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Mapping human–wildlife conflict hotspots in a transboundary landscape, Eastern Himalaya

Prashanti Sharma [a], Nakul Chettri [a, *], Kabir Uddin [a], Kesang Wangchuk [a], Rajesh Joshi [b], Tandin Tandin [c], Aseesh Pandey [b], Kailash Singh Gaira [b], Khadga Basnet [d], Sonam Wangdi [c], Tashi Dorji [a], Namgay Wangchuk [c], Vishwas Sudhir Chitale [a], Yadav Uprety [d], Eklabya Sharma [a]

[a] *International Centre for Integrated Mountain Development, Kathmandu, Nepal*
[b] *G B Pant National Institute of Himalayan Environment (NIHE), Sikkim Regional Centre, Gangtok, India*
[c] *Nature Conservation Division, Department of Forests and Park Services, Thimphu, Bhutan*
[d] *Research Centre for Applied Science and Technology (RECAST), Tribhuvan University, Kathmandu, Nepal*

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ABSTRACT

The Kangchenjunga Landscape, an important repository of biodiversity, faces several challenges owing to various drivers of change. Human–wildlife conflict (HWC) is one of such issue that transcends social, economic, environmental, as well as national and international borders among the three participating countries — Bhutan, India, and Nepal — making it a complex, transboundary issue. Based on the existing literature, earth observation data, and geographic information system, we used maximum entropy along with relevant environmental predictor variables to model and map HWC hotspots. The results suggested that about 19 per cent of the area within the landscape is at high risk of human–wildlife conflict, with an anthropogenic factor – distance to roads – as the top predictor. Some protected areas are at higher risk than others. The Himalayan subtropical pine forest ecoregion is a high HWC zone (~63 per cent), followed by the Terai–Duars savannah and grasslands ecoregion (~43 per cent). They also revealed that the low- and mid-elevation zones are prone to conflict due to greater forest fragmentation; patchy protected areas are disconnected from each other, and not big enough for large mammals like elephants and tigers. Human-wildlife conflict is observed to vary across different elevation and climate region of the landscape and highly correlated with forest fragmentation of the midhills. Hence, a holistic approach at the landscape level is needed for tackling human–wildlife conflict. Connecting good habitats by restoring fragmented inter and intra-country areas would be an effective measure to mitigate human–wildlife conflict.

1. Introduction

Human–wildlife conflict (HWC) is one of the most prominent global challenges faced by conservation biologists and decision-makers worldwide (Torres et al., 2018) and could be interpreted as wildlife-human conflict as well. It occurs when

* Corresponding author. International Centre for Integrated Mountain Development, GPO Box 3226, Kathmandu, Nepal.
E-mail address: nakul.chettri@icimod.org (N. Chettri).

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the behaviour of humans and wildlife affects each other negatively as a result of competition for space and resources (Karanth and Kudalker, 2017). The increasing need of the growing human population for food and space ultimately results in the shrinkage of wildlife's natural habitat, which further manifests in various types of conflicts between the two (Acharya et al., 2016). The loss of human life, damage to crops and property, and livestock depredation have indirect consequences for the livelihoods of communities, their psychological and economic well-being, and food security (Barua et al., 2013). On the other hand, the retaliatory killing of animals contributes to the loss of biodiversity and changes in ecosystem structure as a whole (Nyhus, 2016).

The Kangchenjunga Landscape (KL) is a transboundary initiative by three countries, Bhutan, India and Nepal, in the Eastern Himalaya. The Kangchenjunga Landscape is one of the richest regions in terms of species, genetic, and ecosystem diversity among the global mountain biomes (Chettri et al., 2010; Choudhury, 1999, 2002; Dorji et al., 2018). It encompasses 19 protected areas, some of which are globally significant, such as the Khangchendzonga Biosphere Reserve and Buxa Tiger Reserve in India, the Jigme Keshar Strict Nature Reserve in Bhutan, and the Kangchenjunga Conservation Area in Nepal. About 45 per cent of the landscape's area is dominated by forests (ICIMOD, WCD, GBPNIHESD, RECAST, 2017), characterized by both the Indo-Malayan realm of Southeast Asia (with species such as *Dipterocarpus*, *Shorea*, and *Terminalia*) as well as the Palearctic realm of Eurasia (including conifers such as spruce, fir, and larch, and deciduous broadleaf taxa such as birch, alder, and willow).

Considered a part of the 36 Global Biodiversity Hotspots – the Himalaya (Mittermeier et al., 2011), the Kangchenjunga Landscape has been experiencing rapid demographic and economic growth, leading to the overexploitation of natural resources, significant land use, land cover changes (LULC), and loss of forests (Chettri et al., 2010). Owing to such changes, the landscape experiences various types of conflicts with wildlife, ranging from monkeys raiding crops to tigers assaulting human beings. For instance, Bhutan experiences an annual crop loss of up to 25 per cent of total household income due to crop raids by foraging animals (Tobgay et al., 2019) and about 10–19 per cent through livestock depredation (Jamtsho and Katel, 2019). An average of 115 people are reported to have been killed or severely injured annually in Nepal between 2010 and 2014 by large mammalian species such as Asian elephants, tigers, common leopards, and bears (Acharya et al., 2016). It is estimated that up to 20,000 people in the southern lowlands of Nepal are affected by conflicts with elephants (*Elephas maximus)* (Yonzon, 2008) that raid, on average, 68 per cent of harvest-ready crops each year (Karmacharya, 2004). Likewise, some anecdotal reports revealed the deaths of at least 450 people in India and Nepal since 1986 due to HWC (ICIMOD, 2019). Losses due to HWC are not only restricted to humans, but extend to wildlife species. About 54 per cent of reported annual elephant deaths in the transboundary habitat of Nepal and India are a result of retaliatory killings due to gunshot, iron wounds, electrocution, and chemical poisoning (Roy, 2015). A recent report documented a loss of 55 per cent of livestock on average annually due to attacks by wild carnivores in villages in the Himalayan state of Sikkim, India (Pradhan, 2018).

Deforestation and forest fragmentation due to anthropogenic factors, such as the construction of transport networks, human encroachment, and the conversion of forest to arable lands are deemed responsible for the reduction in the ability of wildlife to disperse in their home ranges, thereby bringing them into proximity with humans and human settlements (Acharya et al., 2017; Koirala et al., 2015). Topographic factors such as elevation and terrain also influence HWC because a rough terrain can make access difficult and limit human–wildlife interaction (Neilson et al., 2013). The climate exerts a dominant influence over the natural distribution of species by providing unique habitat ranges to wildlife, and hence indirectly affecting the nature and extent of interaction between humans and wildlife (Aryal et al., 2014). Since the region is highly vulnerable to changes in both temperature and precipitation, more than the global average (Sharma et al., 2010), any such climatic changes would affect the wildlife's habitat composition, availability of forage, and water accessibility, triggering conflict beyond political borders (Cushman et al., 2018; Mallick, 2012). It is therefore crucial to identify the areas in the region under high risk of HWC, understand the mechanisms of interaction, analyse possible drivers, and prioritize conservation efforts.

Reducing the damage to livestock requires understanding how depredation varies in space and time (Gastineau et al., 2019), and spatial risk modelling can prove to be a useful tool in predicting and mapping HWC hotspots by using locations of past interaction (Miller, 2015; Ruda et al., 2018). Modelling approaches such as maximum entropy (MaxEnt), when used along with various geospatial datasets, are effective in identifying hotspots of human–wildlife conflict and understanding their potential drivers (Constant et al., 2015; Mateo-Tomas et al., 2012; Phillips et al., 2006; Vilar et al., 2016). Although several researchers have focused their studies on HWC in the region by quantifying the damage, analysing patterns, examining its relationship with habitat use, and mapping conflict in some select areas of Himalayan countries (Chakraborty, 2015; Kshettry et al., 2017; Naha et al., 2018, 2019), knowledge about the regional and geographical patterns of such conflict is limited. The inadequate information and spatial data on HWC in the region, especially in the hills and mountains, coupled with political sensitivities within, calls for efforts towards a better understanding of HWC here (ICIMOD, WCD, GBPNIHESD, RECAST, 2017). This paper, therefore, makes an effort to (a) identify the HWC hotspots in the Kangchenjunga Landscape in the Eastern Himalaya using the MaxEnt modelling approach; and (b) investigate the relationship between the ongoing HWC and associated drivers in the landscape. Since this study also examines conflict hotspots according to protected areas and ecoregions, it would help in the prioritization of areas for the conservation and formulation of future strategies to address the issue.

2. Materials and methods

2.1. Study area

Situated in the Eastern Himalaya, the Kangchenjunga Landscape encompasses parts of eastern Nepal, India (North Bengal and Sikkim), and southwestern Bhutan, and is spread over about 25,100 km^2 (Fig. 1). With elevations ranging from 40 m above sea level (masl) to the third-highest mountain peak in the world, Mount Kangchenjunga at 8586 masl, its pristine and varied habitats support a wide variety of fauna and flora, including 160 species of mammals, 618 species of birds, and 600 butterfly species, some of which are considered globally threatened (Kandel et al., 2016, 2019). The vegetation of the study area is broadly divided into the following groups: (a) tropical, (b) subtropical, (c) warm temperate, (d) cool temperate, (e) subalpine, and (f) alpine (ICIMOD, WCD, GBPNIHESD, RECAST, 2017).

The landscape is home to some flagship species, such as the Asian elephant *(Elephas maximus),* the Royal Bengal tiger (*Panthera tigris)*, the greater one-horned rhinoceros (*Rhinoceros unicornis*), and gaur (*Bos gaurus*) in the low-lying plains; red panda (*Ailurus fulgens*), clouded leopard (*Neofelis nebulosi)*, and takin (*Budorcas taxicolor*) in the hills; and the snow leopard (*Panthera uncia*), musk deer (*Moschus chrysogaster*), the Himalayan black bear (*Ursus thibetanus*), and the Tibetan antelope (*Pantholops hodgsonii*) in the high mountains (ICIMOD, WCD, GBPNIHESD, RECAST, 2017; Kandel et al., 2019).

With appropriately 7.2 million people living in the Kangchenjunga Landscape (Kandel et al., 2016), the high human pressure on natural resources and various developmental activities in the region have led to the degradation and fragmentation of its forest ecosystems. There has been a concomitant reduction in the habitats of megafauna such as elephants, and a loss of biodiversity, frequently leading to HWC (ICIMOD, WCD, GBPNIHESD, RECAST, 2017). The 19 protected areas in the region, established for the conservation of natural habitats and sustaining biodiversity, are often isolated, too small for large, home range animals, and disconnected from each other (Gurung et al., 2019). These factors have led to widespread conflict between humans and wildlife here, in which predators such as clouded leopards, common leopards, tigers, and snow leopards have attacked livestock and even humans. In ecoregions that provide habitats for elephants, rhinoceros, gaurs, and other fauna, crop raiding, the destruction of houses, and attacks on humans are common. At higher elevations of the landscape, predators such as the Himalayan black bear, Asian golden cat (*Pardofelis temminckii*), leopard cat (*Prionailurus bengalensis*), and the Himalayan yellow-throated marten (*Martes flavigula*) predate livestock and poultry, while wild boars (*Sus*

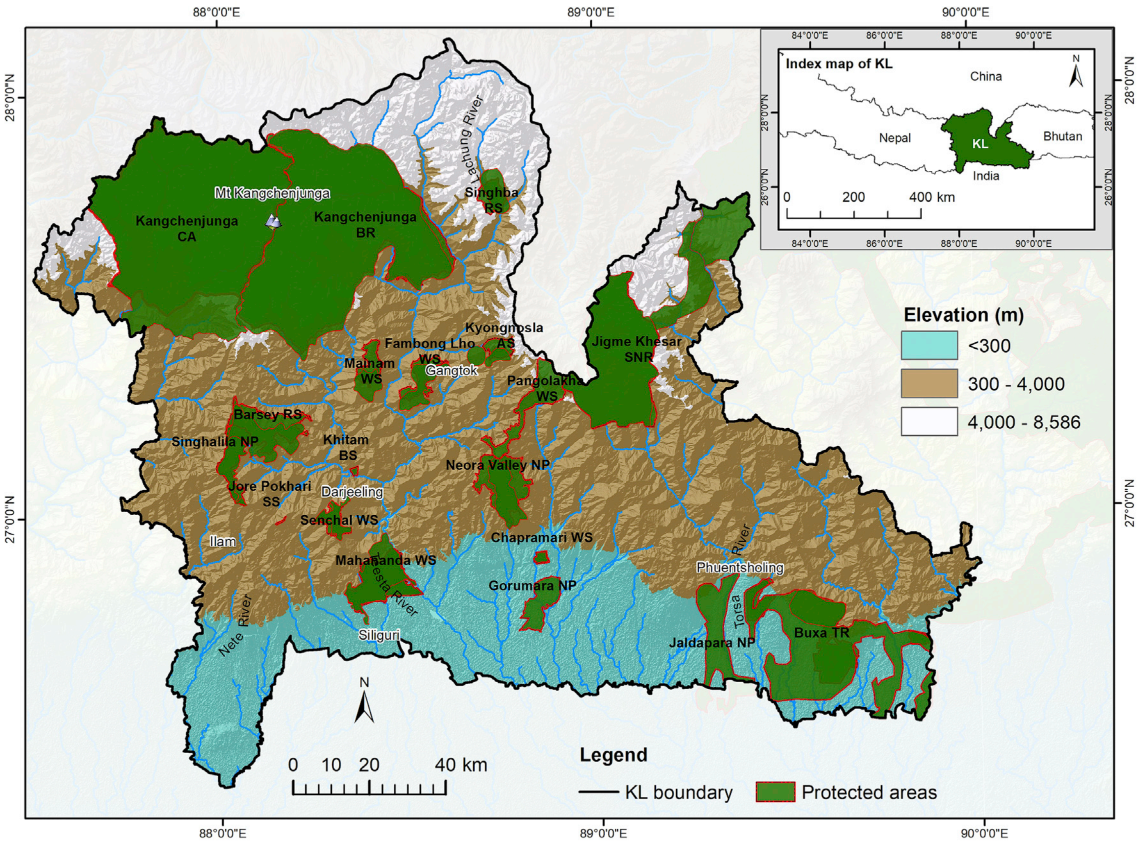


Fig. 1. Study area showing Kangchenjunga Landscape along with elevation zones and protected areas.

scrofa), primates like monkeys (*Macaca mulata*), barking deer (*Muntiacus muntjak*), rodents, including porcupines (*Hystrix* sps.), and peafowls (*Pavo cristatus*) are involved in the depredation of crops (ICIMOD, WCD, GBPNIHESD, RECAST, 2017; Pradhan et al., 2012).

2.2. Data collection

2.2.1. Compiling the conflict incidence data

The points of HWC incidence in the study area were compiled using secondary literature sources. We referred to over 50 news articles, journals, and reports to derive the collective locations of the incidents of HWC with all available species for the last 19 years (2000–2019) from across the landscape. We identified a total of 250 points of HWC occurrence; 60 per cent of these were in low elevation regions (<300 m), and the rest distributed over the landscape. The hilly and high mountain regions of the landscape (300–8586 m) contributed a relatively smaller proportion of the literature data and news articles relating to the incidents. Viewed by country, the maximum amount of data regarding the incidents was captured from studies conducted in India (Bhutia, 2016; Naha et al., 2018, 2019; Rai et al., 2014; Roy, 2017; Sunar et al., 2012), followed by Nepal (Neupane et al., 2018; Sherchan and Bhandari, 2017; Shrestha and Koirala, 2015) and Bhutan (Dorji, 2017; Penjor et al., 2014; Sangay and Vernes, 2008; Wangchuk, 2018; Wangchuk et al., 2018). A list of studies, news sources, and blogs referred to are provided (Supplementary data S1).

2.2.2. Acquiring environmental/predictor variables

Twelve environmental variables considered important for predicting HWC were selected for the current period (Table 1). The major factors considered were climate, topography, anthropogenic pressure, land cover, and availability of livestock (Mateo-Tomas et al., 2012; Naha et al., 2019). For climatic indicators, total annual precipitation and average annual temperature data was downloaded from the WorldClim data hub (Fick et al., 2017). Because the topography or terrain of any region influences the spatial and altitudinal distribution of wildlife, data was derived based on the Shuttle Radar Topographic Mission (SRTM) at 90 m resolution (Jarvis et al., 2008). To include the influence of human interaction on HWC, (a) the Euclidean distance from the road; (b) the Euclidean distance from railways; and (c) the Euclidean distance from settlements were extracted using Open Street Map (Haklay and Weber, 2008). We also accessed the globally available human footprint index dataset for 2009, which represents the relative human influence in each terrestrial biome, expressed as a percentage at a 1 km × 1 km grid level (Venter et al., 2016). The global dataset on livestock density (Robinson et al., 2014) was also considered to include the effects of livestock depredation by wild animals. A land cover classification was carried out at 30 m using Landsat 5, for the median year 2010 to obtain (a) area under forest cover; (b) area under agriculture; (c) area under tea plantations; and (d) area under shrub land and grassland. Finally, all these variables were resampled at the same spatial resolution of 1 km × 1 km to match the resolution.

2.2.3. Land use, land cover mapping

The study used Landsat's 30 m spatial resolution (170 × 185 km swath) on-demand, atmospherically -corrected Level-2 thematic mapper (TM) images for land cover mapping. Two scenes of Landsat images covered the Kangchenjunga Landscape. The images required to cover the study area were downloaded from the Earth Explorer USGS image database (https://earthexplorer.usgs.gov/) for 2010 (Table 2).

A harmonized and hierarchical land cover classification system (LCCS) with 11 classes was developed following Di Gregorio (2005). We used eCognition Developer software for object-based image analysis (OBIA) to derive similar image

Table 1
List of predictor variables.

Factors	Predictor variable	Expected relationship with HWC	Original spatial resolution	Source
Topography	Elevation	–	90 m × 90 m	www.usgs.gov/
Climate	Total annual precipitation	+/–	1 km × 1 km	www.worldclim.com
	Mean annual temperature	+/–	1 km × 1 km	www.worldclim.com
Anthropogenic	Distance from road	+	1 km × 1 km	https://www.openstreetmap.org
	Distance to railway	+	1 km × 1 km	https://www.openstreetmap.org
	Distance to settlement	+	1 km × 1 km	https://www.openstreetmap.org
	Global human footprint index	+	1 km × 1 km	sedac.ciesin.columbia.edu/
Land cover	Area under agriculture	+	30 m × 30 m	Land cover mapping
	Area under tea plantations	+	30 m × 30 m	Land cover mapping
	Area under forest cover	+/–	30 m × 30 m	Land cover mapping
	Area under shrub land and grassland	+/–	30 m × 30 m	Land cover mapping
Availability of livestock	Livestock density	+	1 km × 1 km	https://livestock.geo-wiki.org/home-2/

Note: '+' indicates positive, '–' indicates negative.

Table 2
Satellite imagery used.

Satellite/sensor	Date	Path	Row
Landsat 5/TM	November 5, 2010	138	41
Landsat 5/TM	December 14, 2010	139	41

objects through segmentation. OBIA provides a methodological framework for machine-based interpretation of complex classes, using both spectral and spatial information, and generates better classification results with a higher degree of accuracy than pixel-based methods (Chettri et al., 2013; Lang., 2008; Uddin et al., 2015). The algorithm helps to merge pixels with their neighbours having relative homogeneity criteria based on defined minimum mapping threshold units (Baatz et al., 2006). Information about the spectral values of image layers, slope, and texture was used in land cover mapping. Additional data relating to vegetation indices, for example, the normalized difference vegetation index (NDVI), the normalized difference snow and ice index (NDSII), and a land–water mask was also used for the mapping procedure. This approach to land cover mapping has been widely used and tested by researchers in the region (Chettri et al., 2013; Uddin et al., 2015, 2019), and the dataset is freely accessible and can be downloaded.

2.2.4. Conflict risk mapping

MaxEnt software (version 3.4.1) was downloaded and used for the modelling of HWC risk mapping (Phillips et al., 2017). Data points regarding the incidence of conflict were extracted for their coordinates (latitude and longitude) and saved in the csv format. All the 12 environmental variables listed above were clipped to the study area and converted into an ASCII format. The MaxEnt model was run for the 1000 iteration, setting aside a random 30 per cent of the incidence data for testing the model. A default setting of 10,000 maximum background points was accepted for the model run. In addition, the built-in jackknife test in the model was also selected, which allows users to estimate the importance of individual variables in any distributional modelling (Phillips et al., 2006; Phillips and Dudík, 2008).

The model's output was generated using the default format of Cloglog. This format provides an estimate of the probability of presence between 0 and 1, that is from the lowest to the highest probability of distribution (Phillips et al., 2006). The predictive accuracy of the model was accessed on the basis of the area with the Receiver Operating Characteristics (ROC) curve under the Area Under The Curve (AUC) for both training and testing of data, plotted against sensitivity (correctly classified presences in the y-axis) and specificity (correctly classified absences in the x-axis) for all possible thresholds. The AUC value ranks between 0 and 1, in which <0.5 means no discrimination, 0.5–0.69 poor, 0.7–0.79 reasonable, 0.8–0.89 excellent, and >0.9 exceptional (Vilar et al., 2016). Jackknife tests of a variable's importance were conducted to determine the most important variable of the 12 chosen (Phillips et al., 2006). HWC hotspots were extracted from the probability ranges and analysed with respect to 19 protected areas, 3 km radius around each of the protected areas and 10 ecoregions of the landscape. For this, we calculated the proportion of the hotspot area as a percentage of the total size of each protected area, its buffer radius and ecoregion.

2.2.5. Forest fragmentation statistics

In this regard, the study also conducted an analysis of forest fragmentation in the Kangchenjunga Landscape by using effective mesh size (MESH) statistics. MESH (McGarigal et al., 2002) is a landscape metric, a fragmentation index that serves to measure landscape connectivity and gives an account of the degree to which two points are separate from each other because of various fragmentation agents such as transport routes, cropland, or built-up areas. MESH gives the area-weighted mean patch size of patches of the corresponding patch size (in hectares). The proportional area of each patch is based on the total landscape area. The lower limit of MESH is constrained by the ratio of cell size to landscape area and is achieved when the corresponding patch type consists of a single, one-pixel patch. MESH is maximum when the landscape consists of a single patch (McGarigal, 2015), where a_{ij} = area (m^2) of patch ij, and A = total landscape area (m^2).

We measured MESH, using class-level metric patterns in FRAGSTATS (McGarigal et al., 2002), the most widely-used spatial analysis programme for calculating pattern metrics (Wang et al., 2014). For this, we first reclassified the land cover map into a binary of 1 (forest, that is, needle-leaved forests, broadleaved forests, and mixed forests) and 2 (non-forest areas, including built-up areas, croplands, and grasslands). An aggregation of classes also reduces the chances of misclassification of pixels (for example, shrub land and grassland can be cultivated land) (Acharya et al., 2017). Thus, the land cover map with two classes, forest and non-forest, was then used as the input in calculating fragmentation metrics. Since the landscape has a vast altitudinal range, the characteristics of fragmentation and its underlying mechanism in each of the elevation zones would differ. Therefore, it is important to divide the region into elevation zones to better understand the relationship between HWC and fragmentation.

Three major elevation zones were considered: (a) Low-lying plains and the Duars (≤300 masl); (b) Hills and mountains (300–4000 masl); and (c) High mountains (4000–8586 masl). A binary land cover map was extracted for each elevation zone and the MESH calculated for each of them using a moving window sampling strategy. We used a moving window of 5 km^2 as a landscape unit to measure MESH statistics in FRAGSTATS (Fig. 2).

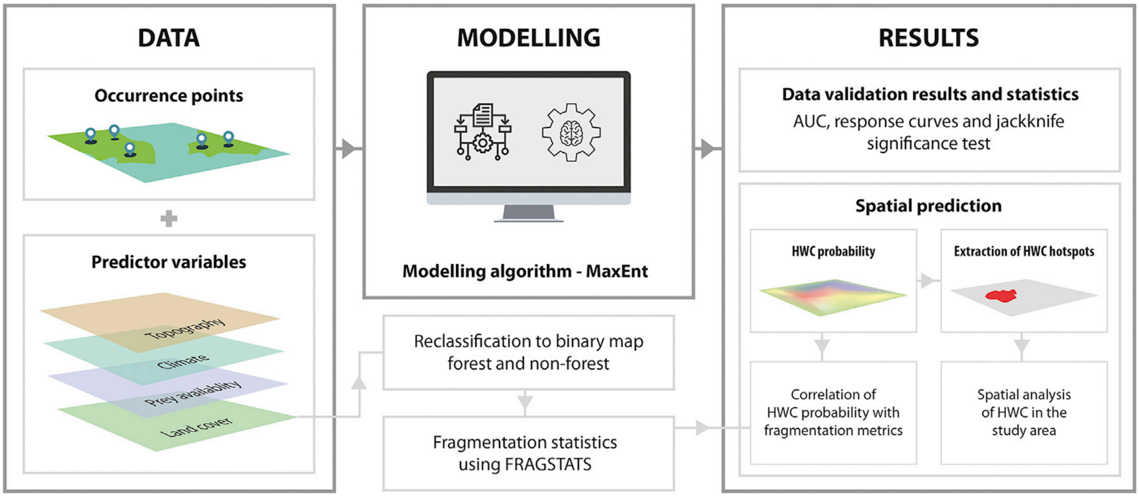


Fig. 2. Schematic flowchart showing the methodological approach used in hotspot mapping.

3. Results

3.1. Model's accuracy in HWC prediction

We received an AUC value of 0.86 for training and 0.84 for the testing of data, representing the high accuracy of the model. The AUC value for the data testing, 0.84, indicates the real test of the model's predictive power and is very close to the AUC value of the training data (0.86). Also, a value of 0.8 for the AUC means that, for 80% of the time, a random selection from the positive group (sensitivity) will have a score greater than a random selection from the negative class (specificity) (DeLeo, 1993). Hence, the results from this model can accurately predict the probability of the incidence of HWC in the study area.

3.2. HWC hotspot areas

We generated an HWC probability map with a spatial resolution of 1 km × 1 km, with values ranging from 0 (low probability) to 1 (high probability) (Fig. 3a). The map shows that HWC is well-distributed in the landscape, with the southern and central regions of the study area showing higher probability values for HWC compared to the northern highlands. The output was imported to ArcGIS 10.6.1 in a .tiff format, where the probability values were classified into ten classes based on percentiles. The combined values of the top 20th percentile class were considered as a 'conflict hotspot zone' (Allen and Bradley, 2016; Shrestha and Shrestha, 2019) (Fig. 3b). A total of 4710 km^2 of the landscape (~19 per cent of its area) was estimated to be in the high HWC zone. This zone was then analysed with respect to physiographic and administrative units such as ecoregions and protected areas of the landscape.

HWC is found to be highly prevalent in and around the region's isolated and disconnected protected areas. Our identification of conflict hotspots showed the highest risk of HWC within the protected areas of Chapramari Wildlife Sanctuary (~58%), followed by the Fambonglho Wildlife Sanctuary (~52%), and Senchal Wildlife Sanctuary (~49%) (Fig. 4a). Large proportions of the protected areas in Mahananda Wildlife Sanctuary (~39%) and Barsay Rhododendron Sanctuary (~33%) as well showed a high risk of HWC. On the other hand, the Kyongnosla Alpine Sanctuary, Kitam Bird Sanctuary, and Jigme Khesar Strict Nature Reserve showed the least risk of HWC within their protected areas.

An analysis of HWC hotspots in buffer zones within a 3-km radius of protected areas showed an intensification of the risk of conflict there. This increase was the highest for the Kitam Bird Sanctuary, where ~53% of the area in the buffer zone was a HWC hotspot area. About 37% of the buffer area around Gorumara National Park also experienced a high level of HWC compared to a much lower 6% in its core area. Little over half the buffer zone of Barsay Rhododendron Sanctuary was a hotspot area for HWC, higher by 19% than its core area (~33%) (Fig. 4a).

Going by ecoregion, the highest proportion of area under conflict was observed in the Himalayan subtropical pine forest ecoregion, with ~63% of its area comprising a high HWC zone (Fig. 4b). This was followed by the Terai–Duars savannah and grasslands ecoregion (~43%) and the Eastern Himalayan broadleaf forest (~18%). The high-altitude, Eastern Himalayan subalpine conifer forests showed a small percentage of its area under HWC (~7%), whereas Rock and ice and Eastern Himalayan alpine shrub and meadows were estimated to have the least area under conflict hotspots and negligible conflict calculated from Yarlung Tsangpo arid steppe (Fig. 4b).

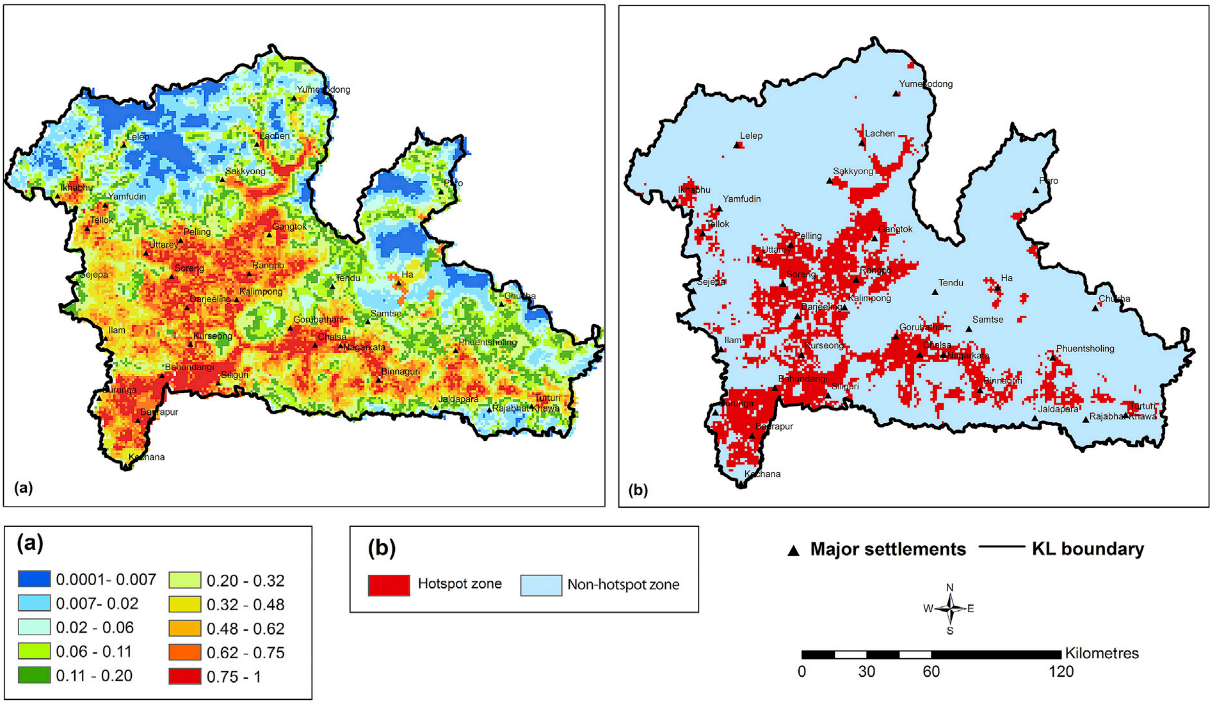
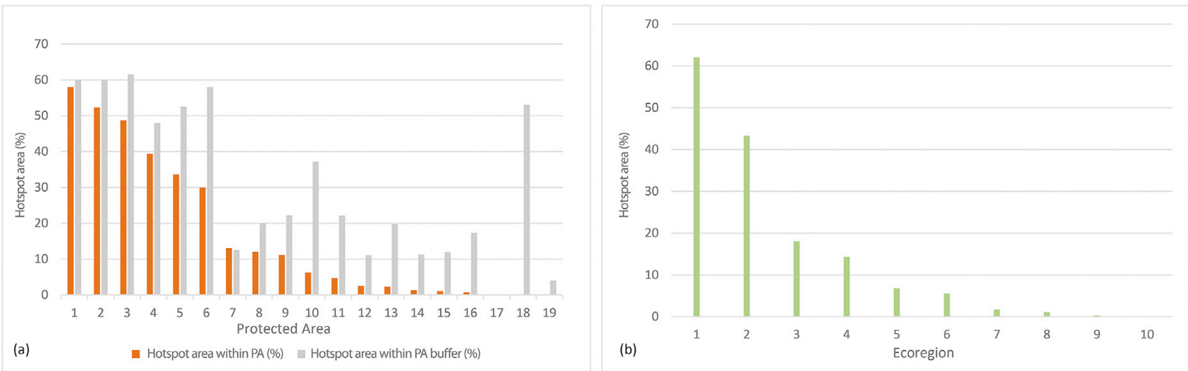


Fig. 3. Maps showing (a) HWC probability, and (b) HWC hotspot zones.



1. Chapramari NP
2. Fambonglho WS
3. Senchal WS;
4. Mahananda WS
5. Bersay RS
6. Jore Pokhari WS
7. Singbha RS
8. Jaldapara NP
9. Buxa WS
10. Gorumara NP
11. Pangolakha WS
12. Kangchenjunga CA
13. Mainam WS
14. Singalila NP
15. Neora Valley NP
16. Khangchendzonga BR
17. Jigme Khesar SR
18. Kitam BS
19. Kyongnosla AS

1. Himalayan subtropical pine forests
2. Terai-Duars savanna and grasslands
3. Himalayan subtropical broadleaf forests
4. Eastern Himalayan broadleaf forests
5. Eastern Himalayan subalpine conifer forests
6. Brahmaputra Valley semi-evergreen forests
7. Lower Gangetic plains moist deciduous forests
8. Eastern Himalayan alpine shrub and meadows
9. Rock and ice
10. Yarlung Tsangpo arid steppe

Fig. 4. (a) HWC hotspots in and around protected areas, and (b) HWC hotspots in the ecoregions of the Kangchenjunga Landscape.

3.3. Major factors affecting HWC

The four most important variables estimated by jackknife test to have the highest contribution to AUC were: (a) Distance to a road; (b) Elevation; (c) livestock density; and (d) Mean annual temperature. It is noteworthy that the variable connected to anthropogenic factors – distance to a road – had the highest contribution, with a variable importance of 0.76. This variable produces the highest gain when used in isolation and therefore appears to have the most useful information by itself. It was followed by elevation and livestock density (Table 3). Climate also tends to influence the probability of conflict as indicated by the fact that the contribution of mean annual temperature to AUC has a value of 0.73 for the modelling. Other factors relating to land cover such as area under agriculture, climatic factors such as total annual precipitation, and anthropogenic factors

Table 3
Top four factors contributing to HWC in the study area.

Factors	Predictor variable	Contribution to AUC (jackknife test)
Anthropogenic	Distance to a road	0.76
Topography	Elevation	0.75
Availability of livestock	Livestock density	0.75
Climate	Mean annual temperature	0.73

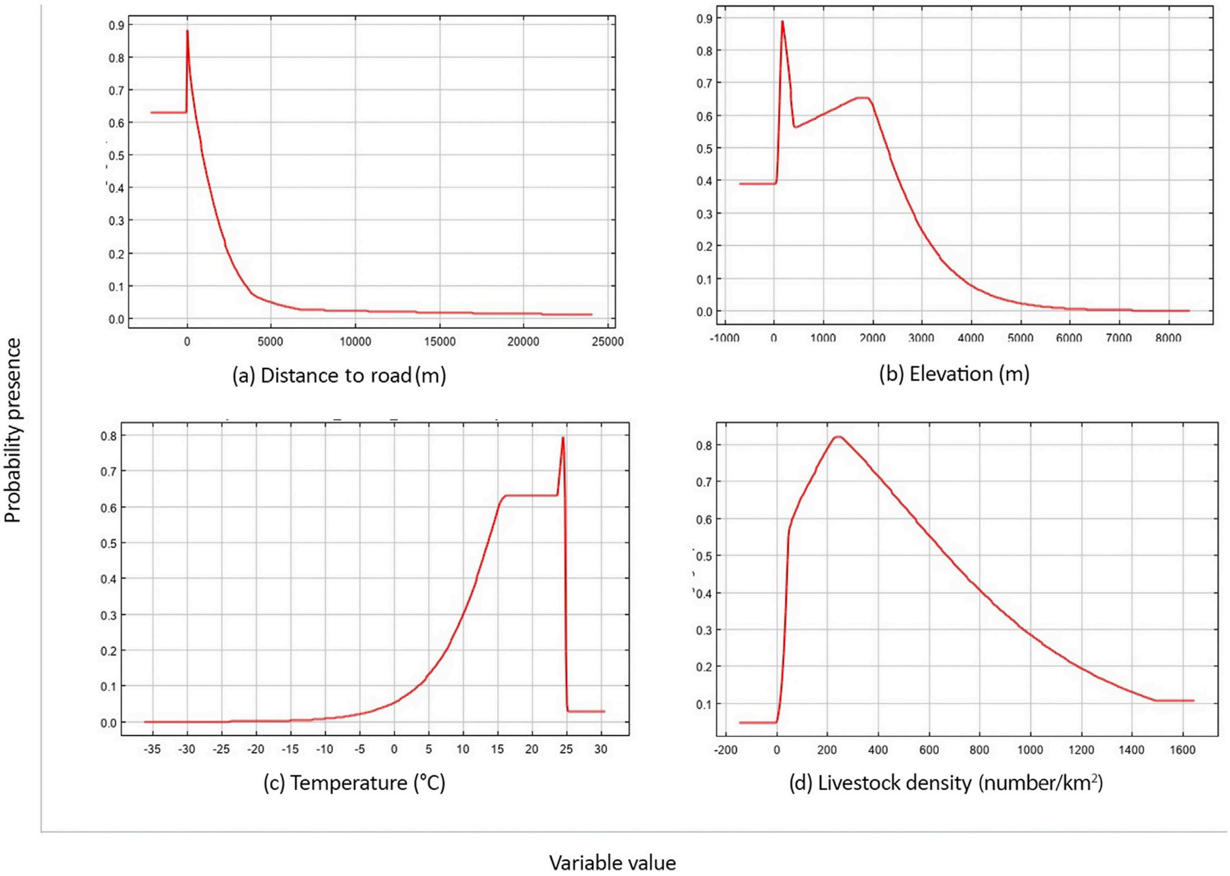


Fig. 5. Response curves showing probability of HWC for four key variables: (a) Distance to road, (b) Elevation, (c) Temperature, and (d) Livestock density.

such as distance to railway tracks showed lower contributions in modelling HWC. Fig. 5 further depicts the response curves of the four important contributors to HWC.

3.4. Relationship between HWC and forest fragmentation

High values of MESH represent grids with a single forest patch (low patchiness), middle values represent grids with both forest and non-forest patches (high patchiness), and low values represent grids with mostly non-forest patches (low patchiness). The values extracted from MESH of each grid, when correlated with the mean HWC probability of that grid, showed different correlation scenarios for the three elevation zones (Fig. 6).

At elevations below 300 m, mostly representing the Terai–Duars savannah ecoregion, the correlation between the probability of HWC and MESH was significantly negative ($r = -0.6$, $p < 0.05$). This means that HWC is higher in areas with a lower MESH size, which represents greater patchiness or fragmentation (Fig. 6a). However, this correlation is lower compared to regions at elevations between 300 and 4000 m, comprising hills and mountains of the landscape. They have a negative correlation of $r = -0.8$ at a $p < 0.05$ significance level. The probability of HWC at this elevation is highest with middle values of MESH size, representing high patchiness or fragmentation, which then decreases progressively with increasing MESH size (Fig. 6b).

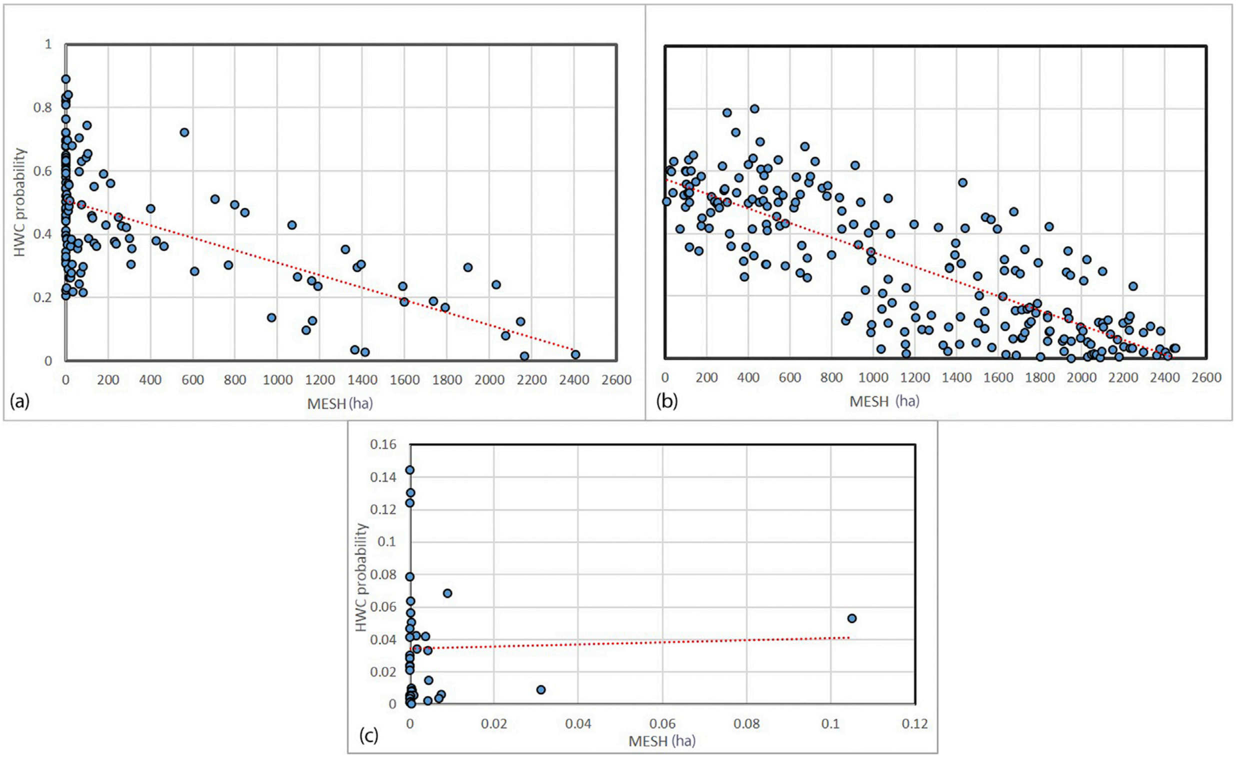


Fig. 6. Relationship between MESH and HWC at different altitudes: (a) < 300 m, (b) 300–4000 m, and (c) 4000–8586 m.

In regions at high elevations of 4000–8586 m, there is a positive correlation between MESH and HWC probability, with $r = 0.03$, non significant at $p = 0.05$ (Fig. 6c). This is because of the negligible forest cover and human interaction in the region. The area mainly consists of shrub land, barren land, and snow/glaciers, and falls under the category 'non-forest', therefore accounting for its low patchiness. Though predators such as snow leopards show their presence, HWC in the high mountains is constrained to only certain regions in the study area. Therefore there is a need to better understand HWC in the high mountains and its relationship with other factors such as livestock availability, including with the use of niche-based modelling.

4. Discussion and conclusions

Our study shows variations in hotspot areas across the Kangchenjunga Landscape. The analysis revealed that ~19 per cent of the area falls under the high HWC risk zone, and that most of the conflict areas are at lower elevations and relate to large mammals. This is similar to the global trend, one in which large mammals are reported as the most damaging, both for crops and for human lives (Holland et al., 2018). The conflict areas, at least in northern Bengal and eastern Nepal, were once an extended habitat for big mammals, including the tiger and gaur, and on the migratory route of elephants (Choudhury, 1999, 2002; Joshi et al., 2016). However, extreme land use changes due to developmental works, including the establishment of tea gardens, villages, railway lines, and roads, has limited the original habitats of species, extirpating some or confining them to patches of protected areas (Mallick, 2019). The major conflict areas from our results coincide with those of previous studies indicating human-inhabited areas, highways, and railways as hotspots (Dasgupta and Ghosh, 2015; Naha et al., 2018, 2019; Roy and Sukumar, 2017).

Analysing the top four factors revealed that there is a combination of both environmental and anthropogenic variables responsible for HWC conflict, with distance to roads contributing highly to the modelling results. Roads, highways, and even small footpaths open up areas for human intervention and increase the proximity of human beings and wildlife (Dasgupta and Ghosh, 2015; Mann et al., 2019; Roy and Sukumar, 2017). The response curve for distance to roads generated by the model shows a higher probability of HWC at distances less than 5 km from a road than distances further away. Such trends are apparent as forest degradation through developmental activities affects the size of habitat of many megafauna, including elephants (Padalia et al., 2019), making the Terai and lowland areas more prone to HWC (Naha et al., 2018, 2019).

In addition, physical factors such as a location's altitude are also crucial in determining the severity of the risk of conflict and the associated species. High-altitude regions in the Kangchenjunga Landscape, mostly under rock and ice, showed a low to very low hotspot percentage, most of which was restricted to livestock predation by snow leopards and wild dogs

(Sathyakumar et al., 2011; Sherchan and Bhandari, 2017). This is mainly due to low levels of inhabitation and low density of wildlife populations, as has been reported elsewhere (Bhatia et al., 2019; Rovero et al., 2020). On the other hand, regions in the landscape at elevations of 300–4000 m are characterized by various types of HWC, ranging from crop foraging by monkeys and wild boar to human and livestock depredation by black bears and common leopards. However, the intensity differs, depending on the terrain, land use types, and species involved. A similar, distinct pattern of conflict differing in intensity, depending on altitude, was also reported by Anand and Radhakrishna (2017). According to a study by Rai et al. (2014), villages around the Barsey Rhododendron Sanctuary in this elevation zone experienced a crop loss of up to 64% due to foraging by wild boars, porcupines, and barking deer.

Low-altitude areas below 300 m, comprising the Terai–Duars savannah and grasslands ecoregion of the landscape, provide an ideal habitat for megafauna such as elephants, gaur, leopards, and tigers, which are frequently involved in conflict with humans. The recent, increasing urbanization, due to population growth and migration into cities (such as Jalpaiguri and Siliguri), has added pressure on the region's natural resources, mostly its forests (Sarkar and Chouhan, 2019).

The third important factor contributing to HWC in the landscape is the availability of livestock. Carnivores such as common leopards, tigers, yellow-throated martens, wild dogs, and snow leopards are known to prey on livestock like goats, sheep, pigs, poultry, and even yaks, in addition to wild prey. Bhutan reported a loss of 1375 livestock between 2003 and 2005 due to predation by large carnivores (Wangchuk et al., 2018). The probability of HWC was found to be highest in areas with moderately dense concentrations of livestock, about 200–400 livestock/sq km. This is possible as communities living in the fringe areas of forests mostly practice livestock rearing in low to moderate numbers, mainly for subsistence (Bargali and Ahmad, 2018).

Climate too plays an important role in guiding vegetation characteristics and suitable habitats for wildlife (Gupta et al., 2017). This was indicated by the fact that the mean annual temperature in our study showed a high significance value of 0.73 in the landscape. The response curve for temperature shows a high probability of HWC in regions with a mean annual temperature around 24 °C (Fig. 5c). Recent research suggests that climatic factors and associated changes play a fundamental role in the distribution and movement of Himalayan black bear, bringing them in proximity to village communities and increasing the risk of conflict (Bashir et al., 2018). In the context of prevailing climate change and warming at higher elevations, there is likely to be an increase in conflicts as shifts in species' range are reported (Singh et al., 2020). Many lowland megafauna are likely to use higher elevations as climate refugia, as tigers are already reported to be doing at altitudes of 4000 m (Vernes, 2008) and elephant habitats are predicted to shift to higher elevations (Kanagaraj et al., 2019).

The results of this study suggest that the Chapramari Wildlife Sanctuary, Fambonglho Wildlife Sanctuary, and Senchal Wildlife Sanctuary should be prioritized for human–wildlife conflict management due to the higher risk of conflicts that prevails. Also, the buffer area within Gorumara National Park and Kitam Wildlife Sanctuary should be aided through better strategies and building the capacities of local communities to address HWC (Kshettry et al., 2017). HWC is prominent here since these protected areas account for some amount of human activities such as agriculture and livestock rearing by village communities within and along their peripheries. Villages within and along the fringes of protected areas, especially in Senchal Wildlife Sanctuary, Fambonglho Wildlife Sanctuary, and Kitam Bird Sanctuary, experience the raiding of crops by wild boars, Asiatic bears, barking deer, and porcupines (Rai et al., 2012; Sunar et al., 2012). Villagers here also depend on natural resources such as fuelwood, medicinal plants, and food from nearby forests, and are frequently attacked by wild animals while collecting these. The fragmentation of habitats due to the construction of railway lines and roads through protected areas of Chapramari, Jaldapara, and Buxa in northern West Bengal contributes to frequent conflict between humans and large mammals such as elephants (Roy et al., 2009). Areas outside the protected area boundary, such as tea gardens and fringe villages, provide suitable habitat and food during the shortage of forage in the wild and should therefore also be prioritized for minimizing conflict (Kshettry et al., 2020).

Of the ten ecoregions surveyed, the one with the highest proportion (~63%) of hotspot area was the Himalayan sub-tropical pine forests. Being the largest in the Indo-Malayan realm, this ecoregion is characterized by conifer forests, home to several mammalian and bird species (Dinerstein et al., 2017). In recent years, more than half the forest in this densely populated ecoregion has been cleared due to overgrazing and overexploitation for fuelwood and fodder (Shrestha et al., 2018). Most of the region's forests, especially between 1000–2,000m, have been replaced by terraced agriculture (Theobald et al., 2020). Such severe human intervention in a substantially fragile ecosystem can lead to drastic changes in wildlife and their interaction with humans. It is followed by the Terai–Duars savannah and grasslands ecoregion (~43%). A narrow stretch in this ecoregion, between India and Nepal, forms an important ecological corridor for wildlife, especially elephants (Roy and Sukumar, 2017). Elephants are known to migrate from the Koshi Tappu Wildlife Reserve in eastern Nepal through Darjeeling and Jalpaiguri in West Bengal, India, and Bhutan to Assam in Northeast India (Choudhury, 1999). Thus, this region that is a significant elephant habitat has undergone alteration through the conversion of land into settlements, agricultural lands, tea gardens, and teak plantations, in turn affecting the foraging behaviour and migratory routes of elephants (Singh et al., 2019).

This study also points out that areas at an elevation range of 300–4000 m within the landscape are witnessing high levels of HWC where there are high rates of forest fragmentation, as is suggested by a significant negative correlation of $r = -0.8$ between effective mesh size and the probability of HWC. The patchy agricultural lands within the mosaic of forested areas are infested by small mammals, including macaques and wild boars (Pandey et al., 2016), and the pathways around forested regions used for collecting fuelwood frequently witness bear and leopard attacks (Naha et al., 2018). With success in conservation and the increasing number of large mammals such as rhinos and elephants, there is a need for extended habitats beyond protected areas (Mukherjee et al., 2020). A similar trend was also observed in Nepal, where human deaths were higher in fragmented areas (Acharya et al., 2017). In developmental activities such as the construction of dams, highways, and railways, the protection of ecologically sensitive areas, their species, and habitats should be made a major priority for all countries of the landscape.

It is also noted that with conservation interventions, wildlife populations have increased even as their habitats have been degraded, resulting in small, patchy protected areas disconnected from each other, and which are not big enough for large mammals such as elephants and tigers (Gurung et al., 2019; Talukdar et al., 2019). This trend is likely to increase HWC in the near future. Hence, a holistic approach at the landscape level for tackling HWC, by connecting the forests of the Darjeeling and Jhapa forest divisions and identifying corridors, could be useful in tackling this issue, as also suggested by Mallick (2012) and Dhakal and Thapa (2019). The need for landscape planning in this region, providing a minimum of 1000 km^2 of good habitat by restoring fragmented inter- and intra-country forest patches would be an effective measure to mitigate HWC (Roy, 2015).

In summary, it is obvious that Eastern Himalaya and Kanchenjunga Landscape are part of the global HWC hotspot areas, and that there is an increasing trend of incidents of HWC in the region. Some of the areas within are more prone to HWC than others. The major drivers are human-induced fragmentation of habitats and shrinking historical ranges, especially for large mammals. The issue of HWC is complex and directly related to the local economy, land use patterns, success of conservation, and one that goes beyond political borders. In addition, the emerging challenges of climate change and shifts in habitat across the region, and losing the battle of conservation add more challenges at the regional level. Therefore, HWC is no more a single-country issue, and goes well beyond international borders. It is a fundamental cross-border issue, as has also been indicated by other studies. Our analysis rationalizes the need for regional cooperation and common strategies to address HWC. Various international conventions, such as the Convention on Biological Diversity (CBD) and the United Nations Framework Convention on Climate Change (UNFCCC), have strongly advocated the landscape approach and regional cooperation to address problems related to drivers of change. Hence, a transboundary cooperation programme like Kangchenjunga Landscape could bring synergies between countries to develop better strategies and capitalize on opportunities to tackle HWC. It could pave the way for human–wildlife co-existence by urging countries to adopt better legislative provisions and build awareness among community groups for informed decision-making. Since the present analysis constitutes a unique study in mapping HWC at the landscape level based on an intensive literature survey and existing data, it could also be replicated in other landscapes of the region.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gecco.2020.e01284.

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