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1 **Landscape transform and spatial metrics for mapping spatio-temporal land cover dynamics**
2
3 **using Earth Observation datasets**
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51

26 ABSTRACT

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

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

42 1. INTRODUCTION

43 India is one of the 12 mega-biodiversity countries of the world. The total protected area network in
44 India includes 100 National Parks and 515 Wildlife Sanctuaries, 43 Conservation Reserves and
45 four Community Reserves (<http://envfor.nic.in/report/report.html>). However, after industrial
46 revolution in India, the rapid development of human societies has intensified which caused a
47 continuous and noticeable influence on natural resources (Gadgil and Guha 1995). A rapid growth
48 of human population during last three decades has been noticed in Census of India datasets
49 (censusindia.gov.in/). This expansion in population causes adverse impacts on natural resources

1 50 and wildlife. The changes that have taken place are especially important and intense, as society is
2
3 51 becoming increasingly modernized and urbanized, while natural ecosystems are continuously
4
5 52 deteriorated or almost losing their original structure and forms (Islam and Weil 2000, Pandey et al.
6
7
8 53 2012, Srivastava et al. 2014). This increasing human growth resulted in a shrinkage in the natural
9
10 54 habitat (Venture 2005).

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12 55
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14
15 56 Land cover constitutes a key variable of the Earth's system that has in general shown a close
16
17 57 correlation with human activities and the physical environment (Bell et al. 2005, Srivastava et al.
18
19
20 58 2010). The Land cover mostly changes due to its interaction with physical, ecological, geomorphic
21
22 59 and anthropogenic processes (Naveh 1987, Paudel et al. 2015). In all the above mentioned driving
23
24 60 factors, anthropogenic factors are emerged as a serious factor for changing landscape structure,
25
26
27 61 pattern and dynamics (Naveh and Lieberman 1990, Petropoulos et al. 2015, Srivastava, Han, et al.
28
29 62 2012). Because of high anthropogenic pressure on natural and semi-natural habitats conservation
30
31 63 and sustainable practices for land cover has become a priority (De Groot 2006). Hence,
32
33 64 quantifying the temporal and spatial patterns of LULC change and its corresponding consequences
34
35
36 65 – particularly so over protected areas - is recognized as a highly significant topic (Fraser and
37
38 66 Latifovic 2005). Earth Observation (EO) technology is very well-suited for mapping and
39
40
41 67 monitoring of habitats because of its synoptic repetitive coverage over the same area at various
42
43 68 spatial and temporal scales, even available for inaccessible locations (Sanchez-Hernandez et al.
44
45
46 69 2007). These EO datasets on geospatial platform can provide an effective set of tools for analysing
47
48 70 and extracting spatial information to support decision making with more reliable and consistent
49
50 71 (Jankowski and Richard 1994).

51
52 72
53
54
55 73 A large number of landscape change studies in technical literature domain are available employing
56
57 74 different EO datasets. The Landsat sensors have shown an excellent promise for synoptic and
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1 75 temporal analysis of the changes (Gupta and Srivastava 2010, Hansen and Loveland 2012) and
2
3 76 provide images at high resolution. However, very rare studies are available for developing
4
5 77 countries like India. The land cover change studies are very important to understand the
6
7 78 exploitation patterns and assessment of area (Banerjee and Srivastava 2014, Srivastava, Kiran, et
8
9 79 al. 2012). If landscape changes occurred for prolonged period, it may eliminate species and disturb
10
11 80 the ecosystem functioning and services (Martínez et al. 2009, Priess et al. 2007). Yet, most of
12
13 81 them considered only forest to agricultural conversions (Singh et al. 2013).
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18 82 For biodiversity point of view fragmentation, loss and degradation of habitat are widely
19
20 83 considered as the most important driving factors (Hanski 2005, Lindenmayer and Fischer 2006)
21
22 84 and hence is the topic of research. The term fragmentation has been defined as simultaneous
23
24 85 reduction of forest area and subdivision of large forest areas into smaller non-contiguous
25
26 86 fragments (Laurance 2000, Midha and Mathur 2010). It is a dynamic development that results in
27
28 87 change in pattern of the habitats (Midha and Mathur 2010). The serious impact of fragmentation
29
30 88 include loss of habitat, decreased connectivity between ecological entities, reduction in patch size,
31
32 89 elevated distance between patches, and an abrupt increase in the edge at the expense of interior
33
34 90 habitat (Midha and Mathur 2010). Other causes of fragmentation and habitat loss can be linked to
35
36 91 agriculture and infrastructure development, over-exploitation of natural resources, pollution and
37
38 92 invasive species (Semwal et al. 2005). At the landscape level, disturbance is related to patch
39
40 93 structure, spatial arrangement, their size and duration (McGarigal and Marks 1995) and can be
41
42 94 quantified using the spatial landscape metrics. Landscape metrics are the algorithms designed for
43
44 95 quantifying landscape pattern depicting the spatial arrangement of land cover patches over a
45
46 96 particular geographic area (Herold et al. 2003, McGarigal and Marks 1995, Rimmel et al. 2002).
47
48 97 These landscape and class level metrics can be used to see the impact of anthropogenic activities
49
50 98 on natural cover such as forest. In this context, the present study aim to combine remote sensing
51
52 99 and GIS techniques with the landscape transform concept to characterize the dynamics of land
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1 100 cover change and quantifying the fragmentation pattern of Rajaji National Park (RNP). The
2
3 101 outputs obtained in this study can be used for sustainable management of this ecologically and
4
5 102 economically vital ecosystem.
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7

8 103 **2. STUDY AREA**

10 104 The Rajaji National Park (RNP) is located in Shiwalik range of Himalaya of India and lies
11
12 105 between coordinates 29°15' N to 30°31' N and 77°52' E to 78°22' E (**Figure 1**). Elevation of the
13
14 106 area varies widely from 250 to 1100 m above mean sea level. This entire belt is natural home of
15
16 107 Asian elephants (*Elephas maximus*). Besides, many other wild animals like tiger (*Panthera tigris*),
17
18 108 leopard (*Panthera pardus*), Sloth bear (*Melursus ursinus*), Hyaena (*Hyaena hyaena*), Barking
19
20 109 deer (*Muntiacus muntjak*), Spotted deer (*Axis axis*), Sambhar (*Cervous unicolor*), Wild boar (*Sus*
21
22 110 *scrofa*) and King cobra (*Ophiophagus hannah*) are also common in this region (Joshi 2009). The
23
24 111 under-wood is light and often absent, consisting of Rohini (*Malollotus philippinensis*), Amaltas
25
26 112 (*Cassia fistula*), Shisham (*Dalbergia sissoo*), Sal (*Shorea robusta*), Palash (*Butea monosperma*),
27
28 113 Arjun (*Terminalia arjuna*), Khair (*Acacia catechu*), Baans (*Dendrocalamus strictus*), Semul
29
30 114 (*Bombax ceiba*), Sandan (*Ougeinia Oojeinensis*), Chamaror (*Ehretia laevis*), Aonla (*Embllica*
31
32 115 *officinalis*), Kachnar (*Bauhienia variegata*), Ber (*Ziziphus mauritiana*), Chilla (*Casearia*
33
34 116 *tomentosa*), Bel (*Aegle Marmelos*) etc.

35
36 117 In 1983, RNP has been created by amalgamation of three sanctuaries Rajaji sanctuary (estd. 1948),
37
38 118 Motichur sanctuary (estd. 1964) and Chilla sanctuary (estd. 1977) and considered as national park
39
40 119 to protect Asian elephant's habitat and currently covering an area of ~820.42 km². It has been
41
42 120 designated as a reserved area for both "Elephant and Tiger" by the Ministry of Environment and
43
44 121 Forests, Government of India, with the sole aim for maintaining the viable wildlife population. It
45
46 122 comes under International Union for Conservation of Nature and Natural Resources (IUCN)
47
48 123 Category II by the World Conservation Union. There are three main seasons at RNP as winter,
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1 124 summer and monsoon. The average temperature during the winter (November to February) varies
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3 125 from 20-15°C while during the summer (May to June) temperature up to 32-40°C are also very
4
5 126 common in this area. The annual rainfall over the region ranges from 1200-1500 mm with very
6
7 127 high humidity.
8
9

10 128 **Figure 1 Geographical location of the study area**
11

12 129 **3. DATASETS**

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16 130 In this study, the Landsat datasets are used. A total of eight Survey of India topographical-sheets
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18 131 (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
19
20 132 from the United State Geological Survey (USGS) archive (<http://glovis.usgs.gov/>) at no cost. All
21
22 133 satellite images were acquired in different years during the studied period but around the same
23
24 134 date to minimize any seasonal and phenological variations (Lillesand et al. 2004).
25
26
27

28 135 **4. METHODOLOGY**

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30
31 136 The land use land cover estimation for the studied region was carried out using ENVI (v. 5.0, ITT
32
33 137 Visual Solutions) and ArcGIS (v. 10.1, ESRI) software platforms. Further the output product of
34
35 138 ENVI and ArcGIS was used in Fragstat (v. 3.3) to compute ecological metrics. An overview of the
36
37 139 methodology implemented is depicted in **Figure 2**. A description of the steps taken in evaluating
38
39 140 the land cover spatio-temporal dynamics at RNP during the studied period is provided in
40
41 141 following subsections.
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45 142 **4.1 Pre-processing**

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48
49 143 The Landsat images were imported into ENVI and were converted to radiance values (Irons, 2011)
50
51 144 and subsequently layer stacking were performed except for the thermal infrared band (i.e. band 6).
52
53 145 Image atmospheric calibration was conducted by adopting the procedure as documented by USGS.
54
55 146 After layer stacking an empirical line normalisation to all images were implemented using the
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1 147 Landsat 1990 image as a base (Guide 2008). In order to analyse multi-date satellite imagery
 2
 3 148 stacked layers must be spatially co-registered in the same spatial reference frame (Schmidt and
 4
 5 149 Glaesser 1998), hence an image to image co-registration has been performed in ENVI to a
 6
 7
 8 150 common WGS84 ellipsoid projection.

10 151 **Figure 2 Flow chart depicting the methodology applied in this study**

12 152 4.2 Classification of satellite images

13
 14
 15
 16 153 In the next step, LULC maps were derived from the Landsat images by following the Maximum
 17
 18 154 Likelihood Classifier (MLC) approach (Richards, 1997). MLC considers not only the mean or
 19
 20 155 average values in assigning classification, but also the variability of brightness values in each class
 21
 22 156 (Banerjee and Srivastava 2013). It is based on Bayes' theorem and the equation used in MLC
 23
 24 157 classification can be represented by equation 1 (Guide 2008).

$$25 158 D = \ln(a_c) - [0.5 \ln(|\text{cov}_c|)] - [0.5(\mathbf{X} - \mathbf{M}_c)^T (\text{cov}_c^{-1})(\mathbf{X} - \mathbf{M}_c)] \quad (1)$$

26
 27
 28
 29
 30
 31
 32 159 where, D is weighted distance; c is a particular class; \mathbf{X} is the measurement vector of the
 33
 34 160 particular pixel; \mathbf{M}_c is the mean vector of the sample of class; a_c is percent probability that any
 35
 36 161 particular pixel is a member of class c; (Defaults to 1.0); Cov_c is the covariance matrix of the
 37
 38 162 pixels in the sample of class c; $|\text{Cov}_c|$ is determinant of Cov_c ; Cov_c^{-1} is inverse of Cov_c ; \ln is
 39
 40 163 natural logarithm function; T= transposition function.

41
 42
 43
 44
 45 164 For ML classification, first the classification key was formulated, consisting of the classes “built-
 46
 47 165 up”, “forest open”, “forest mixed”, “forest dense”, “crop land” and “water bodies” then the
 48
 49 166 training pixels representative of each class were collected from the homogeneous regions.
 50
 51 167 Approximately 30 pixels of each class included in our classification scheme (a total of
 52
 53 168 approximately 180 pixels) were identified as training data. By using the collected training points,
 54
 55 169 the ML classifier was parameterised and implemented on all pre-processed images. Bands 2, 3,
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1 170 and 4 were utilised from both Landsat images with a single probability threshold value of zero for
2
3 171 all the LULC classifications using the ML classifier.
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5

6 172 **4.3 Ecological metrics analysis**

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9 173 The relevant landscape metrics such as area, perimeter, core area, shape and fragmentation at
10
11 174 patch and class level were used in this study. The Fragstats 3.3 developed by McGarigal and
12
13 175 Marks, 1995 is used in this study for estimation of all the spatial statistics. This software platform
14
15 176 is widely implemented nowadays by decision maker, ecologists, wildlife experts and statistician to
16
17 177 analyze, characterize and describe the landscape fragmentation (Çakir et al. 2008, Ricketts 2001).
18
19 178 The advantage of FRAGSTATS is that the calculations are applied in a GIS environment and thus
20
21 179 can be used with satellite images (McGarigal et al. 2002, Rempel et al. 1999). Area provided
22
23 180 information to explore the proportion of LULC categories and perimeter-indices helped to
24
25 181 understand the role of the edges. The longer the edge of a patch to a given area, the more complex
26
27 182 the shape it means patch stability can be judged from ecological perspective. Edge depth was also
28
29 183 considered with a buffer zone of 100 m, to calculate the inner undisturbed area, core area, of the
30
31 184 patches. Furthermore, distance between the patches belonging to the same LULC class and the
32
33 185 fragmentation was determined, too. In the analysis, the following landscape metrics were
34
35 186 involved:
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41

42 187 - Area and perimeter metrics: area (AREA, ha), perimeter (PERIM, m), and their
43
44 188 summarized or averaged quantities (sum of patch areas by LULC classes; mean of patch
45
46 189 areas summarized by LULC classes, AREA_MN; mean of edge lengths, PERIM_MN);
47
48 190 total edge (TE, m); patch density (ratio of number of patches and the area of investigated,
49
50 191 PD, per unit per ha) and largest patch index (ratio of largest patch the area of investigated
51
52 192 area).
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- 1 193 - Core area metrics: core area (CORE, ha), core area index (core areas expressed as the
2
3 194 function of the whole area of the LULC class, CAI, %) and the disjunct core area density
4
5 195 (ratio of the number of disjunct core areas within a specified distance and the whole area,
6
7 196 DCAD, number per km²).
- 8
9
10 197 - Shape metrics: related circumscribing circle in patch and in class level (CIRCLE and
11
12 198 CIRCLE_MN, respectively; ratio of the area of a given patch and the area of the smallest
13
14 199 circumscribing circle, CIRCLE, between 0-1).
- 15
16
17 200 - Distance metrics: Nearest neighbor Euclidean distance between patches belonging to the
18
19 201 same LULC class in patch and class level (ENN and ENN_MN, respectively, m).
- 20
21
22 202 - Fragmentation metrics: effective mesh size (MESH, ha) is in high correlation with
23
24 203 landscape division which expresses the probability that two randomly placed in the
25
26 204 landscape are in the same patch; mesh size is the area of equal sized patches that necessary
27
28 205 to be divide the whole area to reach the above probability value (Jaeger, 2000).

206 4.4 Statistical evaluation

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

215 4.5 Accuracy Assessment

216 The accuracy of the different thematic maps produced from the classifiers, accuracy assessment
 217 was performed based on the computation of the error matrix statistics (Congalton and Green,
 218 1999). As a result, the overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA) and
 219 the kappa coefficient (Kc) were computed, as follows (Congalton and Green 2008):

$$220 \quad OA = \frac{1}{N} \sum_{i=1}^r n_{ii}, \quad (7), \quad PA = \frac{n_{ii}}{n_{icol}}, \quad (8), \quad UA = \frac{n_{ii}}{n_{irow}}, \quad (2)$$

$$221 \quad K_c = \frac{1}{N} \sum_{i=1}^r n_{ii} - \frac{\sum_{i=1}^r n_{icol} n_{irow}}{N^2} - \sum_{i=1}^r n_{icol} n_{irow}, \quad (10)$$

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

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

231

232 5. RESULTS AND DISCUSSION

233 5.1 Accuracy of classified images

234 The accuracy analysis of the classified maps computed in this study is summarized in **Table 1**. On
 235 the basis of the OA, it can be seen that the highest overall classification accuracy was achieved for
 236 the year 2009 image (82.05%) followed by that of 1990 (77.78%) and of 2000 (75.00%). In 2009,
 237 the least performance of cropland can be attributed to mixed pixel response (Agro-forestry

238 system). Similar lower performances for that particular class were also obtained with the 2000
239 satellite imagery. The 1990 image classification performance was slightly better and can be linked
240 to less cropland area and dense forest system. For the built-up area, open and mixed forest classes
241 a PA of >75% were obtained, suggesting that all of the collected validation samples also belonged
242 in the same class more number of times. For the same classes, UA was also reported in range 75-
243 100% indicating that all of the points classified as built-up area, open and mixed forest classes
244 could be expected to be the same area when a field survey is performed. The classification of the
245 cropland, dense forest and water bodies' classes indicate a lower PA and UA than the other classes
246 can be attributed to closed resemblance of dense forest with mixed forest and hence complicated
247 the classification procedure. On the other hand, poor classification accuracy of water bodies and
248 cropland can be related to the encroachment of forest canopies over the water body. The low
249 performance of forest class may also be attributed to incapability of classifier to separate the three
250 forest type that is open forest and mixed forest from the dense forest class. Similarly, for water
251 body class, Landsat performance was slightly lower in comparison to the 2009 image.

252

253 **Table 1: Classification Accuracy of the satellite images**

254

255 **5.2 Spatial changes in LULC**

256 The classification maps produced from the implementation of the MLC are illustrated in **Figure 3**.

257 The classes created and the area under the class provides an insight to the composition of the total

258 area. Based on the results of the classification, it is possible to conclude up to a certain extent the

259 changes that occurred in the area. The analysis of result of water body showed overall change in

260 area from 83.60 to 87.59 km² from 1990 to 2000 and after this increment, in the year 2009 the area

261 further decreased to 85.47 km². The analysis of result of built-up area showed an increase in area

1 262 from 6.50 km² in 1990 to 7.85 km² in 2000 and it further showed an increasing trend to 9.35 km²
2
3 263 in 2009, this increase in the built-up area may be attributed to the increase in population in this
4
5 264 region and dense forest area showed nominal decrease in area from 568.19 km² in 1990 to 562.18
6
7 265 km² in 2000 which further showed slightly declined to 550.17 km² in 2009. This continuous
8
9 266 declining trend of dense forest area may be because of developmental activities which have
10
11 267 occurred in this region. Open forest has the area 54.44 km² to 35.74 km² in 1990 to 2000 and
12
13 268 increased up to 66.02 km² in 2009. However, there is small change in area of mixed forest which
14
15 269 increased from 153.95 km² in 1990 to 175.03 km² in 2000 and then decreased to 155.24 km² in
16
17 270 2009. The main reason behind these changes can be attributed to increase in population and
18
19 271 encroachment of local people who use this area's forest resources (fuel wood, timber, non timber
20
21 272 forest products and fodder) or possibly it may be due to the main industrial area of the state (State
22
23 273 Infrastructure and Industrial Development Corporation of Uttarakhand Limited (SIDCUL) at
24
25 274 district Hardiwar, Uttarakhand). The SIDCUL is found to be associated with rapid expansion of
26
27 275 developmental activities near to the forest area and it requires natural resources like land, water
28
29 276 and forest wood as a raw material. The crop land area decreases from 7.77 km² in 1990 to 6.29
30
31 277 km² in 2000 which further declined up to 6.16 km² in 2009 (**Table 2**). Around the RNP, during
32
33 278 years (2001-2004), over 900 cases of crop raiding by elephants were recorded which occurred due
34
35 279 to illegal encroachment of the park area by the local people.
36
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44 **Table 2: Area of different land use classes in km² for the year 1990-2000-2009**

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46 281

47
48 **Figure 3 Unclassified and classified satellite images of the year 1990, 2000 and 2009**

49
50 283

respectively

51
52
53
54 284 **5.4 Fragmentation analysis**

1 285 The analysis of results showed that forests had the largest relevance in the land cover in the study
2
3 286 area, while built-up areas and croplands had only smaller proportion in all dates of the
4
5 287 investigation (**Table 3**). Class of DF had the largest proportion, but in the same time it was
6
7 288 consisted of the largest number of patches, too; consequently, however its level of fragmentation
8
9 289 was not far-gone due to its large area (MESH was between 902-1886 ha, which was the largest
10
11 290 among all classes). An important change was that in 2009 MESH decreased to the half of the area
12
13 291 of 2000. For MF, the proportion was between 6-7% related the whole area, but the average patch
14
15 292 size was the largest in each year (more than 1000 ha, i.e. twice the average size of other
16
17 293 categories). Also, LPI was the highest for this class, too; largest patch covered 6-7% of the class
18
19 294 area. OFs had smaller proportion (~2%) in a spatially dispersed pattern and were rather
20
21 295 fragmented (see Table 3, MESH). CLs' relevance was very low, and also, their average patch size
22
23 296 was the smallest; furthermore, they appearance in the landscape was dispersed.

24
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28
29 297 PCA indicated a large overlap among the dates in the ordinals space (**Figure 4**). All symbols of
30
31 298 the LULC classes were found in the same section of the diagram and can be discriminated well
32
33 299 with the help of the involved landscape metrics (PLAND, PD, ED, CIRCLE, DCAD, MESH,
34
35 300 ENN); accordingly, in general, the changes were slight. Largest changes were observed in case of
36
37 301 MF and DF classes, while, as it can be waited, water bodies changed the smallest. Furthermore,
38
39 302 only in case of BU can be identified a trend.

40
41
42
43
44 303 There was overall loss of forest area means loss of dense forest, and open forest which suggest that
45
46 304 the population pressure, expansion of city area or other development activities may be responsible
47
48 305 for this loss which was further proved by the increased in built-up core area showed the increasing
49
50 306 trend from 1990 was 6.51 km², in 2000 it was 7.86 km² and 9.28 km² in 2009 respectively. This
51
52 307 increase in built-up area has occurred on the verge of forested area of national park. PLAND for
53
54 308 class level metric analysis showed that how much particular land use/cover becomes under
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56
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1 309 fragmentation. Water hyacinth, locally called Jalkumbhi, is choking many wetlands and water
2
3 310 bodies in the central part of the landscape, especially near agricultural fields (Semwal, Forests and
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5 311 Programme 2005).
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8 312 These changes in MPS are further suggesting that the forest was more fragmented in 1990 than in
9
10 313 2000 and again it was more fragmented in 2009. Indeed, between year 1990 to 2000 was the
11
12 314 period where natural condition or human activities was having less impact on forest landscape and
13
14 315 thus fragmentation was less in 2000 because after the creation of separate state Uttrakhand in year
15
16 316 2000 many new development activities are witnessed in this region. But during the last two
17
18 317 decades enhancement of vehicle traffic on national highways (5 nos.), train traffic in Haridwar –
19
20 318 Dehradun railway track, rapid construction of motor roads (Joshi and Singh 2010). From 2000 to
21
22 319 2009 either human pressure or a natural condition has played a major role in the decrease of MPS
23
24 320 which needs to be further explored. Large-scale habitat loss and human encroachment into the
25
26 321 deeper forest regime are responsible for many changes in the park (Joshi and Singh 2010). Just
27
28 322 one decade back elephant movement in this track was very common as this forest comprises of
29
30 323 rich fodder and perennial water sources. Nevertheless, slowly their movement became restricted in
31
32 324 this part primarily due to increasing rate of anthropogenic activities inside the deeper forest
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34 325 regime, ongoing developmental activities, wildfires and shrinking of perennial water sources
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36 326 (Joshi 2009).
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44 327 Indeed, to our knowledge, from 2002 onwards rapid expansion of developmental activities nearer
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46 328 to the forest area has caused obstruction in frequent movement of elephants besides other wildlife
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48 329 in adjoining forest beats. Tiger movement was frequently recorded before 2002 but after that tiger
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50 330 movement in these forest tracks has got obstructed. As a result of establishment of more than a
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52 331 dozen of industries, demand for water has been increasing and to meet the demand groundwater is
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1 332 being extracted by various stakeholder industries and that has caused the major impact on ground
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3 333 water of adjacent areas.
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6 334 **Table 3 Class level landscape metrics of the LULC classes by dates (MN: mean of patch level**
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8 335 **metrics)**
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11 336 **Figure 4 Biplot diagram of the PCA conducted with landscape metrics of the three dates**
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15 16 338 **6. CONCLUSIONS**

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19 339 The importance of land use/cover pattern using class level metric analysis is to assess the
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21 340 transformation types which affect the spatial pattern of the landscape. The diversity of metrics
22
23 341 available and the complexity of habitat loss and fragmentation effects make it difficult to choose
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25 342 an appropriate metric or suite of metrics for a particular situation. The aim of the present study has
26
27 343 been to exploit contemporary technologies such as EO and GIS to quantify the changes in the
28
29 344 landscape spatio-temporal dynamics occurred in the Rajaji National Park (RNP) during a period of
30
31 345 19 years (1990-2009). Results from this study unveil the degree of land use change, diversity and
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33 346 fragmentation patterns occurred during the periods under study, which indicates that notable
34
35 347 changes have taken place in the studied area. Landscape metric and landscape transformation
36
37 348 analysis showed that over the time spatial configuration and composition of the landscape has
38
39 349 changed drastically, which leads to the degradation of the forest area. The landscape metric
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41 350 analysis showed that from 1990 to 2000 the fragmentation of landscape was slightly low because
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43 351 the natural and climate condition are probably good while, from the year 2000 to 2009 indicates
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45 352 that could be due to human induced disturbance which have increased over this time.
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53 353 The study demonstrates the immense value of the use of contemporary technologies such
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55 354 as remote sensing and GIS in assessing spatial structure and spatio-temporal changes in landscape
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57 355 dynamics in a cost-effective, semi-automatic and rapid manner. The study provides considerable
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1 356 scientific and practical value to the wider scientific community, which can be used with the
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3 357 present and future open access EO datasets from various other satellites. There are number
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5 358 statistics available in the literatures such as contagion, juxtaposition, evenness and patchiness for
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7
8 359 the fragmentation analysis. Hence, further exploration of this potentially valuable fragmentation
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10 360 tool by the geospatial community is recommended, so that useful experience and knowledge could
11
12 361 be accumulated in the technical literature domain for different geographical locations and
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14 362 environmental conditions.
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31 369 Landsat satellite datasets.
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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 km² 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

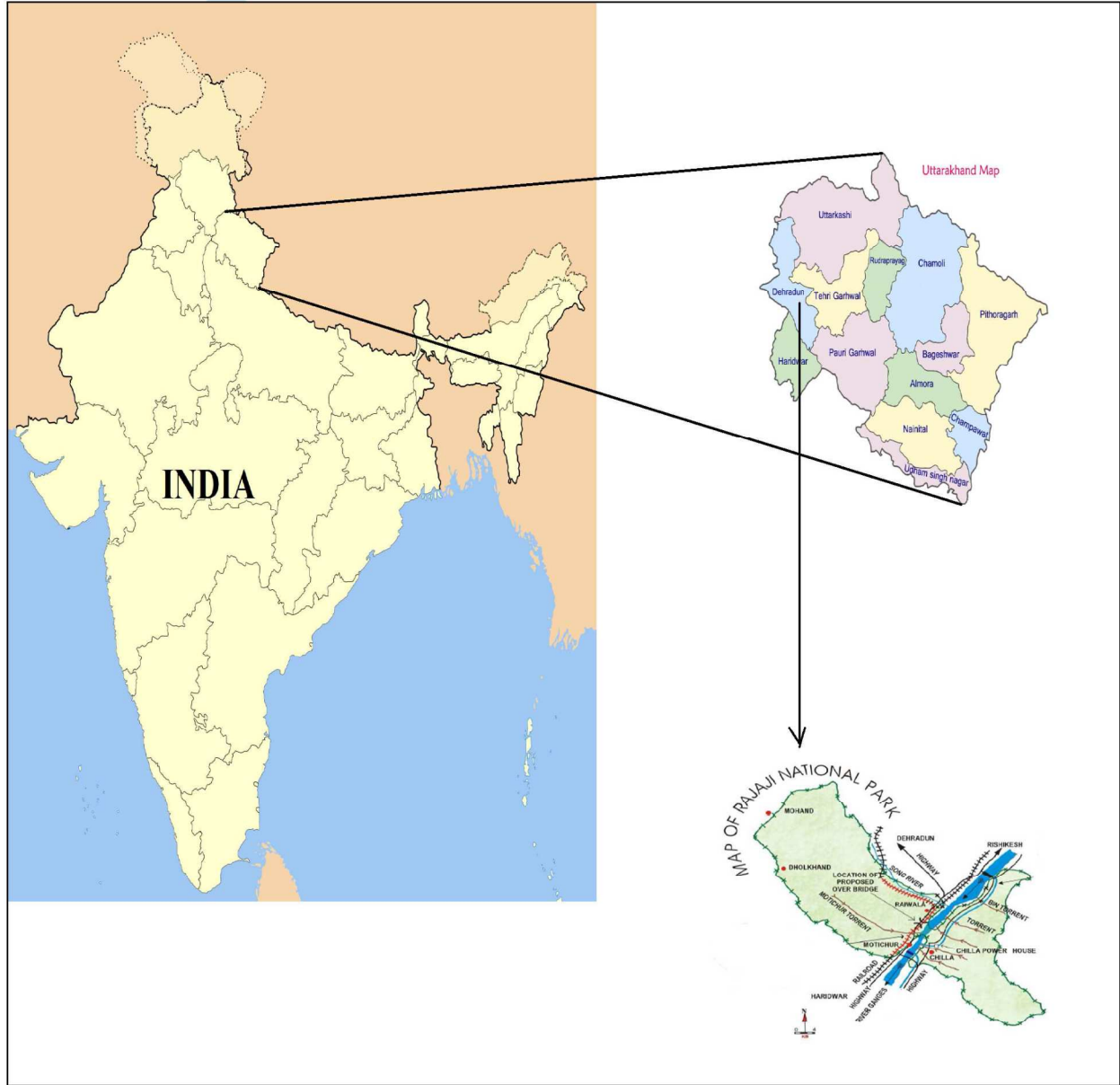


Figure 1 Geographical location of the study area

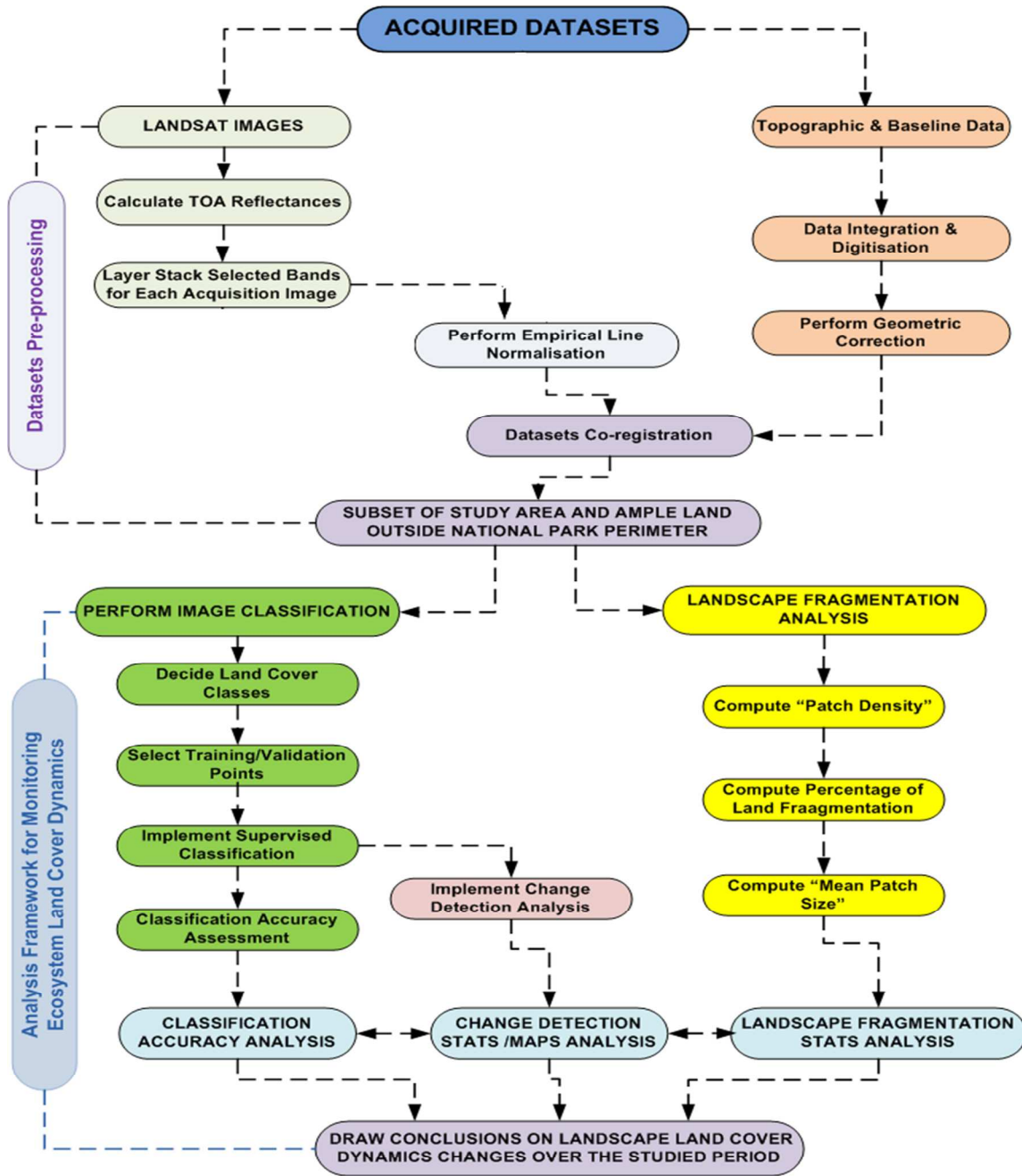


Figure 2 Flow chart of the methodology used in this study

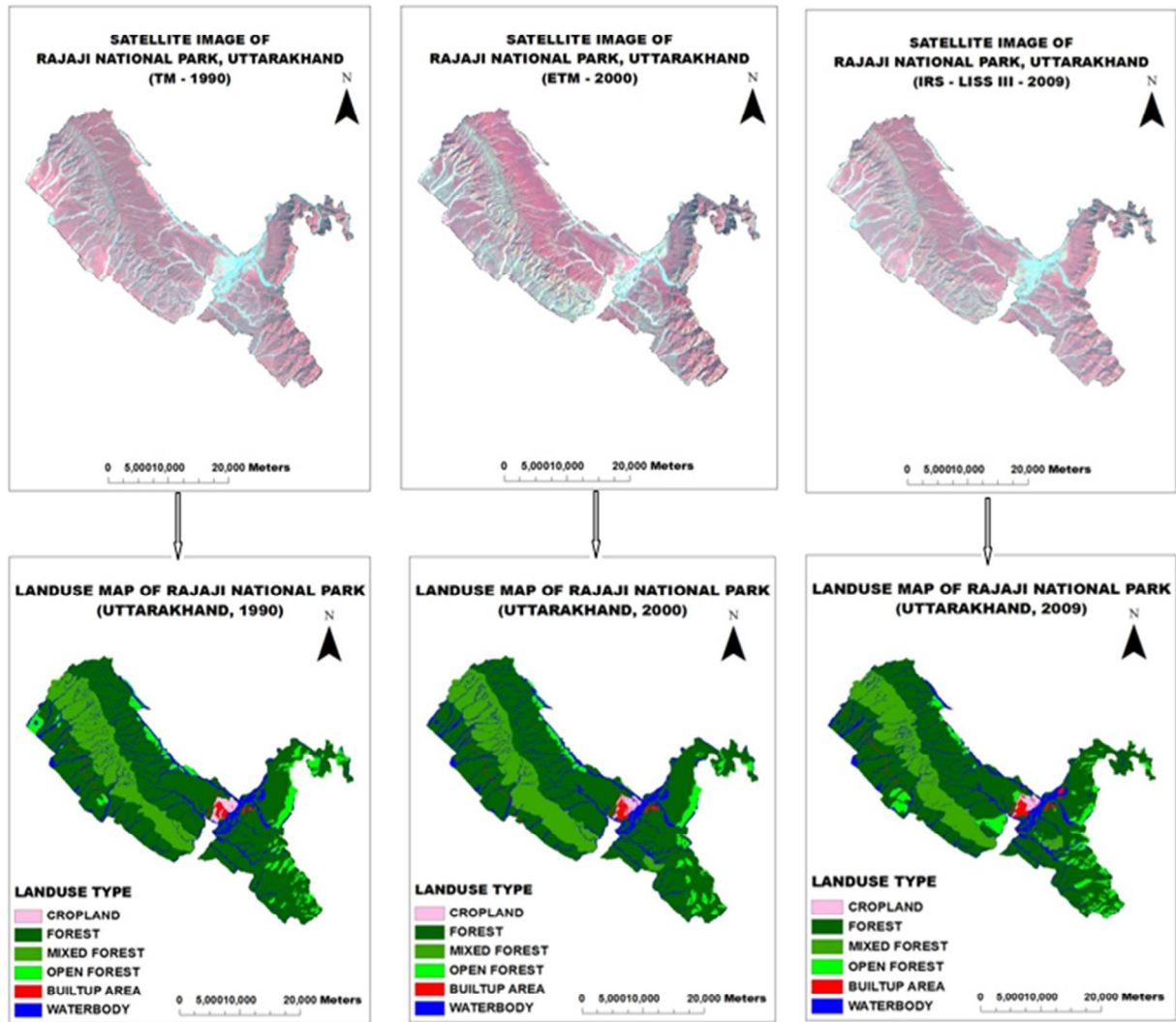


Figure 3 Unclassified and classified satellite images of the year 1990, 2000 and 2009 respectively

Only