Environmental Challenges 7 (2022) 100384

Contents lists available at ScienceDirect

Environmental Challenges

journal homepage: www.elsevier.com/locate/envc

"Human elephant conflict in changing land-use land-cover scenario in and adjoining region of Buxa tiger reserve, India"

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ARTICLE INFO

Keywords:
Buxa tiger reserve (BTR)
Elephant corridor
Human elephant conflict (HEC)
Killer railway tract
Land use land cover change (LULCC)

ABSTRACT

The land use land cover changes (LULCC) in and around wildlife habitat are one of the major driving forces behind frequent human elephant conflict (HEC). The present study aims to determine the spatiotemporal LULC changes and its impact on Human – Elephant conflict in and adjoining Buxa Tiger Reserve (BTR). Landsat TM and OLI images of 1990, 2000, 2010, and 2019 were used and supervised classification using maximum likelihood classification algorithm applied to classify the LULC attributes. Each sign of elephant presence was recorded using GPS used for corridor mapping. The recorded sign of conflict was collected, used for settlement based human elephant conflict probability zone identification mapping by areal interpolation method. We found that (1990 - 2019) dense forest, surface water bodies, scrub land and agricultural fallow land decreased by 184.04 sq km, 21.94 sq km, 142.48 sq km, and 130.21 sq km respectively. On the other hand crop land, sparse vegetation, tea garden, open forest, degraded forest and built up areas increased by 119.74 sq km, 90.96 sq km, 87.05 sq km, 57.02 sq km, 19.07 sq km and 32.21 sq km respectively. The visual overlay method was performed between LULC map, and settlement based HEC probability map, therefore impact of spatiotemporal LULC change on HEC was determined. It finds out moderate to very high HE conflict settlement zone lies where nearby forest tract either degraded or large areas of open forest, scrub land replaced into crop fields and settlements. In addition, elephant sign along the broad gauge rail line were collected on foot, recorded using GPS used to prepared accident prone susceptibility map by Inverse Distance Weighting (IDW) interpolation technique to estimate where accidents were more likely to occur due to the concentration of elephant activity. It finds out high to very high accident prone susceptible zone lies in between Rajabhatkhawa station (st) – Damanpur st, Gorapara st- Rajabhatkhawa st, and railway line within Hamiltonganj range. The study wants to draw attention to the concerned authority and policy makers on that there is a need of long term land use planning to save BTR forest and its biodiversity as well as need for proper mitigate method for HE conflict for peaceful coexistences of both the species.

1. Introduction

1.1. Background of the study

The land use land cover changes in and adjoining wildlife habitat is a leading driver of worldwide biodiversity loss and one of the major driving force behind frequent human – elephant conflict (Neupane et al., 2017; Billah et al., 2021). These land use influence the spatial patterns of HEC in both the habitat of Africa and Asia (Neupane et al., 2017). Land use defines human activities with respect of land; on the other hand land cover is the natural plaster or envelope on the land surface (Burley, 1961; Chamling and Bera, 2020). Land is the main source of the livelihood for millions of people (Desta and Fetene, 2020). Land use land cover (LULC) is an essential part in understanding the interactions between human activities with the physical environment. It is vital to monitor and detect the change to maintain a sustainable environment balance. Primarily LULCC has been studied in cases where it leads to severe environmental problems (Liu et al., 2009). LULC changes are the major issues of global environmental change (Andualem et al., 2018) and are important for addressing the geo-environmental impacts (Arnous et al., 2017). Change detection can be performed on temporal scale such as decades to assess LULC changes. Human activity can change natural land cover very quickly, as present land use practice focused on satisfying short-term supply of needs (Duraisamy et al., 2018). These changes lead to prolonged impact on flora and fauna that are not immediately noticeable. In today's world the intensity and degree of LULC change are far bigger than ever in history (Obeidat et al., 2019). The rate of LULCC is higher in developing country like India. Protected areas within and adjacent to forest boundaries face critical management threat because of changing LULC types (Wang et al., 2009; Bungnamei and Saikia, 2020) as a result the study area witnessed fre-

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https://doi.org/10.1016/j.envc.2021.100384
Received 12 July 2021; Received in revised form 15 November 2021; Accepted 18 November 2021

quent Human – Wildlife conflict. Conflict is a negative interaction between human and wildlife (Dhakal, 2016). There is no problematic wild species that puts the challenges of human- wildlife conflict like the elephant (Buchholtz et al., 2019).

The study area has been confronted with large- scale deforestation, intervened through the foundation of tea plantations, settlement development and crop cultivation (Prokop and Sarkar, 2012). Under the combined effect of population growth, the land for settlement, cultivable land, and so on dense forest adjacent open forest and scrub land are being stormed by local inhabitant, and are subject to traditional land use systems such as subsistence cultivation, commercial farming like tea, extensive livestock grazing, ground for firewood, non- timber forest products (NTFPs) collection, transportation, mining, tourism etc. (Hailu et al., 2020). The broad gauge railway stretch is a major threat for free movement of the elephant population in the fragmented forest habitat, as a result we witness number of elephant dash with train in this killer tract. All these LULCC on wildlife habitat can incredibly alter the chain of ecosystem service like supplies of food, water, and forage for wildlife (Mmbaga et al., 2017), as a results increasing transformation of natural habitat to human dominated landscapes, bringing elephants and humans into close contact and conflict. Increased settlement along regular and seasonal corridor intimidates with migration routes of elephant. Simultaneously, animal movements in the changed landscape may also impact people (Buchholtz et al., 2019) life and livelihood in and around corridor. The LULC change induced by anthropogenic activity may restrict or modify the tracks of animal movement lead to more casualties resulting losses in both sides in form of death, injury and property damage. According to MOEF 2010 in India, it is estimated that around 400 people are killed annually and elephant's rampage causes damage to 500,000 families through crop depredation in HEC related incidences (Gubbi et al., 2014). The BTR and its adjoining is not an exceptional one where people witness frequent HEC in different form and in different magnitude.

Using remote sensing techniques is suitable than traditional ground survey because it takes lesser time to detect the changes preceded through the area, as well as less expensive and provides real or nearly real picture of larger and physically inaccessible areas. Therefore multispectral satellite data at regular interval with geographical information system (GIS) provides suitable platform for data analysis (Muhati et al., 2018). Remote sensing (RS) is an alternative and attractive source of thematic maps such as those depicting land cover as it provides a map-like representation of the Earth's surface (Foody, 2002). Various types of satellite imagery and methods have been explored for providing a reliable and up-to- date information on LULC (Nguyen et al., 2018). The multispectral satellite images acquired periodically have a powerful capability to discriminate and quantify the LULC changes in space and time (Islam et al., 2016). Today RS and GIS both has emerged as a useful tool for monitoring ecological impacts, changes in green corridors and offering capabilities to detect, interpret floral and faunal habitat quality (Nandy et al., 2007; Areendran et al., 2020). Therefore, extensive study on LULCC pattern is crucial along with their social and environmental implications at different spatial and temporal scale (Islam et al., 2018; López et al., 2001). For decision making and administration purpose, rapid and precise information on existing LULC is required (Arulbalaji, 2019). The data on LULC change will provide key information for planning future management strategies for policy maker, land managers, conservation organization and developing resources as per requirements (Thakur, Sep. 2018; Thakur et al., 2020; Rimal et al., 2019).

It's an urgent need of time to solve the issue of HEC. There is no such study were conducted regarding the impact of LULCC on HEC in BTR and its adjoining areas. Therefore, a big research gap that has been found and the present study is an attempt to document and quantify the impact of LULC change on HEC in and adjoining areas of BTR. The present study sought to answer two specific questions, as follows:

(i) What were the spatiotemporal LULCC in and adjoining BTR took place from 1990- 2019?
(ii) If there is a relationship between LULCC and HEC existed in the study area?

The result of the study will be helpful for providing baseline information to management authority to propose future reasonable LULC planning and for taking action plan to mitigate HEC.

1.2. Geographic details of study area

BTR is a type II protected area according to the International Union for Conservation of Nature and Natural Resource (IUCN) list with an area of 761 km^2. Although to fulfill aims of the study the study area extended beyond protected forest, the geographical extension of present study is 26° 23′ 29.17″ N- 26° 51′ 2.49″ N and 89° 18′ 39.14″ E – 89° 52′ 37.92″ E with the total area of 1851 km^2. The study area is bounded by International border of Bhutan in the North, Cooch Bihar in the south, Torsa River in the west and Sankosh River in the east. Topography of the study area fluctuates, hilly areas in the north and undulating vast plain in southern part. Torsa, Kaljani, Sankosh are the major river, although several perennial in nature river and their tributaries like Rydak II, Gholani, Nonai, Dima, Doriya, Poro, Gadadhar, Checko, Pana, Bala, Jainty, Dhok, Basra, Gabbarjyoti, Gangutia, Narathali, Sikiajhora, and Dhantalighat river drained in the study area.

Tropically the area belongs to typical Sub- Himalayan geological formation. According to BTR annual report 2011- 12 the reserve has tropical moist humid monsoon climate, temperature varies from 10–32°C and average rainfall is 4100 mm. The floral endemic species, about 60% of northeast India are available in Buxa. No other Tiger Reserve (TR) of India except Namdapha TR matches Buxa in richness of floral species (Das, 2005). It is the home of Asian elephant, Bengal Tiger and many other endangered animals. The BTR and its adjoining areas are characterized by frequent human elephant conflict. The tribe of Chotonagpur plateau like Oraon, Minz, Munda along with few indigenous tribes (called them as Bhumiputra i.e. they are originated from the soil of study area) like Rajbanshi, Mech, Rava are the inhabitant of study area.Figure 1

2. Data sources and methodology

2.1. Satellite data acquisition and processing

The Landsat program was added to NASA's Earth Observing System in 1994, which is an integrated network of satellites devoted to the study of global change (Pax-Lenney et al., 2001). One of the most important uses of Landsat imagery is for monitoring environmental change, land use land cover change (Desta and Fetene, 2020; Teferi et al., 2013; Andualem et al., 2018; Arnous et al., 2017; Gong et al., 2017; Obeidat et al., 2019; Betru et al., 2019; Rimal, 2019; Abdullah et al., 2019; Zaidi et al., 2017), forest resource mapping and change detection (Negassa et al., 2020; Pasquarella et al., 2018; Townshend, 2012; Zhu et al., 2012). Landsat has the longest data record (since 1972) (Zhu and Liu, 2014), the policy of free, open access has greatly benefited operational application, scientific studies, and discoveries (Zhu et al., 2019). Maintaining the temporal gap, ortho-rectified Landsat images of 1990, 2000, 2010 (Landsat 4, 5 Thematic Mapper) and 2019 (Landsat 8 Operational Land Imager) were acquired from United States Geological Survey. To avoid misclassification all the image were collected in November and December. The satellite data were geo-referenced in Universal Transverse Mercator (UTM) Projection and World Geodetic System (WGS) 84 datum and North 45 zone. The images were preprocessed, mosaicking and the present study area was extracted using clipping and subsetting method.Table 1:

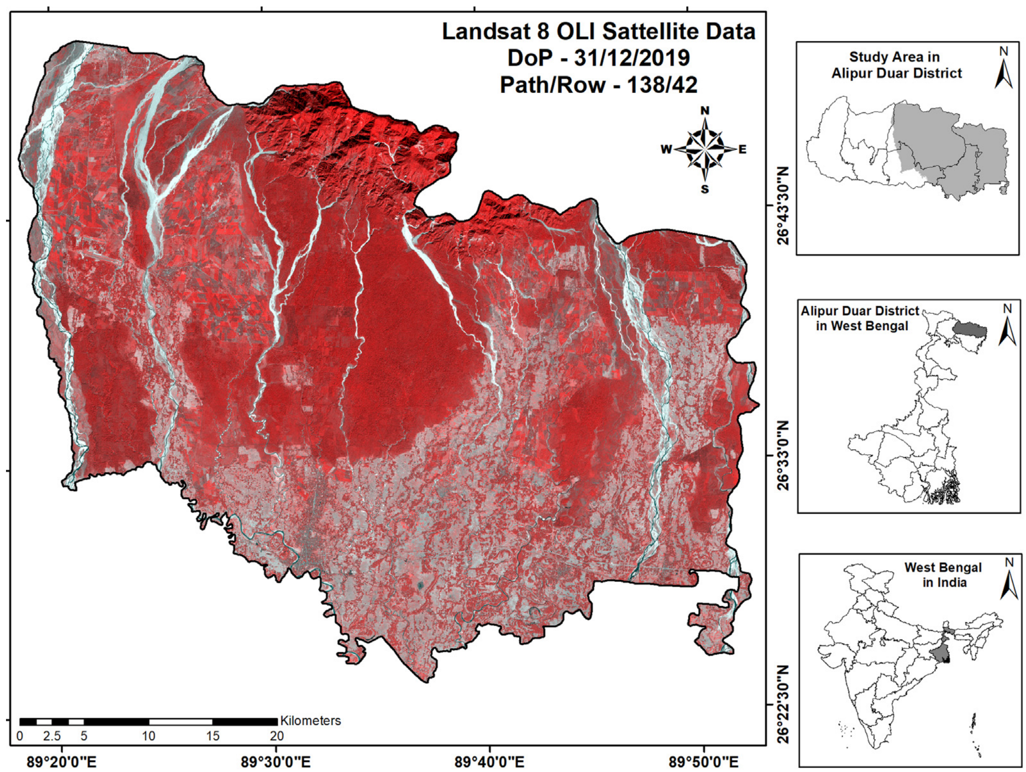


Fig. 1. Location map of the Study area.

Table 1
Specification of the analyzed satellite data.

Satellite	Sensor	Path/row	Spectral Resolution (μm)	Spatial Resolution	Band Details	Acquisition	Sources
Landsat 4	TM	138 & 042	0.45-0.52	30 m	Band 1= Blue	14-11-1990	USGS
Landsat 5	TM	138 & 042	0.52-0.60	30 m	Band 2= Green	18-12-2000	USGS
			0.63-0.69	30 m	Band 3= Red		
			0.76-0.90	30 m	Band 4= NIR		
Landsat 5	TM	138 & 042	1.55-1.75	30 m	Band 5= SWIR 1	05-11-2010	USGS
			10.41-12.50	120 m	Band 6= Thermal		
			2.08-2.35	30 m	Band 7= SWIR 2		
			0.433–0.453	30 m	Band 1= Coastal Aerosol		
			0.450–0.515	30 m	Band 2= Blue		
			0.525–0.600	30 m	Band 3= Green		
			0.630–0.680	30 m	Band 4= Red		
			0.845–0.885	30 m	Band 5= NIR		
Landsat 8	OLI	138 & 042	1.560–1.660	30 m	Band 6= SWIR 1	23-11-2019	USGS
			2.100–2.300	30 m	Band 7= SWIR 2		
			0.500–0.680	15 m	Band 8= Panchromatic		
			1.360–1.390	30 m	Band 9= Cirrus		
			10.6-11.2	100 m	Band10=ThermalInfrared1		
			11.5-12.5	100 m	Band11=ThermalInfrared2		

TM: Thematic Mapper, OLI: Operational Land Imager, USGS: United States Geological Survey, m: meter

2.2. Image classification

Image classification is the process by which each pixel of the original image is grouping and labeling to a LULC information class. Supervised classification is performed for the present study; it is the type of image classification which is mainly controlled by the analyst as the analyst selects the training pixels (Jog and Dixit, 2016). It was performed by applying maximum likelihood classification (MLC) algorithm on the images. The algorithms that is used by MLC tool based on Bayes' theorem (Srivastava et al., 2012). It is used the training data to estimates means and variances of class and compute the statistical probability, pixels are assigned to the class of highest probability (Mahmon et al., 2015). It is the most powerful classification method if accurate ground truth training data (polygons that represent sample areas with particular categories of land cover) is provided. The training samples were collected randomly. For each type of LULC classes minimum 5 sites have been chosen. Therefore, 13 individual classes of LULC were identified. To avoid misclassification, these LULC classes were further checked with field level observations and secondary information in terms of Google EarthProTM data.Table 2

Table 2
Land use land cover classes delineated.

Sl. no.	Class	Description
1	Dense Forest	Areas with tree canopy cover 40% and above were considered as dense forest while tree canopy cover between 10 and 40% was considered open forest and area less than 10% canopy density was considered as scrub land
2	Degraded Forest	
3	Open Forest	
4	Scrub land	
5	Sparse Vegetation	Area thinly covered with scattered vegetation with rural settlement
6	Surface Water Bodies	Manmade and natural water bodies including wet lands
7	River	River and its tributaries with natural Jhoras (small stream), area cover with river wet and dry sand.
8	River Wet Sand	
9	River Dry Sand	
10	Crop land	Land designated for cultivation.
11	Agricultural Fallow	Land designated for cultivation but not being used.
12	Tea Garden	Area covered with tea plantation
13	Built up areas	Settlements, commercial and industrial establishment etc.

2.3. Accuracy assessment

The accuracy assessment estimates the actual difference between the classification and the reference map or data (Negassa et al., 2020). Accuracy measures based on the proportion of area correctly classified are then calculated from the number of pixels that are correctly classified (Lewis and Brown, 2001). The ground truth data in the form of reference data points (100 points) was collected using Geographical Positioning System (GPS) from January to October 2019 for 2019 image analysis, used for image classification and accuracy assessment of the results. For earlier years (1990, 2000. 2010) the ground samples (100 point for each year) have been chosen from Topographical sheet, Google Earth Map of respective times and previous published research work. The ideal method for the estimation of the correctness of a classified image is the "error or confusion matrix" (Foody, 2002; Prasad and Ramesh, 2018; Ahlqvist et al., 2000). It is appropriate for traditional methods of classification (Lewis and Brown, 2001) and the most commonly used accuracy estimation method (Yi and Zhang, 2012). Therefore, the classified map and the ground reference test information are compared by a confusion matrix. The content of a "confusion or error matrix" is a set of values accounting for the degree of similarity between a controlled data set and a reference data set (e.g. ground truth) (Ariza-López et al., 2018).The nonparametric Kappa coefficient, which is used to quantify the classification accuracy required for all elements, including the diagonal ones (Prasad and Ramesh, 2018; Coppin and Bauer, 1996; Foody, Oct. 2010). Therefore, the accuracy assessment includes an error matrix, producer's and user's accuracy, an overall accuracy, and Kappa statistics. The formulas of producer's and user's accuracy, overall accuracy, and Kappa statistics are following below:Eqn 1

$$Producer's\ Accuracy = \frac{Total\ number\ of\ pixels\ in\ a\ category}{Total\ number\ of\ pixels\ of\ that\ category\ derived\ from\ the\ reference\ data\ (i.e.,\ row\ total)}. \quad (1)$$

Eqn 2

$$User's\ Accuracy = \frac{Total\ number\ of\ pixels\ in\ a\ category}{Total\ number\ of\ pixels\ of\ that\ category\ derived\ from\ the\ reference\ data\ (i.e.,\ column\ total)}. \quad (2)$$

Eqn 3

$$Overall\ Accuracy = \frac{Sum\ of\ diagonal\ elements}{Total\ number\ of\ accuracy\ sites\ pixels\ (column\ total)} \quad (3)$$

Eqn 4

$$\text{The Kappa statistics (K)} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} x x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+} x x_{+i}\right)}. \quad (4)$$

Where, N = total number of samples in the matrix, r = the number of rows in the matrix, x_i = the number in row i and column i, x_{+i} = the total for row i, and x_{i+} = the total for column i.

2.4. Land use / land cover change analysis

Change detection is the operation of comparing two multi-temporal images of the same geographical area acquired in order to map, analyze and estimates spatial patterns of change. Arrays of techniques are available to monitor and detect land- cover changes from multi- temporal remote sensing image data sets (Coppin and Bauer, 1996; Hayes and Sader, 2001). Many change detection analysis methods have been developed in the last few decades like image differencing, post classification change matrix, comparison technique and principal component analysis (Hussain et al., 2013; Mishra et al., 2020). In the algebra-based change detection category, image differencing is the most common used change detection method in practice (Lu et al., 2004), Image algebra (Image differencing) is a pre- classification change detection techniques (Knight et al., 2017) that evaluate and compare pixel by pixel (Lu et al., 2004; Knight et al., 2017) on the multi-date images to reveal changes between acquisition dates. It was performed by subtracting the DN value of one image for a particular band from the DN value of the corresponding pixel in the same band of the second image.

Mathematically, it is express as -Eqn 5

$$\begin{array}{lll} \text{Difference image,} & D(x) = I2(x) - - I1(x) & (i) \\ \text{Change mask,} & B(x) = 1 \text{ if } |D(x)| > T & \\ & \quad 0 \text{ otherwise} & (ii) \quad (5) \end{array}$$

Where, I1 &I2 = images from time t1 and t2; x = coordinates of each pixel value; D = difference image (Kotkar and Jadhav, 2015)

2.5. Field survey

The past 5 years record (2011- 12 to 2015- 16) of injury and death of people were collected from BTR east and west division. As proper location of conflict in case of injury and death is difficult to find out from office data GPS location of settlement center taken as a reference point of conflict. The office record on HEC inside forest was not taken into consideration for the study because to locate actual place of conflict inside forest is often more difficult. Each and every single reference point of conflict on settlement was recorded by GPS and mapped using ArcGIS software v9.0. In addition, the sign of elephant presence like footprint sign, dung sign, feeding sign, sign of damaged hut and part of house was recorded by random sampling unit using GPS and used to validate the map.

2.6. Questionnaires survey

Cochran's (1977) rule of thumb was adopted for infinite population used to determine the sampling size. After that, questionnaires survey on 500 individual were carried out to know the location where peoples witness conflict in recent past, type and form of conflict, time of conflict, season of conflict, type of elephant (Bull or Cow/ Solitary or elephant herd) raid crop, type of crop raid, pattern of land use/ cover change they noticed.

2.7. Corridor mapping and settlement based conflict probability mapping

Moreover, location of settlement was extracted from LULC classification image (2019) and elephant movement map (corridor map) was prepared by extensive field study and literature review. Each sign of elephant presence was recorded using GPS in corridor (non-forested) area and plotted in ArcGIS. Finally corridor map with 2 km buffer area was created for each corridor. The conflict map was generated based on two criteria i.e. habitation and connectivity. By overlying the settlement index map and corridor map the settlement based conflict probability map was developed.

Therefore, the conflict area was validated based on random sign of elephant presence, literature review (Naha et al., 2019) and historical database. Finally, areal interpolation technique was applied to identify and prepare the human elephant conflict probability zone of entire study area. The method of areal interpolation is the aggregation of data from source polygons to the target polygons, it is more commonly associated with geographical analysis than any other fields (Comber and Zeng, 2019; Lam, 1983). Areal interpolation was performed by weightage overlay analysis techniques. The Mean Error and Root Mean Square Error (RMSE) were used to measure accuracy assessment of the HEC probability zone model (1).

2.8. Railway accidental prone zone identification

Primary information on elephant deaths due to train accidents between 1996 and 2014 was obtained from DFDs offices of BTR East and West division and the Alipurduar Divisional Railway Manager's Office. The survey was done along a 33 km stretch, excluding a part of the railway station on foot, aiming to detect elephant signs (dung, tracks, footprints, feeding signs), as well as direct sightings, on both sides of the track, up to a distance of 8 - 10 m. Elephant sign were recorded through handheld GPS device and GPS-referenced points were plotted on Arc GIS 9.0. Using the spatial distribution of elephant signs, a point layer (.shp) was generated. The weightage based on the elephant sign was integrated; the "susceptibility map" was prepared using Inverse Distance Weighting (IDW) interpolation technique. IDW interpolation considers a number of known values at sampling sites to calculate unknown values at a gridded area. The Mean Error and Root Mean Square Error (RMSE) were used to measure accuracy assessment of model (2). Mathematically, the IDW formulation is written as follows:Eqn 6

$$\hat{q} = \frac{\sum_{i=1}^{n} \frac{1}{r_i^{\alpha}} q_i}{\sum_{i=1}^{n} \frac{1}{r_i^{\alpha}}}. \tag{6}$$

Where, $\hat{q}$ = interpolation target value; q_i = known value at location I; r_i = distance between the target and known value at location I; α = weighting factor; n = number of known data consider in the interpolation.

2.9. . Impact assessment

Finally, visual map overlay method was performed between LULC map and settlement based HE conflict probability map to determine the impact of LULC change on HEC. It is the oldest and simplest method of impact assessment. In map overlay process, a series of overlaid map transparencies can be used to help identify, predict and communicate the intensity and geographical extent of impacts.

Table 3
Summary of the model 1.

Mean	1.57
Root Mean Square	13.28
Regression function	0.931648373775713* x + 5.40794209360424
Smoothing factor	0.2
Power	1.79

Table 4
Summary of the model 2.

Smoothing Factor	0.02
Major Semi axis	0.065
Mean	0.298
Root Mean Square	0.944
Regression Function	0.041 * x + 2.266

3. Result and analysis

3.1. Accuracy assessment

The Kappa statistics (agreement between classification and reference data) used for accuracy assessment show strong agreement; it was 0.84, 0.87, 0.90, and 0.92 for 1990, 2000, 2010, and 2019 respectively. Whereas, overall accuracy was 87% for 1990, 89% for 2000, 92% for 2010 and 94% for 2019 estimated. In this study change detection of LULC classes in and adjoining BTR was estimated between the years 1990 – 2000, 2000 – 2010, 2010 – 2019 and 1990 – 2019.Figure 2:

3.2. Land use land cover change detection

In the time period of 1990–2000, a major shrink were noticed in dense forest cover, about 103.53 sq km., declining trend were observed on surface water bodies by 5.55 sq km, scrub land by 83.72 sq km and agricultural fallow land by 27.78 sq km. On the contrary, dominant increasing trend on LULC classes were noticed on crop land by 62.11 sq km, followed by tea garden (52.97 sq km), river wet sand (37.56 sq km), sparse vegetation (27.10 sq km), open forest (14.03 sq km), degraded forest (6.39 sq km) and built up areas (3 sq km).

Similar declining trend on LULC classes were noticed in the following decade (2000- 2010), about 26.84 sq km dense forest cover lost. Surface water bodies were also decline by 2.54 sq km, scrub land by 41.73 sq km and agriculture fallow land by 39.18 sq km. Major increasing trend were observed on crop land (41.40 sq km), sparse vegetation (34.91 sq km), and built up areas (7.92 sq km). A good dense forest cover were converted to degraded forest by 7.22 sq km and degraded forest cover change to open forest cover by 4.11 sq km within the decade.

In-Between 2010–2019, about 53.68 sq km dense forest cover (more than twice of last decade) were dramatically disappeared. A substantial amount of surface water bodies (13.84 sq km) were reduced, similarly decline trend of scrub land by 17.03 sq km and agricultural fallow land by 63.25 sq km was noticed. On the other hand, dominant increase on LULC classes were noticed on open forest cover by 38.88 sq km and built up areas by 21.29 sq km. The increasing trend of sparse vegetation by 28.95 sq km, tea garden by 26.06 sq km, crop land by 16.23 sq km, and degraded forest cover by 5.46 sq km were recorded.

The result of LULC classes change in between 1990 and 2019 was shocking. A large portion of good dense forest cover (184.04 sq km) was disappeared; dramatic decline of surface water bodies by 21.94 sq km, scrub land by 142.48 sq km, and agricultural fallow land by 130.21 sq km took place within three decades. Whereas, substantial area of increase were noticed in case of crop land (119.74 sq km), sparse vegetation (90.96 sq km), tea garden (87.05 sq km), open forest cover (57.02 sq km), built up areas (32.21 sq km), and degraded forest cover (19.07 sq km). Figure 3

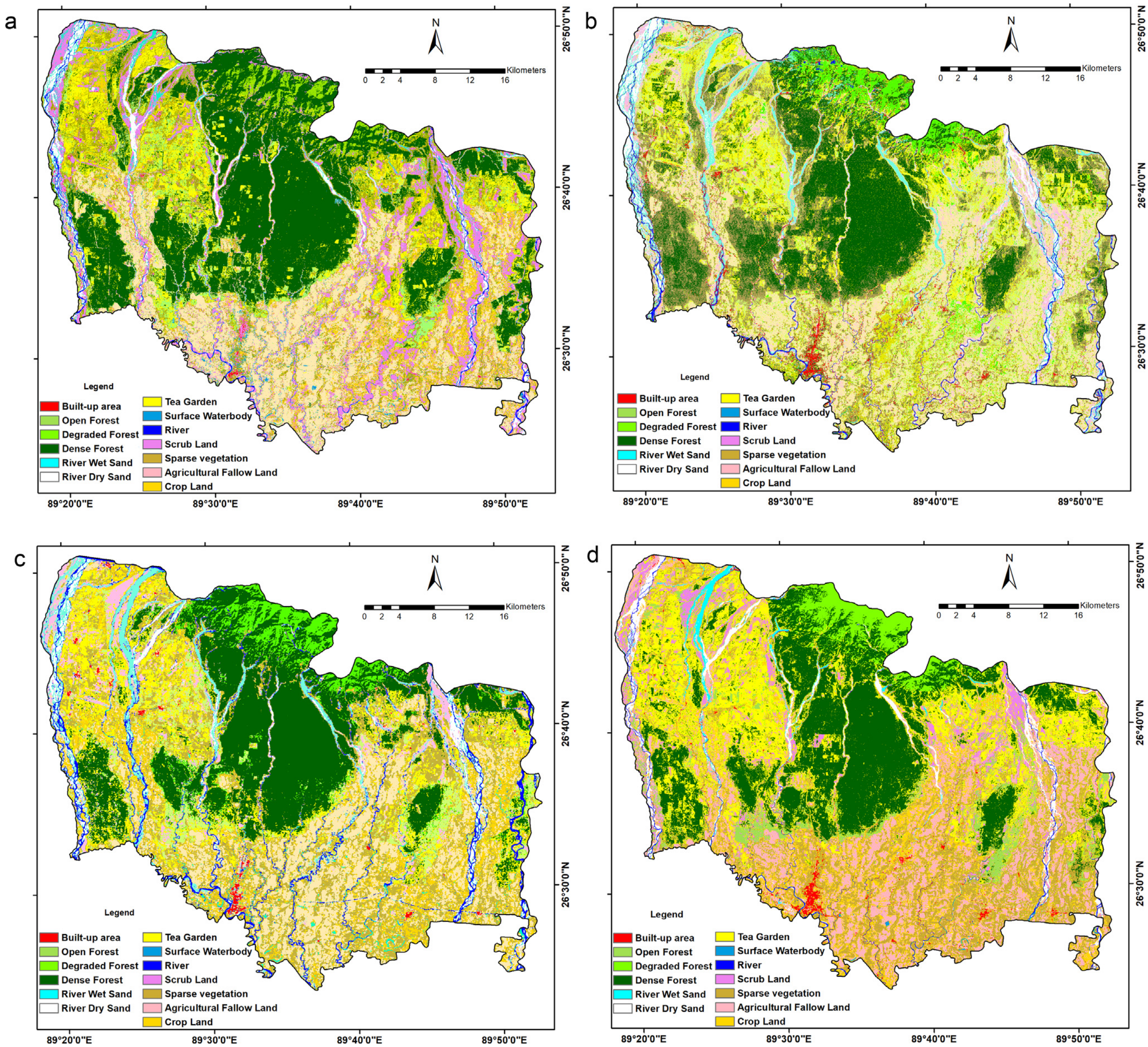


Fig. 2. (a) (b) (c) (d) – Land use land cover classification Map of (Landsat 4, 5 TM) 1990, 2000, 2010 images and (Landsat 8 OLI) 2019 image.

3.3. Human elephant conflict probability zone identification

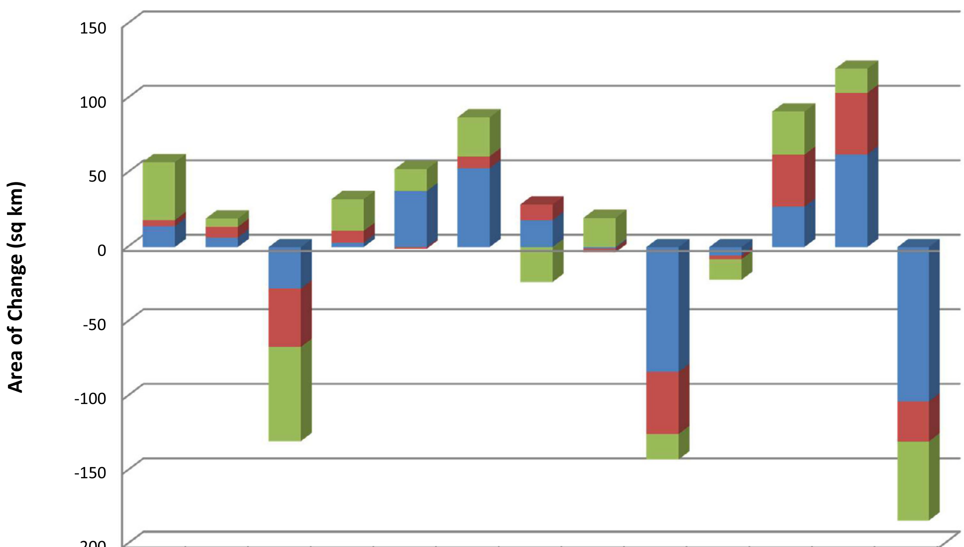
The model (1) runs with considering the smoothing factor of 0.2 and power of 1.79. To determine the validity of model mean error and root mean square error was estimated, it was 1.57 and 13.28. The conflict probability zone was divided into five categories. The very high, high, medium, low and very low HEC probability zone was represented in the map by red, orange, yellow, dark green and light green respectively. The results show that HEC probability zone interspersed with the enclave forest village, forest peripheral villages and corridor dependent villages. Another model (2) runs considering the smoothing factor of 0.02 and major semi axis of 0.065 for prepared the accidental prone susceptibility map on broad gauge railway line. Accuracy of the model was determined by mean error and root mean square error, it was 0.298 and 0.944. The accident prone vulnerability zone from low to very high on railway line was represented in Figs. 4, 5 and Tables 3, 4.

The outcome of questionnaires survey reveals that out of 500 inhabitants 215 (43%) witnessed some sort of conflict in the last year, most of the conflict incident took place at crop fields in the time of paddy and maize cultivation season during night, both solitary bull, small temporary group of bull and elephant herd raid crop. However, elephant raid store grain, homemade liquor, other vegetable and ripe fruit throughout the season.

The presence of broad gauge killer railway tract causes several deaths of wild elephant in this area. Due to laying meter gauge one elephant collided with a train in 1996 near Hamiltonganj and another in 2001 near Rajabhatkhawa. After broad gauge conversion 16 elephants died with the collision of high speed trains. The accident prone zone identification map along the railway reveals that high to very high accident prone susceptible zone lies in between Rajabhatkhawa st – Damanpur st (Railway Km Post (RKP) 158/5 – 164/5), Gorapara st – Rajabhatkhawa st (RKP- 152/5- 157/5), and railway line within Hamiltonganj range (RKP 137/5- 140/5).

3.4. Land use/ cover change impacts on human elephant conflict

There is a significant cause effect relation between LULCC on HEC. Form the visual overlay, it easily interprets from both the LULC images



	Open Forest	Degraded Forest	Agricultural Fallow	Built-up Land	River Wet Sand	Tea Garden	River	River Dry Sand	Scrub Land	Surface Water bodies	Sparse Vegetation	Crop Land	Dense Forest
2010 - 2019	38.88	5.46	-63.25	21.29	14.73	26.06	-23.33	19.53	-17.03	-13.84	28.95	16.23	-53.68
2000 - 2010	4.11	7.22	-39.18	7.92	-1.04	8.02	10.51	-2.75	-41.73	-2.54	34.91	41.4	-26.84
1990 - 2000	14.03	6.39	-27.78	3	37.56	52.97	18.09	-0.67	-83.72	-5.55	27.1	62.11	-103.53

Fig. 3. Diagrammatic representation (including table) of decadal land use land cover change for the period of 1990 – 2000, 2000 – 2010, and 2010 – 2019.

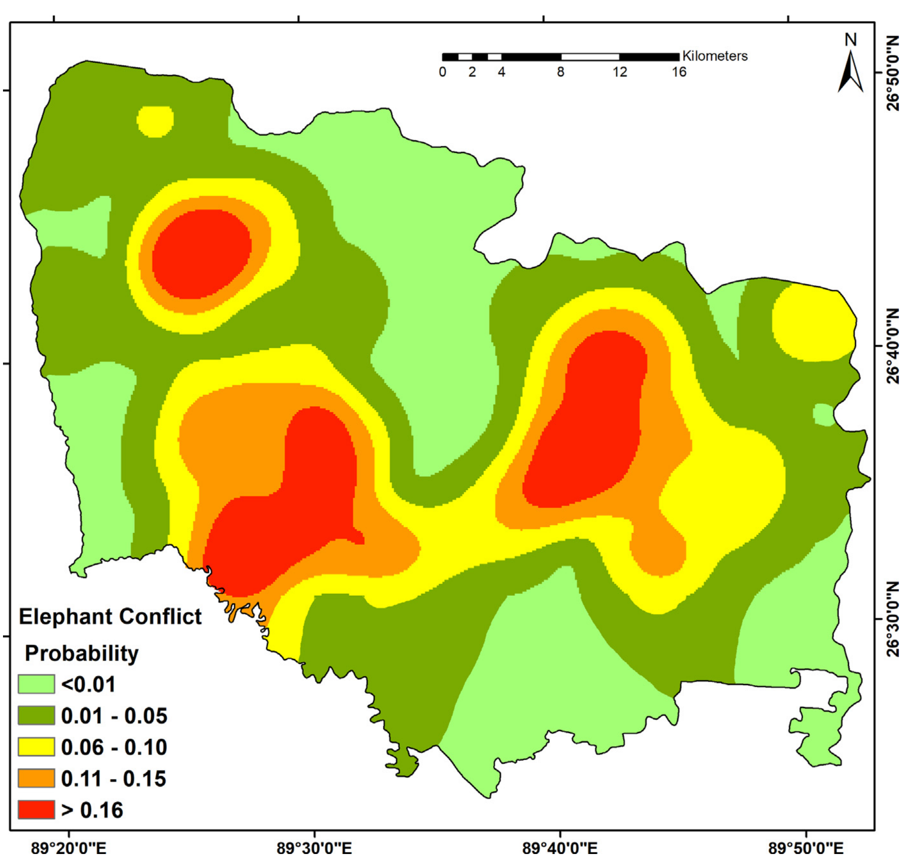


Fig. 4. Settlement based Human – Elephant Conflict Probability zone Map.

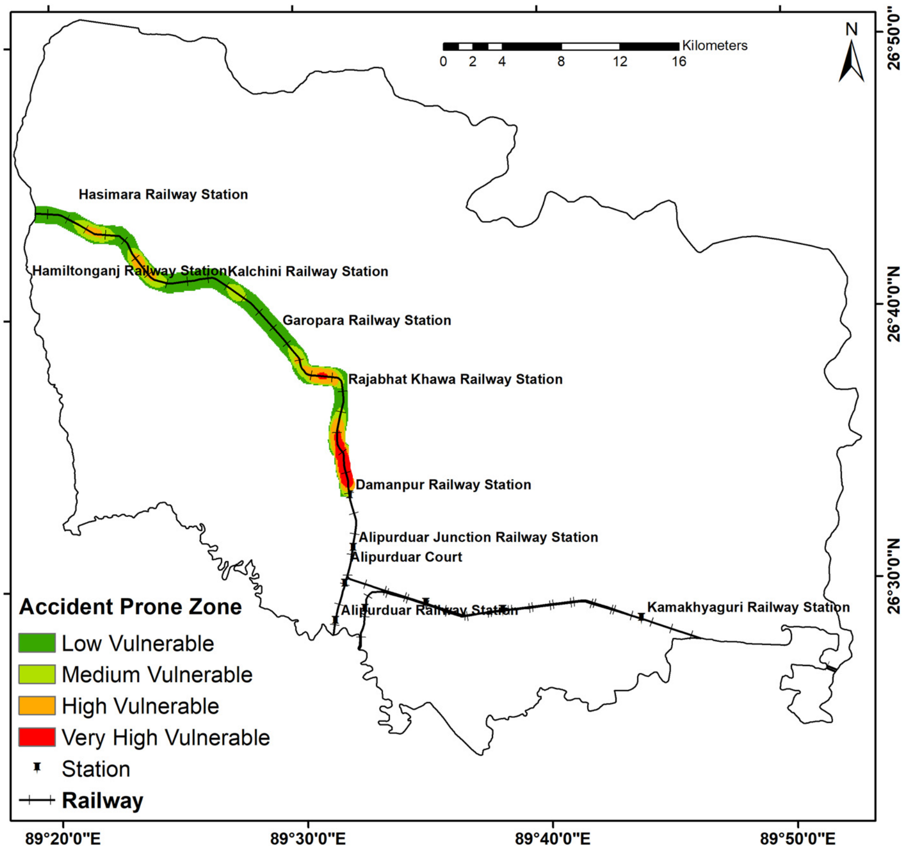


Fig. 5. Accidental prone zone identification Map on Killer railway tract.

of 1990 and 2019 that large areas of forest lands on godamdabri, barnabari, rangamati, bhutri, pana, nimati west, poro west, poro east, west rajabhatkhawa, of BTR west division and kartica, chuniajhora, hatipota, Mainabari, teamari, marakhata, narathali, kumargram, sankosh, changmari, balapara, ghoramara, barobisha beats of BTR east division converted to tea garden, crop land, scrub land, and built up area. Similarly, the result of settlement based conflict probability map reveals that moderate to very high HEC probable zone coincide with the enclave forest village, forest peripheral villages and corridor dependent villages where (the nearby forest beat which discuss before) large scale forest degradation took place or adjacent open forest, scrub land replaced into crops land and settlements. The enclave forest village and peripheral forest village like Bhutri Forest Village (F.V), Dalbadal F.V, Gangutia F.V, Pampubasti F.V, Panijhora F.V, Rajabhatkhawa Fixed Demand Holding (village leased to timber merchant in colonial period) Village, Poro North F.V, Poro south F.V, east Garam F.V, Uttar (north) Dhalkar, Gadadhar F.V, Nurpur, Teamari F.V, Dhantali, Lalchandpur, Narathali, Uttar (north) Narathali, Marakhata, Chipra F.V, Choto Chowkibus are located on medium to high and very high conflict probability zone. The corridor dependent settlement like Tea Garden (TG) labor colony of Bharnobari, Dalsingpara, Beech, and Ran Bahadur Basti, Gopal Bahadur Basti under Bharnabari – Beech Corridor; Nimati – Domohani, Uttar (north) and Dakshin (south) Mandabari under Nimati – Mendabari corridor; Nimtijhora TG labor line, Uttar (north), Madhya (middle) and Dakshin (south) Paitkapara under Nimtijhora – Chilapata corridor; Nurpur, Hatipota, Turturi, and TG labor line like Kartika, Chuniajhora under Panbari – Kartika corridor; TG labor line of Turturi, Dhowlajhora, Kartika, Mainabari under Kartika – Rydak corridor are situated on medium to high conflict probability zone. On the other hand, Torsa and Dalsingpara TG labor line under Gabbarjyoti – Titi Corridor; New Land F.V, Kumargram F.V, Sankosh F.V, TG labor line of Kumargram, New Land and Sankos are under medium conflict probability zone under Kumargram – Bhalka corridor. Forest village like Lapraguri, Khuttimari, Bengdoba and Uttar (north), Madhya (middle), Dakshin (south) Haldibari falls under less conflict probability zone as there is either occasional movement of elephants or elephant movements take place along the riverine flood plain under Sankosh – Bhalka corridor. The another reason is that Bhalka forest is less suitable habitat for elephant due to present day high rate of forest degradation and fragmentation. Recently the urban town area like Alipurduar, Damanpur, Kalchini, Hamiltonganj witnessed the presence of elephants/ elephant herds, though it lies on low to very low HEC probability zone, as no conflict incident has taken place in these areas.

4. Discussion

4.1. Land use land cover change

LULC change is not a newly introduced problem in and around BTR; the changes took place when British rulers took the charges of the territory after Indo – Bhutan War in 1865. Ghosh and Ghosal (2019) illustrated several causes of forest degradation took place since colonial period in western Dooars i.e. large tract of land declared as wasteland to promote tea cultivation, introduced of sal, teak forest by Tangua system, clear- cut felling of forest for enormous demand of sal and teak in European and local market, making railway slipper, furniture for Royal British navy, and other purpose. The British forestry practices and settlement policies completely changed BTR natural landscape by the start of 20th century. Today, timber trafficking and cut of young trees, sampling by inhabitants and govt. organization for agricultural expansion, infrastructural development, firewood and NTFPs collection, encroachment and replace of open forest and scrub land into tea garden, crop land and settlement by inhabitants and private companies are the major causes for forest degradation. Form a century ago, forest inhabitants are residing within and adjoining BTR, it is revealed that more than half about 54% of total families are sustaining their life and livelihoods (Das, 2005) either they use NTFPs for their domestic purpose or it used to generate supplementary income by selling it in local market. The increasing trend of degraded forest and open forest cover class is a sign of unhealthy forest habitat quality and these areas are not suitable for large herbivore like elephant. Good dense forest was degraded and ultimately converted as degraded forest and open forest cover, open forest cover became scrub land and scrub land consists with sparse vegetation owing to continuous LULC change. The development and expansion of existing linear infrastructure like rail and roadways lead to forest fragmentation and further aggravated the deterioration of elephant habitat. Surface water bodies have decreasing trend due to over exploitation and filling of surface water bodies. Tea garden is a dominant industry of Dooars since British India and from 1990 till today tea garden areas have shown an increasing trend in areal coverage. Most of the tea garden was located in the periphery of forest. The dominant economy of the region is based on TTT i.e. Timber, Tea, and Tourism. The BTR is familiar for good Sal (Shorea robusta) forest, and timber extraction is one of the main causes of deforestation. The expansions of existing and newly developed tea garden replace forest adjacent open forest and scrub land. Large numbers of immigrant from Chotonagpur, Nepal settle down a century ago in the tea belt. The tourism is based on forest and wildlife in BTR and adjacent Jaldapara National park. The tourism also plays negative impact on land cover and wildlife. In addition, the presences of hotel, restaurant, home stay adjacent to park, forest safari activity causing pollution, habitat destruction and so on. The increase of built up areas is a sign of population growth and urbanization. There are several political and infrastructural reason of population growth like dolomite mining in last century, establishment of tea garden, establishment of forest villages under Taungya ('Taung refers to hill' and 'Ya refers to cultivation') Act 1894, and migrants from Bangladesh in 1947, during the partition of British India and later during 1971 freedom fight movement were settled down in and around BTR. The increase of crop land area and decline of substantial agricultural fallow land indicates the increasing dependency of inhabitant on agriculture in the study area. Owing to combined effect of population growth, expansion of settlement, agricultural land, and infrastructural development like rail, road the forest habitat of elephants are being degraded and fragmented.

4.2. Human elephant conflict

BTR is the largest intact forest patch of the elephant reserve in North Bengal, during 2012 elephant census of BTR reported presence of 215+ elephants. The study area falls under Eastern Dooars Elephant Reserve. The New Lands, Hatipota, Buxaduar, Bhutanghat, Santrabari, Bhutri, Rangamati and Damanpur forest beat under BTR consists its Core area. The Buffer area of elephant reserved consist of Titi, Dalsingpara, Jaigaon, Hasimara, Mendabari, Godamdabri, Hamiltonganj, Nimati, Poro, Raimatang, North Rajabhatkhawa, South Rajabhatkhawa, Cheeko, part of Raidak forest block, North Bhalka, and South Bhalka.

The BTR annual report of 2011- 2012 to 2015- 2016 reported that 48 deaths and 70 injuries of human took place in the adjoining settlement of BTR in this time periods. From the questionnaires survey it reveals that around half (43%) of the villagers witness conflict, most of the conflict took place in human occupied landscape on crop fields and settlements in between 6 P.M to 6 A.M. during the paddy and maize season. The forest department has to pay large amount of compensation for crop depredation. In the annual report of BTR 2013–14 and 2014- 15 reported that in this period 6758.30 Bigha and 4414.05 Bigha (3.03 Bigha= 1 Acre) crop were depredated by wild elephants. The report of 2014- 15 also reveals that in this period 2889 numbers of family faced crop depredation and government has to paid Rs. 27.55 lakh as a compensation. On the other hand Broad gauge railway killer tract in forest area is a major threat for survival of many wild elephants. During the time of meter gage trains movement 2 elephants were collided with train in 1996 and 2001, while after gauge conversion 13 times elephant collided with train lead to 16 deaths.

Several push factor like change of forest health/ habitat, using every corner of their previous habitat, less in forage quantity and low grade of forage quality, changing of food behavior; pull factor like presence of high nutritional food crop in close proximity, homemade liquor, learned behavior are responsible for frequent human elephant conflict in these settlement. To provide food of growing population natural habitats and its adjoining have been converted to croplands in an alarming rate (Branco et al., 2019) lead to crop depredation. Elephant love to eat mature crops. There is several reason behind crop depredation suggested by different scholar i.e. Crops may be more nutritious (Sukumar, 1989; Sukumar, 1991), unpredictable behavior of male elephant (Sitati et al., 2003) etc.

The conflict has several other associated impacts such as it creates challenge to conservation activity, reduce wellbeing attitude of inhabitants towards problematic animals (Abdullah et al., 2019; Chakraborty and Mondal, 2013; Jasmine et al., 2015; Nsonsi et al., 2017; Vasudev, 2020; Talukdar and Choudhury, 2020), reduce people's economic stability (Webber et al., 2011), physical problem like insomnia during crop guard, injury and mutilation leading to permanent disability, cultural problem like refuse to marry a man those were inhabited or guard crop at night in conflict prone areas etc.

4.3. Land use/ cover change impacts on Human elephant conflict

The massive LULC changes on forest land, adjacent forest boundaries and along the corridor reduce the habitat suitability of wild elephants. The outcome of both LULC maps and HEC maps reveals that from 1990 to 2019 crop field and settlement increased by 119.74 sq. km and 32. 21 sq. km. The result of settlement based HEC probability map showed that conflict was coincided with crop fields and settlements in enclave forest settlement where elephant could enter from all direction, forest peripheral settlement where elephant might enter from one side and corridor dependent settlements. The establishment of crop fields and settlements were the product of LULC change by human activity and occurrences of frequent conflict in these human occupied areas proved that there is a significant relationship exists between LULCC and HEC.

In 2003 the killer railway tract was converted from meter gauge to broad gauge line and train movement started in 2004. Before broad gauge trains that ran on this tract had limited speed, after 2004 the speed became so high that elephant collide several times with train while passing through from one forest patch to another, or passing through settlements, tea garden mainly on paddy and maize season. Elephants food habit change, presence of high nutritional food crop and homemade liquor in close proximity is one of the major reasons of conflict in agricultural field and houses where elephant raid crop, store grain or homemade liquor. Elephants love to eat derivatives of plants from the Gramineae family, which includes maize, paddy and some Solaneceae family, which include potato and some vegetables. Elephants also seemed to love homemade liquor, in many cases when they get the smell they tear down houses in search of the liquor. The fragmented habitat of BTR forest was unable to sustain large number of such big herbivore. Therefore, elephants tend to use each and every corner of their previous habitat, as a result their movement continued beyond protected forest. There are several international, interstate, and inter-district corridors present which are used by elephant generation after generation before the establishment of settlement. Corridors are passages of land wherein wild animals pass from one forest habitat to the other. Being a large herbivore of earth elephants need green fodder which is more than 130- 160 kg per day, so migration from one forest patch to another is necessary for an elephant. In addition, these corridors connect population, facilitate gene flow; provide resources to animals passing through, reduce fatalities due to train accidents, mitigate human elephant conflict, and reduce negative impact of forest fragmentation on wildlife. After establishment of number of settlements, tea gardens and its labor line, agricultural fields, and linear infrastructure for transportation, the suitability of corridor reduced inform of declining forest and vegetation cover, surface water bodies which is essential for life. It also led to conflict associated problem around crop land, near artificial water sources in corridor. Natural habitat of the corridor paths was replaced by human dominated landscape like settlement, crop land, and tea garden reduced the width of corridor even sometimes blocked these paths leading to more casualties associated with HEC in these corridor.

5. Conclusion

In BTR and its adjoining areas face anthropogenic induced threat due to intense human pressure. The development of linear infrastructure like rail, road causes forest fragmentation and forest degradation. To pluck out resources i.e. NTFPs, fire wood, fodder, medicinal plant and infrastructural development like rail, road the stress on forest land increased day after day. The need of agricultural land, land for tea plantation and unscientific settlement or labor line causes encroachment on peripheral forest land as well as change the natural landscape on elephant corridor which led to reduction of connectivity between habitats, sometimes even blocked as a result wild elephants roam outside the forest leading to frequent conflict. The outcome of the study supported the fact that there was dramatic LULC change took place in the last three decades. There was a substantial decline of dense forest cover by 184.04 sq km, scrub land by 142.48 sq km, surface water bodies by 21.94 sq km and agricultural fallow by 130.21 sq km. On the other hand, there was an increase of crop land by 119.74 sq km, sparse vegetation by 90.96 sq km, tea garden by 87.05 sq km, open forest cover by 57.02 sq km, degraded forest cover by 19.07 sq km and built up areas by 32.21 sq km took place within the last three decades. As a result human and elephants come frequently in each other's contact which leads to loss of both species. The result of the study found that HEC coincide with the human occupied changed landscape adjacent to forest and corridor. Crop fields and settlements were vulnerable hotspot point where frequent HEC occurred. The situation will more complicate in near future. Finding the areas where LULC changes have took place will help to fill the gap necessary to lead to prioritization in forest management, wildlife conservation, and biodiversity policies (Batar et al., 2017). Therefore, it's an urgent need to introduced long term land use planning to save BTR forest and adjoining natural habitat. This initiative will help to restore forest habitat and in the same time reduce the frequent occurrence of Human – Elephant Conflict to some extent.

Funding

This research did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interes

The authors declare that they have no competing interests.

Acknowledgements

The authors would like to thank Mr. N.S. Murli, former CCF, BTR for providing valuable input in many ways whenever required. We also express our sincere gratitude to United State Geological Survey. We wish to place on record our thanks to the several governmental organization, local teachers and people for providing valuable information on land use land cover change and Human – Elephant Conflict.

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