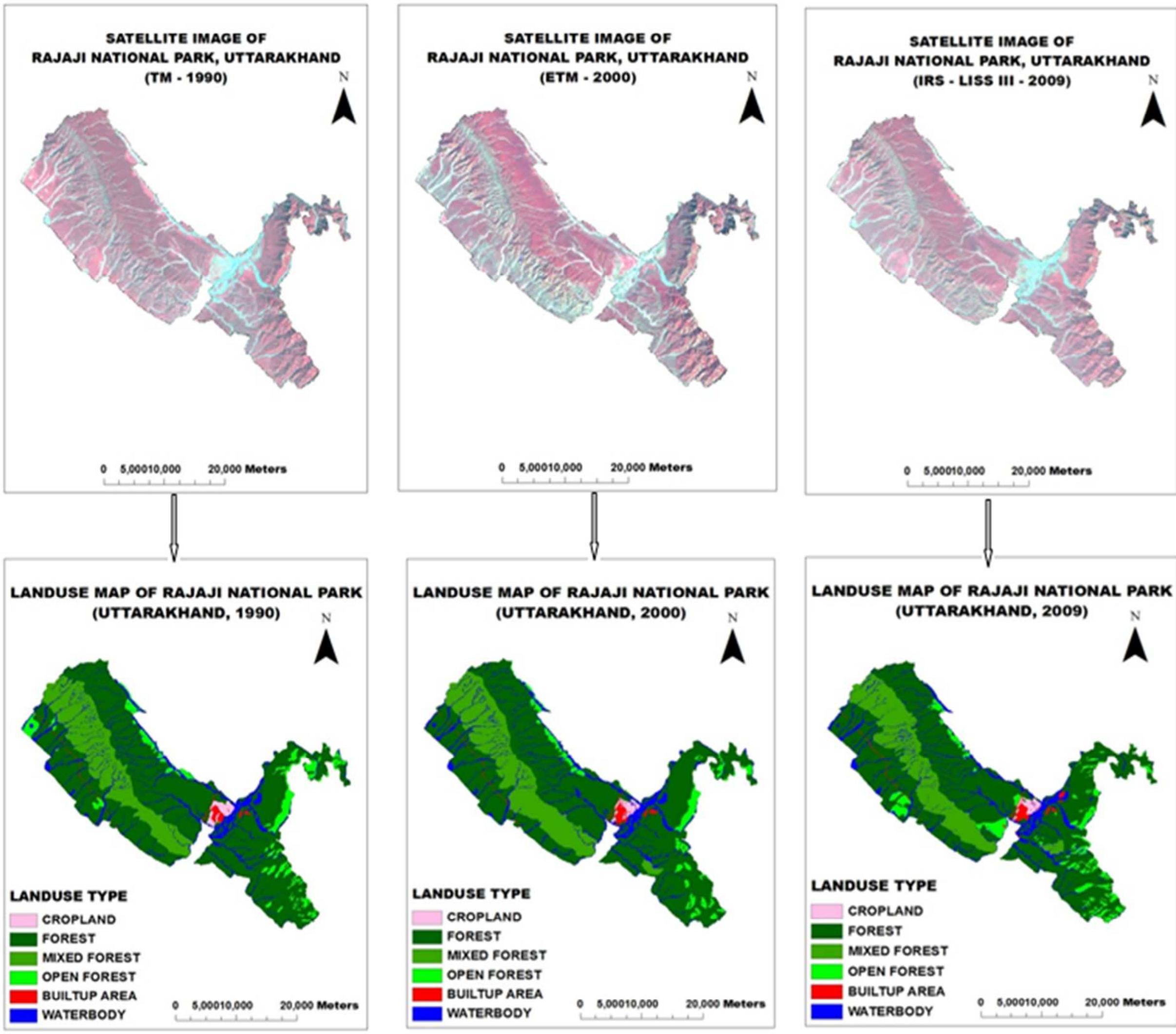

Figure 3 Unclassified and classified satellite images of the year 1990, 2000 and 2009 respectively