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# Characterizing changes in land cover and forest fragmentation from multitemporal Landsat observations (1993-2018) in the Dhorpatan Hunting Reserve, Nepal

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**Abstract** Natural forces and anthropogenic activities greatly alter land cover, deteriorate or alleviate forest fragmentation and affect biodiversity. Thus land cover and forest fragmentation dynamics have become a focus of concern for natural resource management agencies and biodiversity conservation communities. However, there are few land cover datasets and forest fragmentation information available for the Dhorpatan Hunting Reserve (DHR) of Nepal to develop targeted biodiversity conservation plans. In this study, these gaps were filled by characterizing land cover and forest fragmentation trends in the DHR. Using five Landsat images between 1993 and 2018, a support vector machine algorithm was applied to classify six land cover classes: forest, grasslands, barren lands, agricultural and built-up areas, water bodies, and snow and glaciers. Subsequently, two landscape process models and four landscape metrics were used to depict the forest fragmentation situations. Results showed that forest cover increased from 39.4% in 1993 to 39.8% in 2018. Conversely, grasslands decreased from 38.2% in 1993 to 36.9% in 2018. The forest shrinkage was responsible for forest loss during the period, suggesting that the loss of forest cover reduced the connectivity between forest and non-forested areas. Expansion was the dominant component of the forest restoration process, implying that it avoided the occurrence of isolated forests. The maximum value of edge density and perimeter area fractal dimension metrics and the minimum value of aggregation index were observed in 2011, revealing that forests in this year were most fragmented. These specific observations from the current analysis can help local authorities and local communities, who are highly dependent on forest resources, to better develop local forest management and biodiversity conservation plans.

**Keywords** Land cover · Forest fragmentation · Spatial process model · Fragstats

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## Introduction

The Earth has few remaining landscapes that have not been transformed by humans in one way or another (Yang 2001). Land use, land cover (LULC) change is the crucial transformer of landscapes, affecting socio-economic, biological, climatic, and hydrological systems over an extensive range (Sohl and Sohl 2012). Land use refers to human activity on land for various purposes, such as industrial and residential infrastructure. Land cover refers to the surface features of the land such as forests and grasslands, with an emphasis on the natural attributes (Phong 2004; Lambin and Meyfroidt 2010). Land use is one of the main avenues through which

humans influence the environment. It involves both how the biophysical attributes of the land are manipulated and the intent underlying that manipulation (Turner et al. 1995).

Natural forces such as landslides and volcanic eruptions and human activities such as deforestation change the land cover, and further aggravate or alleviate forest fragmentation (Broadbent et al. 2008). Forest fragmentation is the process of dissecting large and contiguous forest areas into smaller units and isolated patches (Saunders et al. 1991; Sahana et al. 2015). It has a wide variety of adverse effects on ecosystems, including an increase in forest fire vulnerability, tree mortality, changes in species composition, seed dispersion and predation (Forman and Godron 1986; Becker and Bugmann 1999; McGarigal 2002; Ramanathan et al. 2005). Furthermore, forest fragmentation results in easier access to interior forests, opening the areas to increased hunting and resource extraction (Cramer et al. 2007; Peres et al. 2010).

Nepal has undergone considerable changes over the past few decades, driven by anthropogenic and natural factors, and their impacts on national and regional environments and by climate changes are documented (Paudel et al. 2016). Compared to the low-land areas of Nepal, the middle and high mountainous regions are more sensitive to small changes in LULC and subsequent forest fragmentation has a deeper impact (Khanal 2002). Specifically, studies have shown that land cover and forest fragmentation in the Hindu Kush-Himalaya (HKH) region of Nepal have undergone rapid changes due to social, economic and environmental factors and in turn, these changes affect the ecosystems and the services they provide (Uddin et al. 2015). One of the ecologically critical areas located within the HKH is the Dhorpatan Hunting Reserve (DHR), which is also confronted with increased anthropogenic and natural disturbances (Sharma and Belant 2010). The population of 43,078 in nearly 47 villages scattered in and around the DHR relies heavily on forest resources of this reserve for their daily livelihoods, where 98% use firewood as the primary source of energy (CBS 2011). These disturbances cause changes in the land cover along with forest fragmentation (Hansen et al. 2001; Crooks et al. 2011), threatening the reserve's biodiversity. Therefore, thorough understanding by the public of land cover change and forest fragmentation and the introduction of adaptive interventions for ecological restoration are urgently needed (Nagendra et al. 2008; Bharti et al. 2012). Understanding of these dynamics in the DHR from a long-term historical perspective is essential for land managers, conservation partners and related stakeholders to develop targeted policies and management strategies. Specifically, the dynamics can be helpful for the development of sustainable forest management actions and to effectively make concessions to the need for natural resource conservation and for the poverty reduction of highly dependent forest communities.

To characterize the land cover changes and forest fragmentation, studies based on multitemporal Landsat images and landscape indices have previously been carried out in some protected mountainous areas rich in species (Sharma et al. 2016, 2017). These studies have reported on changes in land cover and identified forest fragmentation as a result of anthropogenic disturbances. Generally, the fragmentation analysis results are presented by comparing the temporal differences of the derived values of the landscape indices used. These outcomes are less useful and targeted when developing management strategies because they do not have adequate spatially explicit implications, only statistics. Additionally, some studies conducted in the DHR focused on the distribution of species such as common leopard (*Panthera pardus* L.), red panda (*Ailurus fulgens*) and blue sheep (*Pseudois nayaur*) (Achyut and Kreigenhofer 2009; Karki and Thapa 2011; Panthi and Thagunna 2013). None of the studies have addressed the LULC change and forest fragmentation issue. However, the status of LULC of a protected area is a fundamental input when establishing administrative rules and designing strategies for biodiversity conservation along with sustainable development (Martinez del Castillo et al. 2015). Monitoring forest cover change over time also has become increasingly important as a tool for determining the richness of biodiversity (Esbah et al. 2010).

Our research aimed to provide available land cover datasets for the DHR and a clear picture of forest fragmentation trends from a spatio-temporal perspective. The specific objectives were to: (1) analyze the spatiotemporal trends in land cover changes from 1993 to 2018; (2) map forest fragmentation and restoration spatial processes using two process models to understand the trends in forest fragmentation; and, (3) examine the socio-economic drivers contributing to these change processes.

## Materials and methods

### Study area

Dhorpatan Hunting Reserve (DHR) is the only hunting reserve among the 20 protected reserves in Nepal. It extends from 28°15′ N to 28°55′ N latitude and 82°25′ E to 83°35′ E longitude, covering an area of 1325 km$^2$ (Fig. 1). The DHR was established in 1983 and officially declared in 1987. The primary management objectives of the reserve are to allow hunting and to preserve representative high-altitude ecosystems. Geographically, it falls under the Hindu Kush-Himalaya (HKH) region, with altitudinal variations from 2000 to 7246 m a. s. l. Monsoon rains begin in June and last until October, with a rainfall of 144.9 mm in 2018 (WWO 2019). The DHR is comprised of temperate, subalpine, and alpine vegetation and has high biodiversity values. The dominant

**Fig. 1** Location of the study site; the upper left subimage shows the geographic location of the DHR, and the lower right subimage presents the 2018 land cover map derived from the current analysis
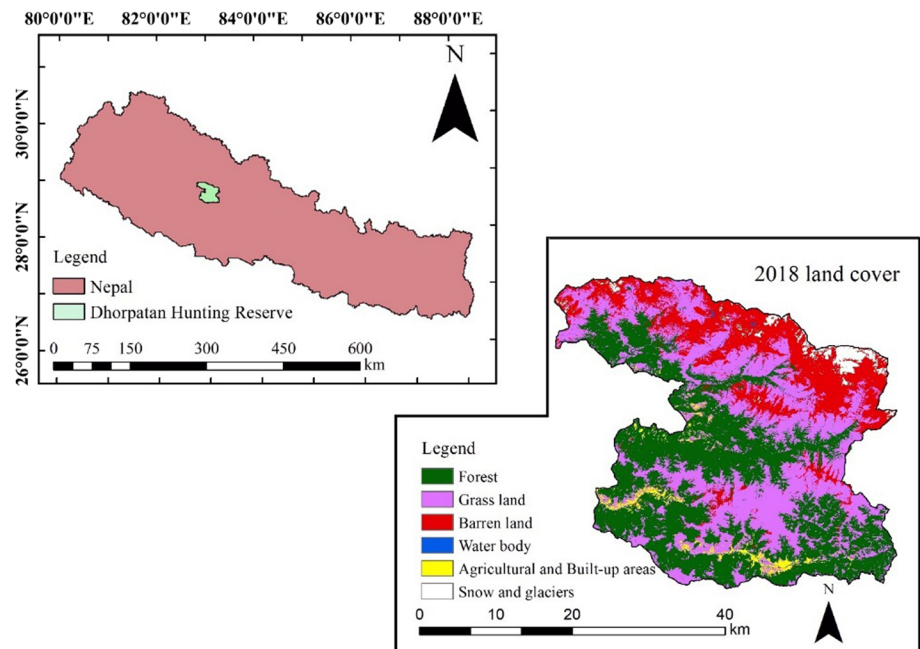


tree species are *Pinus roxburghii, Taxus baccata, Pinus wallichiana* A. B. Jacks*,* and *Abies spectabilis,* while the major faunal species are the Himalaya goral (*Naemorhedus goral* Hardwicke), wild boar (*Sus scrofa*), Himalayan musk deer (*Moschus chrysogaster*), Sumatran serow (*Capricornis sumatraensis* Bechstein), Indian muntjac (*Muntiacus muntjak*), common leopard (*Panthera pardus*), lynx (*Felis lynx*), dhole (*Cuon alpinus* Pallas), red fox (*Vulpes vulpes*), wolf (*Canis lupus*) and red panda (*Ailurus fulgens*) (Panthi et al. 2012; Aryal et al. 2015). The flat alpine pastures above the tree line (4000 m), locally known as *patan,* are very important for animals such as the blue sheep (*Pseudois nayaur* Hodgson), which are the preferred prey of the snow leopard (*Panthera Uncia* Scherber). High elevation areas mostly remain covered with clouds and higher altitude areas with snow. The DHR is surrounded by human settlements except on the northern side.

### Remote sensing data

Five cloud-free Landsat surface reflectance images for 1993, 1999, 2004, 2011 and 2018 (Table 1) were downloaded from the United States Geological Survey (USGS), Center for Earth Resources Observation and Science (EROS), official website (http://earthexplorer.usgs.gov). Images with minimum cloud cover (or contamination) were requested to facilitate the analysis of land cover changes in the study area. All satellite images were ortho-rectified and radiometrically corrected to the level 2 product type that has the highest scientific standards and level of processing (provided directly by USGS).

**Table 1** Details of Landsat data and DEM used in the land cover classification

| Satellite | Sensor | Path/Row | Spatial Resolution (m) | Acquisition Date | Source |
|---|---|---|---|---|---|
| Landsat 5 | TM | 143/40 | 30 | 09/11/1993 | USGS |
| Landsat 5 | TM | 143/40 | 30 | 28/12/1999 | USGS |
| Landsat 5 | TM | 143/40 | 30 | 22/10/2004 | USGS |
| Landsat 5 | TM | 143/40 | 30 | 11/11/2011 | USGS |
| Landsat 8 | OLI | 143/40 | 30 | 29/10/2018 | USGS |
| DEM | – | – | 90 | – | SRTM |

Additionally, because of the undulating mountainous terrain, DEM data was downloaded from the Shuttle Radar Topography Mission (SRTM) with a 90 m resolution (http://dwtkns.com/srtm/), followed by the derivation of slope and aspect variables (Table 1). They were then resampled to 30 m to support necessary terrain corrections and land cover classification.

### Image preprocessing

Due to the high variability in elevation throughout the study area, prior to classifying the Landsat images, a SCS (sun-canopy-sensor model)+C-correction was implemented to minimize the effects of the rugged mountainous terrain on the actual pixel reflectance. This terrain correction strategy is rigorous, comprehensive and flexible, and provides improved corrections compared to SCS alone or four other photometric approaches (cosine, C, Minnaert, statistical-empirical) (Soenen et al. 2005). Once done, normalized

difference vegetation index (NDVI) (Schell 1973), ratio vegetation index (RVI) (Jordan 1969) and greenness from tasseled cap transformation (Crist et al. 1984) were calculated to support subsequent land cover classifications. These indices can enhance vegetation signature and, to some extent, reduce the impacts of atmospheric and topographic variations.

## Training and validation samples for land cover classification

Fieldwork was conducted in the DHR from September 28 to October 11, 2018. Due to the complex terrain, some areas were inaccessible, and only 164 points were randomly selected with GPS and their land cover type information was recorded. In addition, 150 points for 2011 and 74 points for 2004 identified from previous national land use reference data and other ancillary data were derived. These auxiliary points have been checked with the high-resolution images of Google Earth to further ensure the reliability.

These auxiliary points were not sufficient for classification modeling, 60 regions of interest (ROIs; about 2000 points) were additionally selected for each forest, grassland and barren land category on the Google Earth images in 2004, 2011 and 2018. For each of the remaining categories, 8 ROIs (about 150 points) were selected. Due to the unavailability of Google Earth imagery in 1993 and 1999 and the lack of national reference data, only the same number of ROIs on the original Landsat images with the help of local experts were selected and finally these ROIs were combined with the above auxiliary points and fed to support vector machine (SVM) classification. 70% of the samples were randomly used for support vector machine (SVM) classifier training, the remaining 30% samples were superimposed on the classification images to derive statistics for user's accuracy, producer's accuracy and overall accuracy.

## Image classification

The land cover scheme in this study included six major land cover types: forest, grasslands (alpine, sub-alpine and lower meadows), barren land, water bodies, agriculture (including highly dispersed houses), and snow and glaciers. These six types were determined after reconnaissance and discussion with local natural resource management experts. The built-up areas were merged with agricultural land because houses were scattered in small settlements, isolated and small in size, thus, it was difficult to distinguish them from other land cover types within the 30 m resolution of Landsat data. Although it was easier to detect the small built-up areas by combining the Landsat data with publicly available auxiliary geospatial data (Hoffman-Hall et al. 2019), these reliable auxiliary data for this particular region were rare. Thus, to

minimize the complexity of classification, isolated house land cover type was merged into agricultural type.

Support vector machine (SVM) algorithm was used to classify land cover types because it has the advantages of seeking an optimal solution to a classification problem and better ease of handling a small number of samples, (this situation is really the case for this remote and inaccessible region), over other machine learning algorithms such as decision trees and neural networks (Huang et al. 2008). The radial basis function (RBF) was chosen as the kernel function because it is relatively simple and has been proven by classification studies to achieve good accuracy (Huang et al. 2008); a cost parameter C was set to 10, which qualifies the penalty of the misclassification errors, and γ was the reciprocal of the number of input feature bands (1/n_feature). Six surface reflectance data, NDVI, RVI, greenness from tasseled cap transformation, elevation and slope were used as the input features for support vector machine (SVM) classification.

## Forest fragmentation and restoration process analysis

To analyze the spatiotemporal characteristics, the model developed by Li and Yang (2015) for the spatial analysis of the forest fragmentation process was followed, while for the analysis of the forest restoration process, the model developed by Ren et al. (2017) was used. Overlaying bi-temporal classified maps, information about the lost/gained forest and remaining forest patches was acquired. The lost forest patches were then reclassified into four different categories according to the spatial relationships between the lost forest patches and the remaining forest patches. The lost patches surrounded by the remaining patches were classified as perforation, and those connected with two or more remaining patches were classified as subdivisions. If the lost patches were connected with only one remaining patch, they were then categorized as shrinkage and finally, those isolated from the remaining patches were categorized as attrition (Fig. 2). The forest restoration model was applied based on two spatial processes: increment and expansion. Increment referred to the gained patches that were isolated from remaining forest patches, and expansion meant that the patches were connected to the remaining forest patches (Fig. 2).

Specifically, lost (or gained) forest, non-forest, and remaining forest patches were generated by overlaying bi-temporal land cover maps. Firstly, the null represented the lost (or gained) forest pixel, the value 2 and above represented different remaining forest patches, and the non-forest pixels were set to 0. For the fragmentation model, the maximum and minimum values of each lost forest pixel in the eight neighborhoods were calculated, and these were assigned to the central pixel. If the maximum and minimum values of the entire lost forest patch were equal and the value
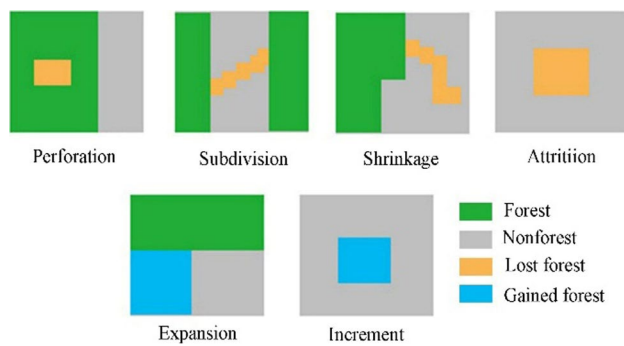
**Fig. 2** Schematic diagram of the forest fragmentation process (upper) and restoration process (lower) models

was 0, it was attrition. If both values were equal and this value was not zero, it was perforation. If the maximum value was not equal to the minimum value, the non-forests was reset to null, and once again the maximum and minimum values for each lost forest patch were calculated. If the two values were equal, it was shrinkage; if not, the lost patch was subdivision. For the restoration process, the maximum value was given to the central pixel in its eight neighborhoods for each gained patch. If the maximum value was 0 in a gained forest patch, the patch was increment, otherwise it was expansion. The spatial analytical models were developed and implemented in the Arcgis model builder.

### Landscape metrics analysis at forest class level

Using fragmentation and restoration models can spatially characterize forest fragmentation; computing and comparing landscape metrics can provide specific values to quantitatively describe the landscape change trends. Fragstats 4.4 is a spatial pattern analysis software that quantifies the composition and configuration of the patches and provides information on the structure of the landscape (McGarigal 2014). In the current study, a binary map of forest versus non-forest was firstly generated by reclassifying the original land cover map for each year, then the eight-neighbor analysis was selected and the largest patch index (LPI), edge density (ED), perimeter area fractal dimension (PAFRAC), and aggregation index (AI) were calculated at the class level. LPI refers to the area percentage of the largest forest patch to total forest area. ED calculates the edge length of forest per unit area. Generally speaking, more fragmented landscapes have higher ED values. The value of PAFRAC becoming close to 1 indicates that the forest landscape shape is not complicated. More fragmented landscapes are expected to have patches with more complex shapes, meaning higher PAFRAC values. AI reflects the aggregation degree of similar patches. High AI reveals that the landscape has better integrity and lower fragmentation (McGarigal 2014).

## Results

### Accuracy assessment of land cover classification

Except for 2011 with an overall accuracy of 84%, overall accuracies of the remaining years were above 85%, and the highest of 88% was observed in 2018. Most of the users' and producers' accuracies of forest class were higher than 90%, and they were generally higher than the remaining classes (Table 2). The validation results showed that forest classes in the DHR were accurately mapped.

### Land cover change analysis

It was apparent that the majority of the DHR was covered by forest and grasslands and both varied from 35 to 41% between 1993 and 2018 (Fig. 3 and Table 3). Barren land was the third largest land class at about 18% during all time periods. Water, agriculture and built-up regions, and those with snow and glaciers occupied approximately 0.3%, 1.8%, and 2%, respectively, of the study area during the five time periods (Table 3). Forests mainly occupied the western and the southern parts of the study area, while grasslands spread from the middle of the reserve towards the northern part. Snow and glaciers occurred in the northeastern region, while agricultural and built-up areas were distributed in the lower altitudes near the forests (Fig. 3). The percentages of land cover change (ratio of the changed area to the total area) in all five time periods were relatively low. The greatest difference did not exceed 2.5% in any time period for any land cover class. The most considerable change over the entire study period was in grasslands, which decreased by 2.4% from 1999 to 2004. Forest cover increased by 0.4% over 25 years, but showed a downward trend from 2004 to 2011, with a maximum rate of change of 0.7%. The water category and its change were relatively stable and less than 0.1% throughout the study period. Agriculture and built-up areas showed a slight change from 1993 to 2018 (Table 4).

### Forest fragmentation and restoration processes analysis

Among the four fragmentation categories, perforation occurred primarily in the core forest patches, while shrinkage occurred near the edges of large forest patches. Subdivision occurred between the core forest area and the small forest patches, whereas attrition was scattered throughout the small forest patches (Fig. 4). During the four time periods, shrinkage was always the foremost spatial process for forest area loss, but compared with the previous two periods, the proportion of shrinkage decreased to 46.2% between 2004 and 2011. For these same periods, subdivision had the second most impact on forest loss with the highest percentage of 35.3% and the lowest of 27.2% (Table 5). The spatial

**Table 2** Accuracy assessment results for 1993, 1999, 2004, 2011 and 2018 classifications

| Land cover | 1993 | | 1999 | | 2004 | | 2011 | | 2018 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) |
| Forest | 92.6 | 94.6 | 92.6 | 92.6 | 94.6 | 89.8 | 91.4 | 88.5 | 93.6 | 90.6 |
| Grassland | 86.3 | 80.8 | 84.4 | 81.3 | 77.8 | 88.7 | 78.8 | 85.9 | 82.7 | 95.7 |
| Barren land | 71.4 | 62.5 | 75.7 | 68.3 | 95.0 | 76.0 | 86.5 | 74.4 | 88.9 | 80.0 |
| Water | 81.8 | 94.7 | 86.4 | 100.0 | 72.7 | 100.0 | 66.7 | 72.7 | 81.3 | 72.2 |
| Agriculture and Built-up area | 80.0 | 100.0 | 77.8 | 100.0 | 100.0 | 50.0 | 100.0 | 55.6 | 100.0 | 60.0 |
| Snow and glacier | 73.3 | 91.7 | 80.0 | 100.0 | 71.4 | 100.0 | 72.2 | 100.0 | 83.3 | 93.8 |
| Overall accuracy | 85.2 | | 86.0 | | 86.4 | | 84.0 | | 88.0 | |

processes of perforation and attrition explained little of the forest loss for all periods and their highest proportions were only 14.5% and 11.3%. In the case of restoration, both categories were dispersed over the whole study area but were more concentrated on the southern and western sides. The expansion category was responsible for more than 90% of forest area gained. The expansion patches varied from 92.2% to 97.5% from 1993 to 2018. The increment category from 1999 to 2004 was the least at 2.5% (Table 5).

## Landscape metrics analysis at the forest class level

The largest patch index (LPI) reached 23.7% in 1999 (Table 6) and varied from 11.1% to 12.2% in the remaining years. The edge density (ED) was highest in 2011 (27.6 m/ha) and lowest in 2004 (22.8 m/ha), showing that less fragmentation occurred in 2004 than in the other three time periods. The perimeter area fractal dimension (PAFRAC) was lowest at 1.40 in 2004, indicating that the shape of the forests was more regular compared to other years. The maximum value of PAFRAC was 1.44 in 2011. The aggregate index (AI) was approximately 92.0% in 1993, 1999, and 2011, and greater than 92.5% in 2004 and 2018. Considering these indices, the forests in 2011 were highly fragmented.

## Discussion

### Land cover change

Land cover in the DHR changed gradually from 1993 to 2018. Forest cover increased by 0.4% which was below the national forest growth rate for Nepal of 5.1% from 1994 to 2014 (DFRS 2015). Effective enforcement of laws, mobilization of the security forces and maintaining a full complement of reserve staff curbed the illicit collection of forest products and the movement of unwanted visitors (DHR 2017), and assisted in enriching the forest. It is possible that the treeline shifted slightly higher due to global warming, as observed in a study in central Nepal, where the Himalayan fir (*Abies spectabilis* (D. Don) Spach.) moved upwards by 2.6 m year$^{-1}$ in the Manaslu Conservation Area (Gaire et al. 2013). In addition, during our field visits and inquiries with local staff, some shrubs have gradually developed into dense shrublands in some areas due to the abandonment of agricultural land.

Grasslands, on the other hand, decreased by 1.3% throughout the study period. Other studies conducted in the highlands of Nepal have found similar results. Chalise et al. (2019) reported that 37.0% of the total rangeland in Nepal was degraded between 1984 and 2003, and approximately 3.6% of grasslands in the hill, middle mountain and high mountain areas decreased between 1979 and 2010 (Paudel

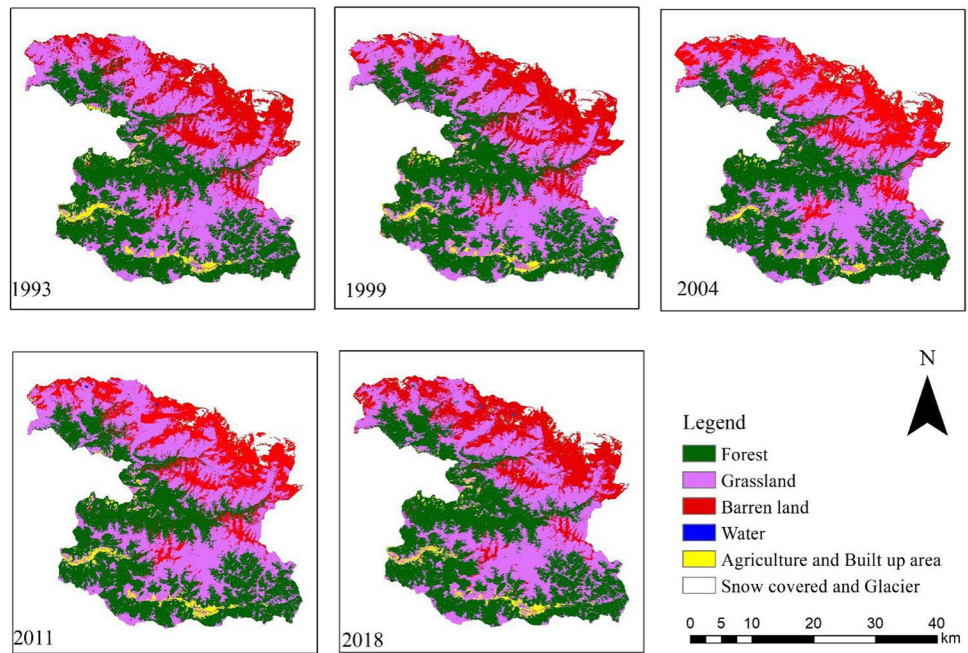**Fig. 3** Land cover maps of the five time periods derived from SVM classifier



**Table 3** Area percentage of the six land cover classes from 1993 to 2018

| land cover categories | 1993 Area (%) | 1999 Area (%) | 2004 Area (%) | 2011 Area (%) | 2018 Area (%) |
|---|---|---|---|---|---|
| Forest | 39.4 | 39.9 | 40.4 | 39.7 | 39.8 |
| Grasslands | 38.2 | 38.2 | 35.9 | 38.1 | 36.9 |
| Barren lands | 18.3 | 18.3 | 19.7 | 17.8 | 19.2 |
| Water bodies | 0.3 | 0.4 | 0.3 | 0.3 | 0.3 |
| Agriculture and built-up areas | 2.2 | 1.1 | 1.3 | 1.9 | 1.8 |
| Snow and glacier | 1.7 | 2.1 | 2.4 | 2.2 | 2.2 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

**Table 4** Change in the percentage of land cover classes from 1993 to 2018 (positive values indicate increase while negative values indicate decrease)

| Land cover classes | Land cover changes (area in %) | | | | |
|---|---|---|---|---|---|
|  | 1993–1999 | 1999–2004 | 2004–2011 | 2011–2018 | 1993–2018 |
| Forest | 0.6 | 0.5 | −0.7 | 0.1 | 0.4 |
| Grassland | 0.1 | −2.4 | 2.2 | −1.2 | −1.3 |
| Barren land | 0.0 | 1.4 | −2.0 | 1.4 | 0.9 |
| Water | 0.0 | 0.0 | 0.0 | −0.1 | −0.1 |
| Agriculture and built-up | −1.1 | 0.2 | 0.6 | −0.1 | -0.4 |
| Snow and glacier | 0.4 | 0.2 | −0.2 | 0.0 | 0.4 |

et al. 2016). One crucial reason for grassland loss may be livestock grazing in the reserve, which not only reduces grassland coverage but also compacts the soil and leads to gully formation (Panthi et al. 2017).

Water resources remained relatively unchanged over the past 25 years. A slight decrease was observed for agricultural and built-up areas. Based on documentation and site visits, most of the agrarian lands situated in the high mountains have been abandoned in recent years (GoN 2014) due to labor shortages, a consequence of youth emigration. Although agriculture lands and built-up areas have decreased, during our field visit, the encroachment of agriculture lands and built-up areas towards the reserve existed in some accessible regions. According to a report from the reserve, people migrating from a more rural part have encroached on 175 hectares of land (DHR 2017).

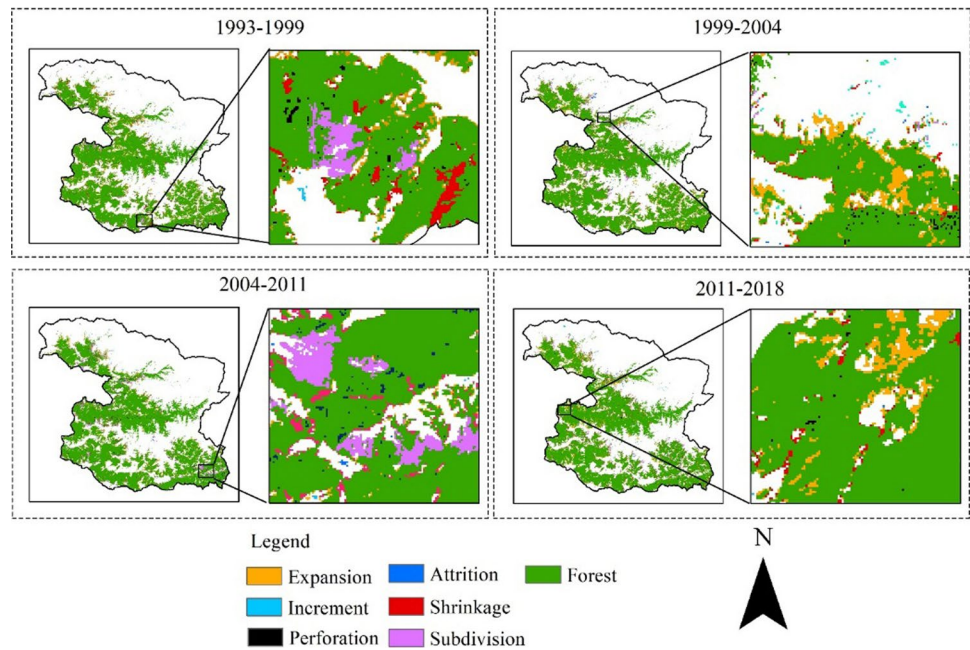**Fig. 4** Spatial processes of forest fragmentation and restoration in the DHR from 1993 to 2018



**Table 5** Spatially explicit analysis of forest fragmentation and restoration processes of the four time periods

| Time period → | 1993 − 1999 | 1999 − 2004 | 2004 − 2011 | 2011 − 2018 |
|---|---|---|---|---|
| Six spatial process | % | % | % | % |
| *Fragmentation* | | | | |
| Perforation | 8.0 | 3.8 | 14.5 | 5.6 |
| Subdivision | 30.7 | 28.6 | 35.3 | 27.2 |
| Shrinkage | 56.2 | 56.3 | 46.2 | 57.8 |
| Attrition | 5.1 | 11.3 | 4.1 | 9.4 |
| *Restoration* | | | | |
| Increment | 4.3 | 2.5 | 7.8 | 4.2 |
| Expansion | 95.7 | 97.5 | 92.2 | 95.8 |

**Table 6** Landscape metric estimates at the forest class level during 1993–2018

| Class Metrics (Unit) | Year | | | | |
|---|---|---|---|---|---|
| | 1993 | 1999 | 2004 | 2011 | 2018 |
| LPI (%) | 11.1 | 23.7 | 12.2 | 11.8 | 12.2 |
| ED (m/ha) | 26.7 | 27.2 | 22.8 | 27.6 | 24.6 |
| PAFRAC (no unit) | 1.42 | 1.43 | 1.40 | 1.44 | 1.41 |
| AI (%) | 92.3 | 92.3 | 93.6 | 92.1 | 93.0 |

## Forest fragmentation and its effect on local biodiversity

Forest fragmentation occurs through the intensification of anthropogenic activities (Peres et al. 2010). However, in this study, although many human settlements exist in and around the DHR and the local people are highly dependent on forest resources, fragmentation was not severe except in 2011. Results of the fragmentation process showed that shrinkage was the most common aspect followed by subdivision. The appearance of these two categories indicated that forest loss reduced the connectivity among forest patches or between forests and non-forested areas. In the process of forest restoration, the area of expansion was much larger than the increment, indicating that there were relatively few isolated forests (increment), and most newly gained forests were extensions from the remaining forests. This information is essential for developing forest management plans with targeted spatial locations, for example, locating proper afforestation sites to increase forest connectivity to improve species of animal movements via forest corridors (Ostapowicz et al. 2008).

Higher edge densities and perimeter area fractal dimension indices indicate higher spatial heterogeneity (McGarigal 2014). These two indices were highest in 2011, meaning that forest patches were distributed in small patches and/or had more irregular shapes than in other years (Hargis et al. 1998). A similar situation occurred in Dudhawa National

Park, India, where a higher edge density value was a result of fragmentation (Midha and Mathur 2010). Furthermore, the higher the aggregation index (AI), the better the integrity of the forest landscape. AI was the lowest in 2011. It was concluded that forest fragmentation in 2011 was the most serious.

Fragmentation tends to negatively impact the continuity and quality of forests (Zomer et al. 2009) and causes the loss of habitat (Fahrig 2003), biodiversity (Wenguang et al. 2008; Biswas and Khan 2011), and ecosystem functions (Nagabhatla et al. 2012). For example, the changes in microclimate and floral composition caused by fragmentation make endemic plants and animals vulnerable (Choudhary 2019). The DHR is one of the prime habitats of endangered fauna such as the red panda, *Ailurus fulgens*. Species such as *Abies* spp., *Quercus* spp., and *Pinus* spp. have been gradually eliminated from the fragmented areas to satisfy timber demands of the local communities. Thus, this situation could be detrimental to *A. fulgens* since these tree species provide necessary resting and nesting cover for these mammals (Panthi et al. 2017). Some mammal species need large core areas of forest as their primary habitat (Tinker et al. 1998), and these species will be affected in the DHR due to fragmentation.

These impacts related to forest fragmentation, which pose a threat to biodiversity, can be diminished by the introduction of adaptive interventions for ecological restoration. This is achievable through an enhanced understanding of the dynamics of land cover change and forest fragmentation (Nagendra et al. 2008; Bharti et al. 2012). Park management and conservation partners can benefit from the results of this study to restore fragmented patches, especially where shrinkage and subdivision have occurred the most, as this increases forest connectivity. The existing increment patches are likely to be divided or disappear in the future, so protection measures should be strengthened. Recovery from fragmentation is necessary, not only for biodiversity protection but also to control the conflicts between humans and wildlife because forest fragmentation is a critical driver of such disputes (Acharya et al. 2017).

### Socio-economic drivers of forest loss and restoration

Research has shown that, when people are dependent on forest resources, socioeconomic factors are responsible for forest loss and further fragmentation, such as in Romania (Vorovencii 2015), India (Reddy et al. 2013) and Bolivia (Millington et al. 2003). Approximately 47 small villages are scattered inside the reserve, and numerous others exist at the periphery. The number of households (5568) and residents (35,310) in 2007 (Sharma and Belant 2010) increased to 9195 and 43,078, respectively, in 2011(CBS 2011), with approximately 98% of the households using firewood as their primary source of energy. Fodder, forage, timber, bamboo, and medicinal herbs are other major resources extracted from the reserve. In addition, a study by Thapa et al. (2014) in the DHR found that 4000–5000 people visit the alpine and subalpine pastures from late spring to early summer in search of the lucrative yarsagumba (*Ophiocordyceps sinensis* (Berk.) Sacc.), a medicinal mushroom. These will cause growing anthropogenic pressures on alpine and subalpine meadows and forests of the DHR. Along with traditional agriculture, the main sources of livelihood for the local people are animal husbandry and trans-boundary trade (Aryal et al. 2015). Widespread, unplanned and unsystematic grazing across the area have contributed to the suppression of new growth which has aided forest fragmentation. Furthermore, some local herdsmen intentionally set fires each year to promote the growth of herbaceous vegetation for livestock forage, which sometimes result in uncontrolled forest fires, leading to more significant catastrophes.

Although forest resources have been exploited, overall forest cover still showed an increase from 1993 to 2018 (Table 4), which was mainly attributed to many polices and legislative instruments for sustaining biodiversity. Nepal is committed to maintaining sustainable forest cover for ecosystem and economic purposes. Since 1990, especially after the adoption of the Convention on Biological Diversity, Nepal's government has made remarkable progress in increasing forest cover, mainly including policy promulgation and community forest programs. Existing legal instruments in the forestry field such as the 1993 Forest Act, the 2007 Plant Protection Act, the 2014 Scientific Forest Management Guidelines and numerous other directives have been implemented and have contributed to forest protection (Dhakal et al. 2018). Similarly, Forest Policy in 2015 outlined a strategy to maintain 40% of the land cover as forest in order to achieve sustainable forest management goals. Nepal's Constitution (2015) stipulates that the country must maintain sufficient forest cover to maintain necessary ecological and environmental balance. The community forestry program is one of the landmark programs that involve local people in the forest management process. According to a recent assessment of forest cover by the Forest Resource Assessment Project, forests in the middle mountains are, in general, better conserved and in many places forest cover has increased in recent years mainly due to the program (Dhakal et al. 2018). In addition, a study investigated on the forest regeneration pattern of the DHR concluded that the forest was sustainable (Duwadi 2017).

It is apparent that local people depend on the forests for their subsistence needs (Gilmour and Fisher 1991; Malla 2000), so methods that can continuously meet the needs of the people and protect the reserve simultaneously should be introduced. Establishment of a buffer zone around the reserve, as in other protected areas of Nepal, is

a possible way to minimize the dependency of local people on the reserve. Additionally, upgrading poverty reduction approaches by supporting more impoverished families in the accumulation of assets and by creating alternatives for higher remunerative livelihood strategies will eventually reduce the pressure on the environment (Walelign and Jiao 2017).

## Conclusion

A support vector machine algorithm, fragmentation and restoration models, and landscape indices were adopted to assess the spatiotemporal changes in land cover and forest fragmentation in the DHR between 1993 and 2018. The forest areas have increased in the past 25 years, while grasslands and agricultural and built-up areas have decreased. The multitemporal overview of forest fragmentation and restoration showed that shrinkage was the most dominant cause of fragmentation, followed by subdivision. Thus, appropriate strategies to control forest shrinkage and subdivision are required. Expansion was more responsible for forest restoration than increment. With the maximum values of edge density and perimeter area fractal dimension, and the minimum aggregation index in 2011, forest fragmentation was the most severe. Forest restoration is mainly attributed to the various national forest protection policies and programs, calling for more attention on biodiversity. Though forest restoration was greater than forest loss over 25 years, the high dependency of the local people on forests appears to be the dominant cause of forest fragmentation and still poses a threat in the future. There should be a precise mechanism for resource sharing, such as the creation of a buffer zone around the reserve and the promotion of poverty reduction approaches.

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