Predicting the current and future potential spatial distribution of endangered *Rucervus eldii eldii* (Sangai) using MaxEnt model

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Abstract   Ecological factors that control the species distribution patterns at various spatiotemporal scales will get affected by climate change. To combat the situation, in the past few decades geographical information system (GIS) and remote sensing have been widely used by the researchers in the field of wildlife and habitat suitability modeling. The main objective of this study is to map and predict the current and future habitat suitability potential of *Rucervus eldii eldii* in Keibul Lamjao National Park (KLNP) using MaxEnt. Presence location data of the species, topographic factors, and bio-climatic variables were used as input in the MaxEnt software to map current habitat suitability potential. To map the habitat suitability potential for future, two representative concentration pathway (RCP) scenarios RCP 2.6 and RCP 8.5 for the years 2050 and 2070 were used. The model returned an average AUC value of 0.944 which indicates the model to be sensitive and descriptive. Isothermality and precipitation in the wettest quarter were found to be two most significant variables. The suitable range of precipitation in the wettest quarter for *Rucervus eldii eldii* varies from 1365 to 1410 mm with an optimal value of 1405 mm and isothermality from 46.43 to 46.6% with an optimal value of 46.5%. Current habitat suitability results of the model show 0.45 km^2 of the area under no potential, 29.25 km^2 of the area under least potential, 8.29 km^2 of the area under moderate potential, 9.21 km^2 of the area under good potential, and 8.82 km^2 of the area under high potential. Both RCPs for the years 2050 and 2070 show the decreasing trend in the area under high suitability potential and increasing trend under no suitability potential. The results of this study can provide aid in the management and protection of *Rucervus eldii eldii*.

Introduction

Functional and structural integrity of ecosystems is often destroyed by the habitat fragmentation; rapid climate change; exploitation of nature; exploitation of forest for raw materials; soil, water, and air pollution; and human population growth (Adhikari et al., 2012; Barnosky et al., 2011). Climate parameters such as humidity, precipitation, and temperature have significant effects on the habitat and spatial distribution of animal species (Bertrand et al., 2011). Change in the climate system is a natural phenomenon throughout the world history (Turkes et al., 2008). In the past, reaction to changing climate has led to extinction of some species or some species has also changed their

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habitats (Worth et al., 2015). In particular this changing climate in the past decades has put pressure on the habitat of endangered species.

In the past few decades, geographical information system (GIS) and remote sensing have been widely used by the researchers in the field of wildlife and habitat suitability modeling. Algorithms like multi-layer perceptron (MLP) neural network (Watts & Worner, 2010), Mahalanobis typicality (Etherington, 2019; Sangermano & Eastman, 2007), multi-criteria evaluation (Kushwaha, 2012; Store & Jokimäki, 2003), and logistic regression (Kushwaha, 2012) have often been coupled with GIS to analyze the species distribution. Digital elevation model (DEM), digital bio-climatic data of the area, point location records of the species are used as input data in the machine learning methods or algorithms to map and analyze the current and future distribution of species (Phillips & Dudik, 2008; Wang et al., 2007). Among all the modeling approaches mentioned above MaxEnt has gained a significant advantage because it uses only categorical and presence data as input variable (Eastmann, 2016; Morales et al., 2017), due to which MaxEnt is being used in the data-scarce regions especially in the developing countries. In addition, even with the small presence of datasets, it can give reliable and stable output (Pearson et al., 2007). Using the inbuilt jackknife test, MaxEnt also evaluates the significance level of individual species (Phillips & Dudik, 2008).

Unprecedented climate change has been seen in the past few decades globally. The global climate change can be more severe than expected. By the end of twenty-first century the minimum temperature is likely to be increased by 0.3 °C to 1.7 C and the maximum temperature is likely to be increased by 2.6 to 4.8 C (IPCC, 2014). To combat the effect of change in climate on the habitat suitability of species with narrow habitat, suitable habitat prediction and population distribution mapping are critical (Gaston, 1996). One of the endangered species with narrow habitat is *Rucervus eldii eldii* (Sangai). As per Schedule 1 of Indian Wildlife protection Act, 1972, in India Eld's deer are considered to be one of the most endangered deer species. *Rucervus eldii eldii* (Sangai) was once reported extinct in 1951 and was re-discovered, and six heads in 1953 (Gee, 1960) were traced in a survey conducted under auspices of the International Union for Conservation of Nature (IUCN). By 1975, the population was found to be 14 individuals (Ranjitsinh,

1975). In the recent census in 2013, the total population of Sangai was found to be 204 with 90 stag, 86 hind, and 28 fawn (Forest Department (GoM), 2013). Nevertheless, largely because of habitat deterioration the species is potentially threatened. There are three species of Rucervus eldii in the world: *Rucervus eldii thamin* of Myanmar, *Rucervus eldii siamensis* of Thailand, and *Rucervus eldii eldii* (Sangai) of Manipur (Forest Department (GoM), 2013). Of the three Eldii species, Sangai, *Rucervus eldii eldii*, has the least population in the wild and thus the most endangered. *Rucervus eldii eldii* is a medium-sized deer; the size of a fully grown *Rucervus eldii eldii* stag is about 110 to 125 cm high at the shoulder and *Rucervus eldii eldii* hind is about 105 cm. The length of an adult buck ranges between 145 and 155 cm. The mature *Rucervus eldii eldii* stag weighs about 110 kg (Forest Department (GoM), 2013). Sangai deer is a noble and graceful animal, which is found nowhere in the world except in Manipur at Keibul Lamjao National Park (KLNP) over the floating biomass in the south eastern part of Loktak Lake, North Eastern part of India (LDA, 2003; Shamungou, 2010).

The KLNP covers an area of 40 km^2, the only floating national park in the world and an integral part of Loktak Lake (LDA, 2003). The national park is characterized by floating biomass locally known as Phumdis. Phumdi is a heterogeneous mass of soil, vegetation, and organic matter at various stages of decomposition (Shamungou, 1990). They float on the lake, one-fifth of their thickness above and four-fifth under the water. Maximum depth of a phumdi is around 7 to 8 feet, but during its formative stage depending on the conditions its depth varies in space and time (Forest Department (GoM), 2013). Depending upon the composition of grass growing and (0.8–1) m thickness, phumdi can hold the weight of an adult Sangai and human being (Shamungou, 1990). The area experiences an average annual rainfall of 1350 mm, and the temperature varies between 1.7 °C in winter and 34.4 °C in summer. In the unique environment of KLNP, Sangai shares its habitat with wild boar, hog deer, and many other birds, reptiles, amphibians, fishes, etc. (Shamungou, 2010) (Fig. 1).

The existence of *Rucervus eldii eldii* (Sangai) is important in the political expediency and natural calamity and it is vulnerable ecologically, and their last secluded area (KLNP) along with the remnant could demolish or reduce both of them to a desolated
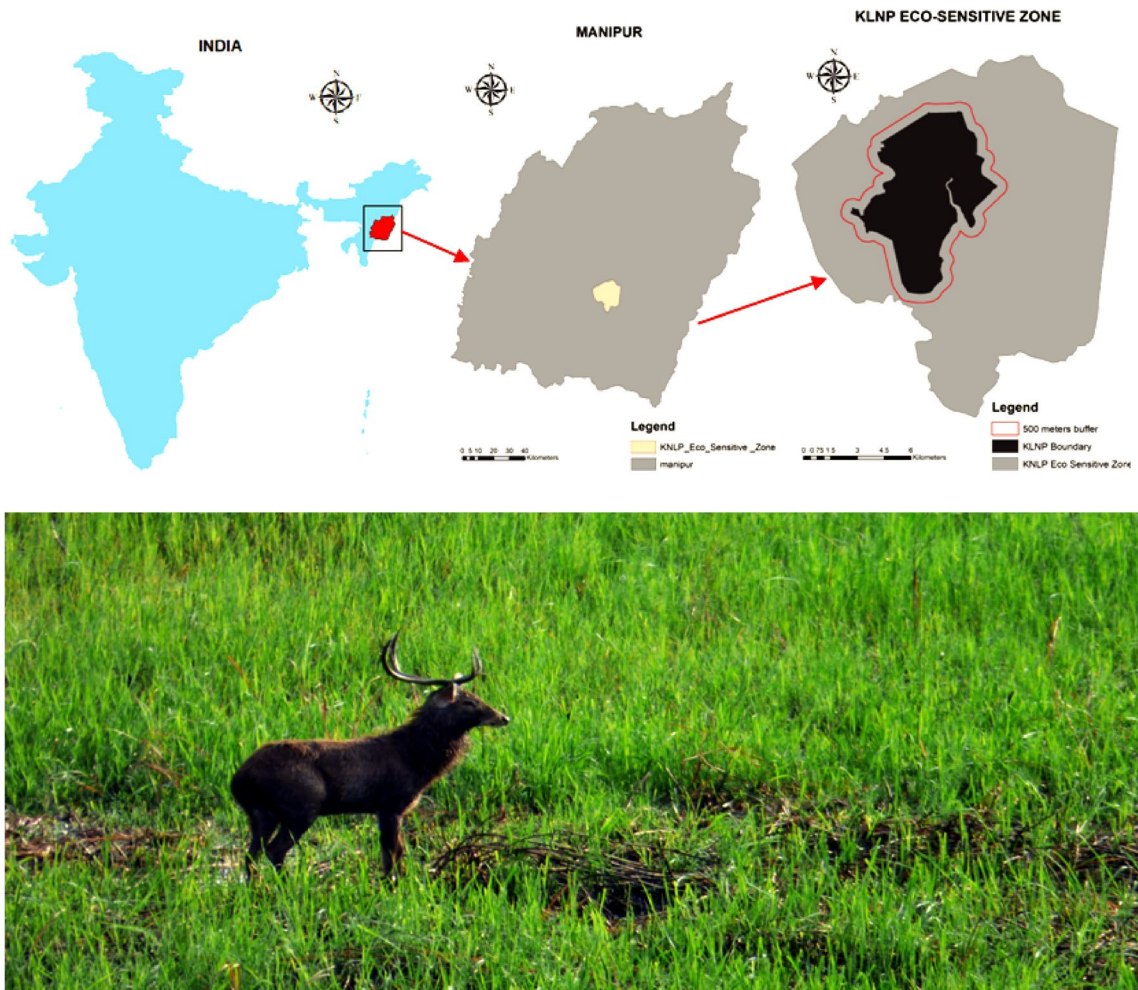
Fig. 1 Geographical location of study area and Sangai at Keibul Lamjao National Park (KLNP)

condition beyond the revival (Shamungou, 2010). A section of wildlife experts believe the Sangai, battling habitat loss and human pressures, may be fighting its "last battle" (Ghosh, 2018). In terrestrial ecosystems, the impact of change in climate on endangered animal species is complex, and in order to identify and rehabilitate them, more information about their potential spatial distribution is needed. This study is the first attempt to model and analyze the habitat suitability potential for the current scenario and project the future scenarios of potential habitat suitability of *Rucervus eldii eldii* (Sangai) in KLNP based on climatic conditions and topography of the region. The main objective of this study is to map and predict the current and future habitat suitability of *Rucervus eldii eldii* (Sangai) in KLNP located in the southeastern part of Loktak Lake in Manipur, India. Using the presence location data of the species, topographic factor, and bio-climatic variable as input in the MaxEnt software, the current suitable habitat of *Rucervus eldii eldii* (Sangai) in KLNP was mapped. In order to map the habitat suitability potential for future, two representative concentration pathway (RCP) scenarios RCP 2.6 and RCP 8.5 were used. Response of the various environmental variables and projected spatial change in the habitat in the future were also analyzed in this study.

Materials and methods

Species occurrence and environmental data

Several habitat suitability modeling studies carried out for various species show the applicability and reliability of MaxEnt modeling with a minimum number of present datasets for narrow-ranged species. Proosdij et al. (2016) used 14 present location data for narrow-ranged species and 25 for wide-ranged species, Jayakumar et al. (2015) used 22 present location data to model habitat suitability of *Myristica dactyloides* using the MaxEnt model in the Eastern Ghats, India. In this study, a total of 31 location data with *Rucervus eldii eldii* occurrence were collected from the Forest Department, Government of Manipur. All the present location data along with longitude and latitude were entered in Microsoft Excel and were saved as "csv" format compatible to be used in MaxEnt. Based on the ecological niche of the species, bioclimatic variables are significant to explicate the habitat allocation ecologically. The 19 bioclimatic variables resulted from the long-term recording of monthly rainfall and temperature value (1950–2000) (Hijmans et al., 2005). The bioclimatic data of 1-km^2 or 30-s spatial resolution was downloaded from the WorldClim dataset. The bioclimatic data was later downscaled to 30-m resolution using bilinear interpolation since the spatial coverage of study area is just 40 km^2. Along with the bioclimatic variables, the topographic data extracted from CartoSat digital elevation model (DEM) (30 m) resolution was also used. To estimate the impact of future climate change on the habitat suitability of *Rucervus eldii eldii*, Hadley Centre Global Environmental Model version 2 (HadGEM2) future datasets downloaded from the worldclim portal were used (Fick & Hijmans, 2017; Hijmans et al., 2005). To test *Rucervus eldii eldii* habitat suitability ranges in the 2050s (2041–2060) and 2070s (2061–2080), representative concentration pathways (RCPs) RCP 2.6 and RCP 8.5 were used. Table 1 shows the list of predictor variables used in this study. The predictor datasets were preprocessed in QGIS 2.6.1 and were converted in ASCII files to make it compatible to the MaxEnt environment. The boundary condition was limited to the spatial extent of Keibul Lanjao National Park (KLNP) with 500-m buffer. The vector boundary map of KLNP was obtained from Forest Department, Government

Table 1 Environmental variables used in species distribution modeling process

Variable code	Variable type	Unit
Bio 1	Annual mean temperature	°C
Bio 2	Mean diurnal range	°C
Bio 3	*Isothermality*	*%*
Bio 4	*Temperature seasonality*	*°C*
Bio 5	Max. temperature of warmest period	°C
Bio 6	Min temperature of coldest period	°C
Bio 7	Temperature annual range	°C
Bio 8	Mean temperature of wettest quarter	°C
Bio 9	Mean temperature of driest quarter	°C
Bio 10	*Mean temperature of warmest quarter*	*°C*
Bio 11	*Mean temperature of coldest quarter*	*°C*
Bio 12	Annual precipitation	mm
Bio 13	Precipitation of wettest period	mm
Bio 14	*Precipitation of driest period*	*mm*
Bio 15	Precipitation seasonality	mm
Bio 16	*Precipitation wettest quarter*	*mm*
Bio 17	*Precipitation of driest quarter*	*mm*
Bio 18	Precipitation of warmest quarter	mm
Bio 19	Precipitation of coldest quarter	mm
Elevation	*Elevation*	*m*
Slope	*Slope*	*degree*

Italicized entries indicates significant variable

of Manipur. In order to minimize multi-collinearity and model overfitting and exclude the extremely correlated variables, the Pearson multi-collinearity test was carried out in R-statistical software, and variables with correlation coefficient greater than 0.8 were removed (Fourcade et al., 2014).

MaxEnt model

In this study, species distribution modeling was done using MaxEnt 3.4.1. For modeling, 75% of the sample data was randomly selected in training whereas 25% of the data was used in testing. The habitat suitability curves for each variable were computed, and the contributions of each variable to the *Rucervus eldii eldii* habitat suitability model were computed using the Jackknife test already inbuilt in the software with ten repetitions (Hill et al., 2012). The result of jackknife test shows the amount of gain obtained from all the variables in combination or from each variable in isolation. An individual variable with greater gain indicates that more contribution or information

is contained in that variable towards species habitat distributions (Wang et al., 2017). In this study, a species distribution model was evaluated based on computed AUC and average omission and prediction statistics. AUC is one of those statistics which is inbuilt in the MaxEnt which provides a good statistics to judge the model performance where only presence data are used (Proosdij et al., 2016). The performance of the forecast model was positively correlated with area under the curve (Elith et al., 2006). In general AUC value should lie between 0.5 and 1; thus, the model performance is graded as fail (0.5–0.6), poor (0.6–0.7), fair (0.7–0.8), good (0.8–0.9), or excellent (0.9–1) (Phillips et al., 2006).

Later the ASCII file was imported to GIS and was reclassified. The generated potential distribution map of Sangai deer had values between 0 and 1. These values have been grouped into various groups: high suitability potential (>0.75), good suitability potential (0.5–0.75), moderate suitability potential (0.25–0.5), least suitability potential (0.01–0.25), and no suitability potential (Çoban et al., 2020).

Future projection and spatial change detection

According to two different projected climate change scenarios, the geographical distribution maps for 2050 and 2070 were created and compared with the current potential distribution map. With a view to determine the spatial changes in the distribution (Coban et al., 2010), the data from different time periods in the raster format were converted into vector using raster-vector conversion tool in GIS. Intersection analysis was performed on the vector data to compute and analyze the differences.

Results

Variable selection, model performance, and variable contribution

Table 2 shows the Pearson correlation matrix analysis performed on the variables to eliminate the multicollinearity between the variables and improve the model performance. Later, the cumulative percentage contribution and permutation importance of individual variable was also computed (Table 3).

The selected variables were preprocessed in QGIS 2.6.1 and were fed into the MaxEnt software, the current distribution of *Rucervus eldii eldii* map was generated, and future distribution was projected. To test the model accuracy, average omission and predicted area of *Rucervus eldii eldii* and the mean AUC value of the model were analyzed (Fig. 2). Figure 3 shows the predicted area and test omission rate as a function of cumulative threshold, averaged over the replicate runs. Because of the designation of the cumulative threshold, predicted omission, and the omission rate was found to be in closer proximity (Phillips et al., 2006). The average AUC value of the model was found to be 0.944, indicates model to be descriptive and sensitive. To determine the most sensitive variable, the Jackknife test inbuilt in the MaxEnt was performed. The test result shows elevation, slope, bio3, bio4, bio10, bio11, bio14, bio16, and bio17 are the variables which are more sensitive to *Rucervus eldii eldii* habitat suitability (Fig. 4).

Variable response curves

To understand the ecological niche of the species and relationship between habitat suitability and the environmental variables, response curves are generated. Using the threshold of normal suitable habitats, the ranges of the suitability for environmental variables were found. The response curves of various environmental variables with the habitat suitability of *Rucervus eldii eldii* are shown in Fig. 5. The output format of the response was set to the latest "Cloglog" (Phillips et al., 2017). The suitable range of elevation for *Rucervus eldii eldii* was from 720 to 780 m with an optimal elevation of 770 m, precipitation in dry period (bio 14) from 13.5 to 15.5 mm with an optimal precipitation of 15.3 mm, precipitation in the wettest quarter (bio16) from 1365 to 1410 mm with an optimal value of 1405 mm, precipitation in the driest quarter (bio 17) from 62 to 62.3 mm with an optimal value of 62.2 mm, whereas mean temperature in the warmest quarter (bio 10) from 24.5 to 24.63 °C with an optimal value of 24.6 °C, mean temperature in coldest quarter (bio 11) from 15.1 to 15.4 °C with an optimal value of 15.3 °C, and isothermality (bio 3) from 46.43 to 46.6% with an optimal value of 46.5%.

Table 2 Pearson correlation matrix for different environmental variables

	Elevation	Slope	bio1	bio2	bio3	bio4	bio5	bio6	bio7	bio8	bio9
Elevation	1										
Slope	0.410343	1									
Bio 1	−0.02625	−0.10673	1								
Bio 2	0.096889	0.167577	−0.80231	1							
Bio 3	0.108212	0.164352	−0.81648	0.967257	1						
Bio 4	0.179902	0.193947	−0.57688	0.8345	0.789161	1					
Bio 5	0.05809	0.145691	−0.75702	0.978942	0.914209	0.747902	1				
Bio 6	−0.11687	−0.17771	0.802394	−0.99188	−0.95427	−0.8897	−0.95388	1			
Bio 7	0.092433	0.165883	−0.79118	0.997662	0.947804	0.83579	0.985625	−0.99087	1		
Bio 8	0.187414	0.062496	0.528235	−0.24529	−0.26324	0.285194	−0.3372	0.157807	−0.2408	1	
Bio 9	−0.10232	−0.16773	0.848354	−0.98231	−0.95158	−0.88416	−0.93732	0.993416	−0.97952	0.18911	1
Bio 10	0.187414	0.062496	0.528235	−0.24529	−0.26324	0.285194	−0.3372	0.157807	−0.2408	1	0.18911
Bio 11	−0.14861	−0.16129	0.599463	−0.72788	−0.6516	−0.72598	−0.67146	0.784829	−0.74247	−0.14963	0.771518
Bio 12	0.138532	0.102004	0.114592	0.083583	0.031325	0.555994	−0.0036	−0.1674	0.090762	0.776529	−0.18043
Bio 13	0.153702	0.136833	−0.04142	0.31169	0.23392	0.719205	0.238231	−0.3878	0.32343	0.693661	−0.39027
Bio 14	0.13556	0.175173	−0.65911	0.912286	0.796696	0.749158	0.861206	−0.92526	0.907721	−0.05532	−0.90044
Bio 15	0.095728	0.156453	−0.5338	0.816295	0.720106	0.933023	0.783346	−0.8531	0.830325	0.1763	−0.85588
Bio 16	0.139649	0.122823	−0.02689	0.257561	0.193123	0.685346	0.174878	−0.33702	0.266294	0.698615	−0.34934
Bio 17	0.19533	0.183316	−0.50165	0.698392	0.723617	0.690086	0.574832	−0.7553	0.682693	0.361669	−0.75377
Bio 18	0.139649	0.122823	−0.02689	0.257561	0.193123	0.685346	0.174878	−0.33702	0.266294	0.698615	−0.34934
Bio 19	0.191824	0.075172	0.295835	−0.16863	−0.10059	0.322868	−0.31771	0.079049	−0.1876	0.876733	0.086271

	bio10	bio11	bio12	bio13	bio14	bio15	bio16	bio17	bio18	bio19
Elevation										
Slope										
Bio 1										
Bio 2										
Bio 3										
Bio 4										
Bio 5										
Bio 6										
Bio 7										
Bio 8										
Bio 9										

Table 2 (continued)

	bio10	bio11	bio12	bio13	bio14	bio15	bio16	bio17	bio18	bio19
Bio 10	1									
Bio 11	−0.14963	1								
Bio 12	0.776529	−0.264	1							
Bio 13	0.693661	−0.42765	0.967771	1						
Bio 14	−0.05532	−0.73105	0.077027	0.285931	1					
Bio 15	0.1763	−0.71504	0.573675	0.745904	0.760501	1				
Bio 16	0.698615	−0.38361	0.982674	0.993679	0.237543	0.715261	1			
Bio 17	0.361669	−0.79788	0.534627	0.64422	0.78042	0.763017	0.630309	1		
Bio 18	0.698615	−0.38361	0.982674	0.993679	0.237543	0.715261	1	0.630309	1	
Bio 19	0.876733	−0.24037	0.694481	0.595996	0.06468	0.136451	0.622887	0.559478	0.622887	1

Table 3 Contribution of each environmental variable to potential distribution of *Rucervus eldii eldii* (Sangai) defined by MaxEnt

Variable	Percent contribution	Permutation importance
Bio 3	34.7	47.1
Bio 4	24.6	1.7
Bio 16	13.1	33.5
Bio 11	11.9	4.3
Slope	8.2	0.6
Bio 17	5	2.7
Bio 14	1	1.9
Bio 10	0.8	6.8
Elevation	0.7	1.3

Future and current potential spatial distribution of Sangai deer and its suitability as per global climate change scenarios

Figure 6 shows the current habitat suitability map of *Rucervus eldii eldii* (Sangai). The future habitat suitability under RCP 2.6 for the years 2050 and 2070 and under RCP 8.5 for the years 2050 and 2070 is shown in Fig. 7a, b, respectively. The habitat suitability was classified in five different categories from no potential to high potential. The current and projected future distribution of *Rucervus eldii eldii* can be tracked in the maps. Table 4 shows spatial coverage of habitat suitability potential under current and future scenarios according to suitability classes.

Under RCP 2.6, there were minor notable changes in the high suitability potential zone by the year 2050, but by year 2070 a significant change in the high suitability potential was observed. In the case of RCP 8.5 in both the time periods 2050 and 2070, significant decreasing trends under high suitability zones can be observed. Both the RCP scenarios RCP 2.6 and RCP 8.5 indicate the decreasing trends in high suitability zones and increase in no potential zones in the projected future time period.

Changes in the spatial coverage of habitat suitability as compared with the current scenario

Spatial changes in the habitat suitability zones were mapped by comparing the current scenario with the future scenarios under RCP 2.6 (Fig. 8) and RCP 8.5 (Fig. 9) for the years 2050 and 2070. For the purpose
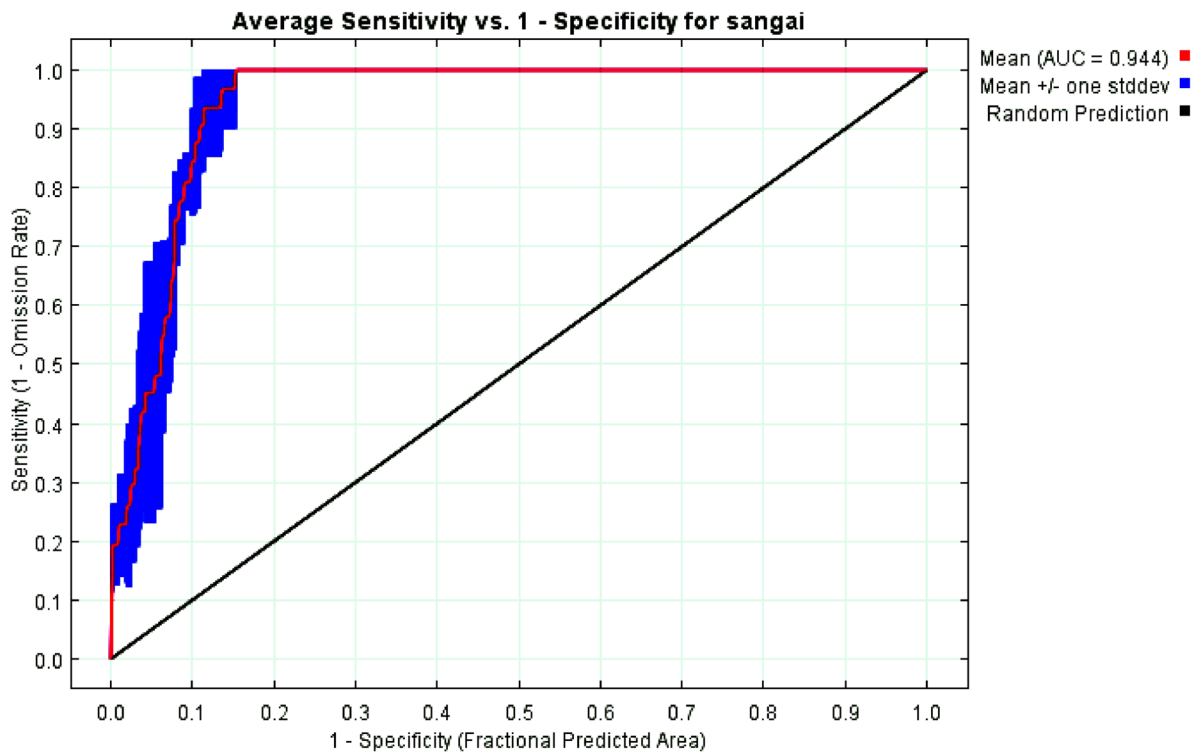
Fig. 2 The AUC curves in the developing *Rucervus eldii eldii* distribution model. (The red (training) line shows the "fit" of the model to the training data. The blue (testing) line indicates the fit of the model to the testing data and is the real test of the model's predictive power.)

of mapping the changes in the future, the vector layer of future projected coverage of various suitability zones from no potential to high potential was intersected with the vector layer of current potential suitability zones using geo-processing tools. Table 5 shows changes in current geographical distribution of *Rucervus eldii eldii* to the projected future distribution for 2050 and 2070 under RCP 2.6 and RCP 8.5. Two major observations can be drawn as shown in Table 5. Firstly, there is a significant increase in the area under category code "0" which indicates no suitability potential by 3.89 km² and 4.03 km² for the years 2050 and 2070, respectively, under the RCP 2.6, whereas for the years 2050 and 2070 under RCP 8.5 the area was found to be getting increased by 0.79 km² and 5.98 km², respectively. Secondly, a significant decreasing trend can be observed in the area under category code "4" which indicates high suitability potential by 2.64 km² and 4.6 km² for the years 2050 and 2070, respectively, under RCP 2.6, whereas for the years 2050 and 2070 under RCP 8.5 the area was found to be getting decreased by 3.41 km² and 3.43 km², respectively. Both the cases, i.e., observed

increasing trend in the no potential suitability and decreasing trend in the high potential suitability by an significant amount, show a potential threat to the natural habitat of *Rucervus eldii eldii* (Sangai) in KLNP in the coming future.

Discussion

Modeling performance and variable influence

The most important factor in species distribution modeling is selection of variables (Fourcade et al., 2017). Removal of redundant variables can further enhance the analytical power of the model and can reduce multi-collinearity between the variables (Yi et al., 2016). To assess the accuracy of the modeling, MaxEnt provides permutation importance or gain analysis of the variable. On the basis of permutation importance result, Pearson's correlation co-efficient test was carried out to eliminate the highly correlated variable. The suitability and variable response curves will provide information regarding the habitat
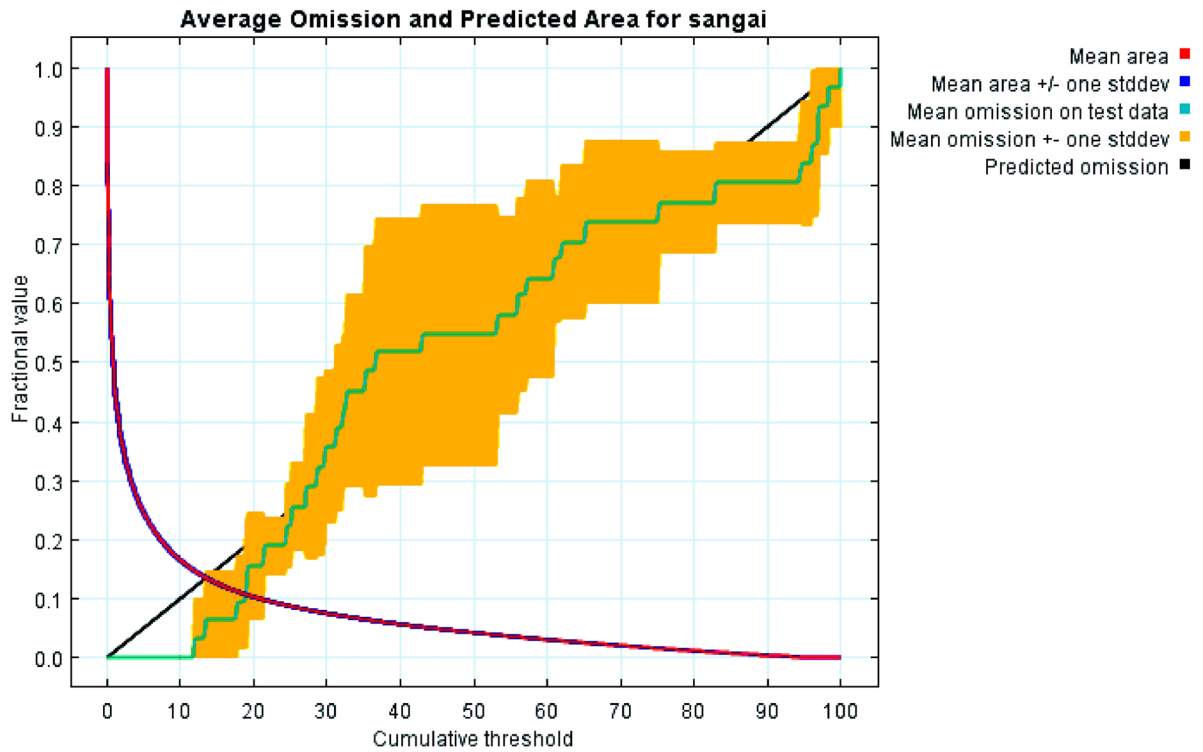
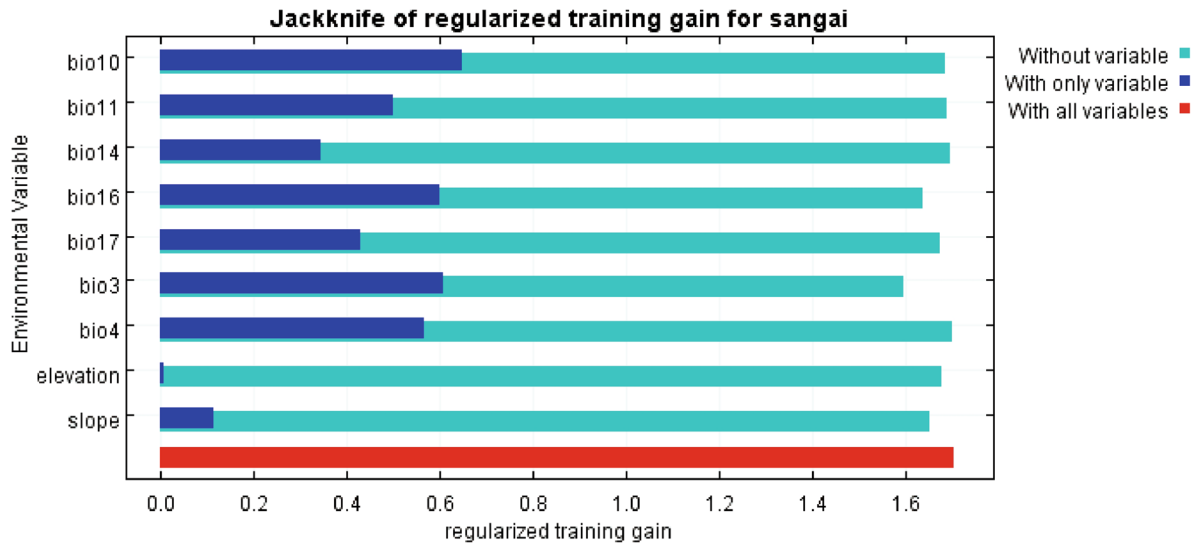**Fig. 3** Average omission and predicted area of *Rucervus eldii eldii* (Sangai)

Fig. 4 Jackknife test regularized training gain result for predicting the sensitivity of variable towards habitat suitability of Sangai
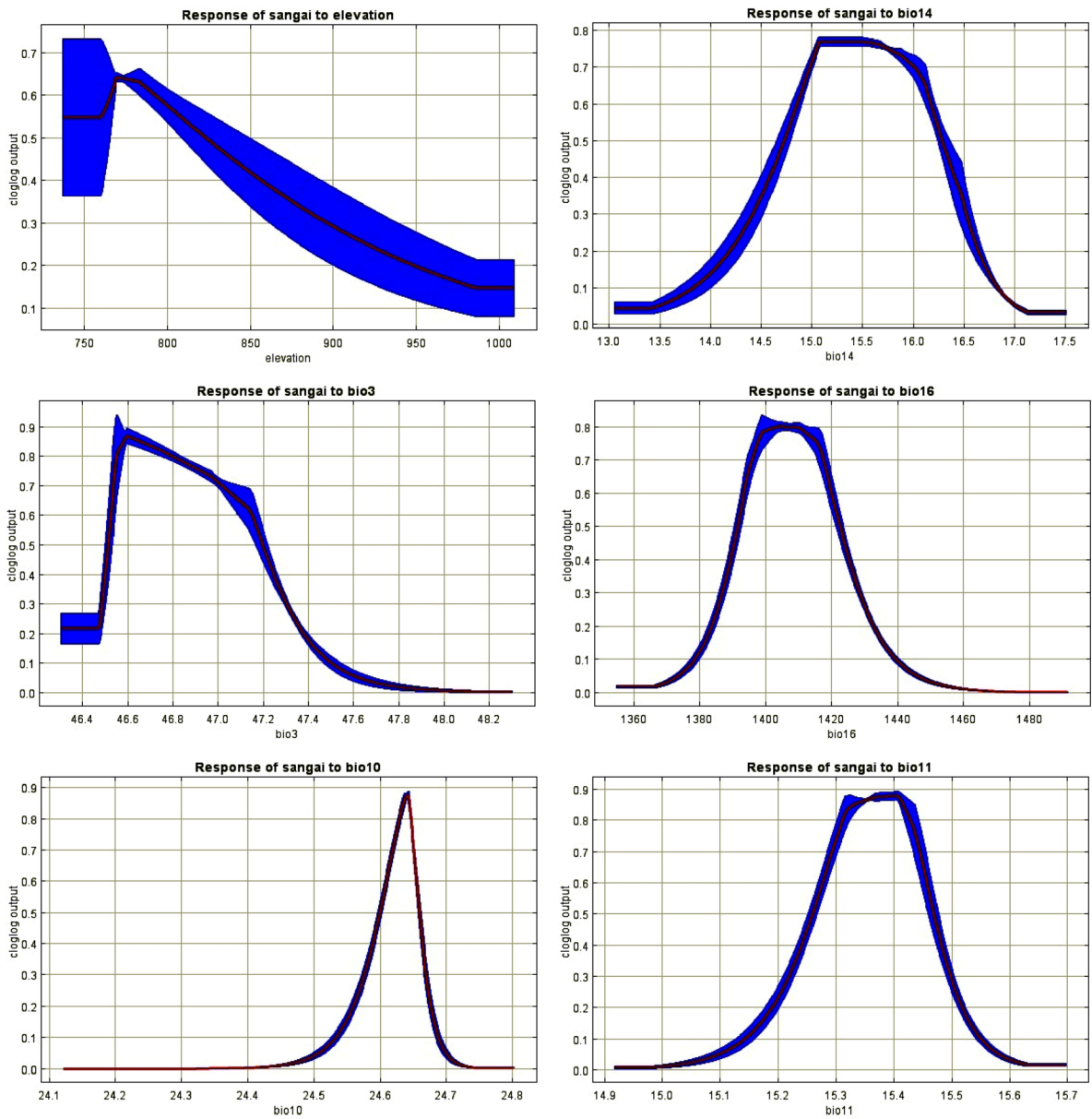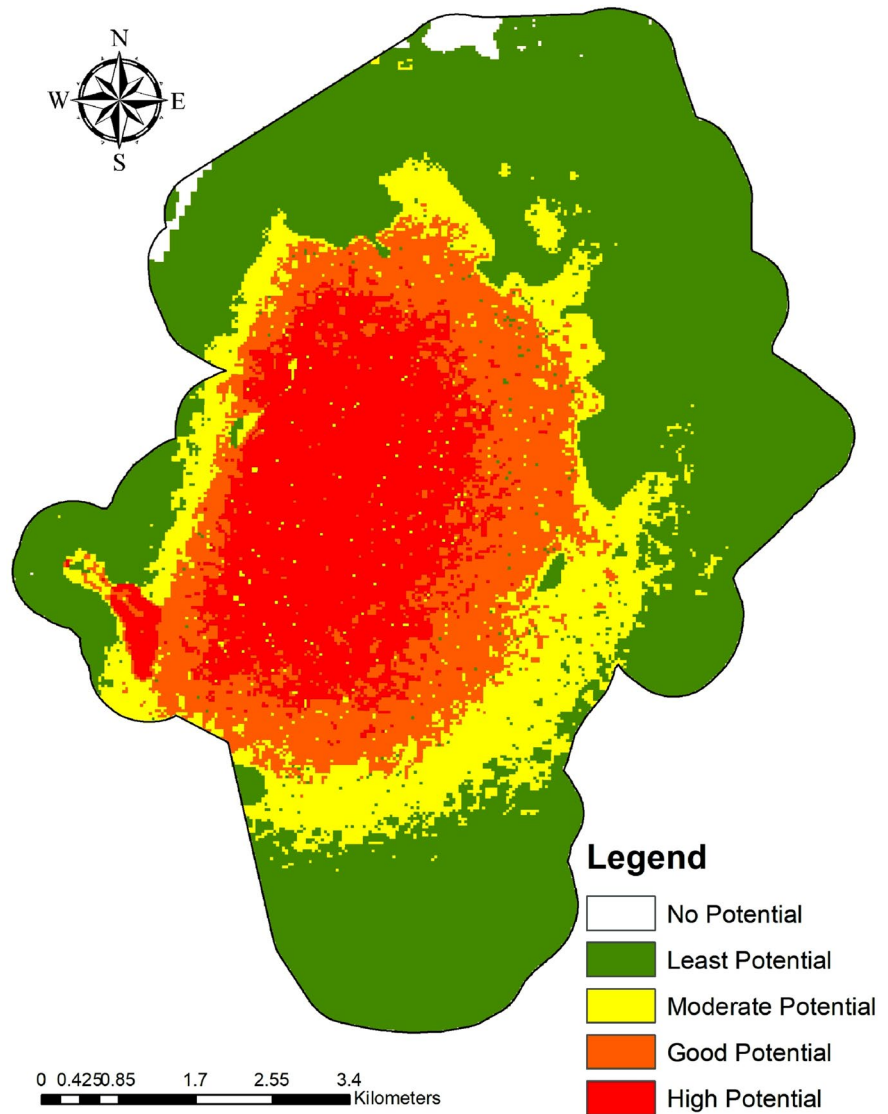
Fig. 5 Response of various environmental variable towards the optimal habitat suitability range in Clog-log output format

Fig. 6 Current habitat suitability at KLNP
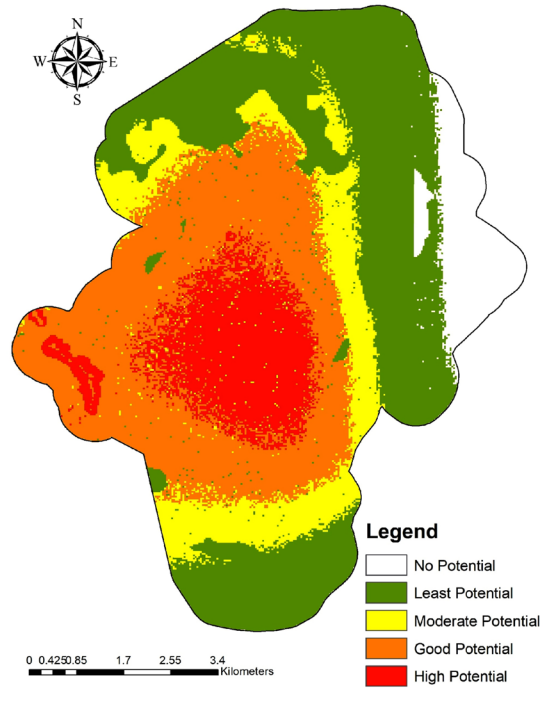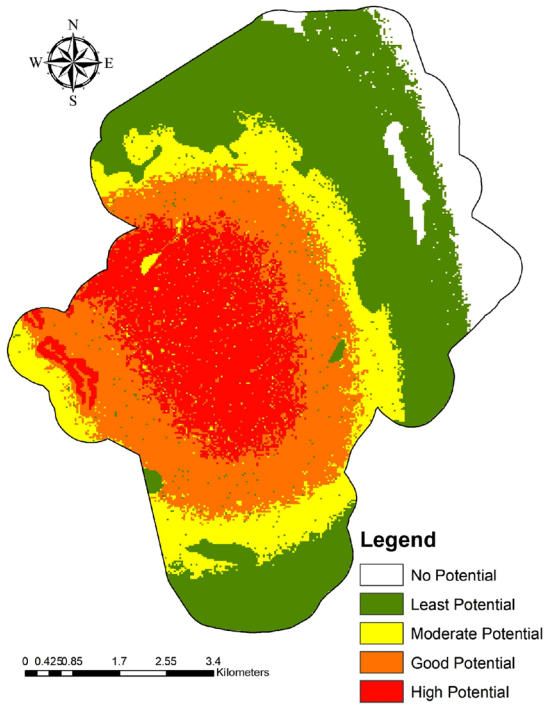
CURRENT HABITAT SUITABILITY

requirements of *Rucervus eldii eldii* if the ecological and predictive responses of the species are in close proximity. Therefore, for the biology research and population ecology the obtained values could serve as a reference range (Liu et al., 2019).

Through the Jackknife test, it was observed that the isothermality (bio3) and precipitation of the wettest quarter are the two most important or significant climatic variables which influence the habitat of *Rucervus eldii eldii* (Sangai). Since isothermality is an index which is based on the ratio

of annual mean temperature (bio1) and annual temperature range (bio7), from the response curve of bio3 there is a clear indication of adverse effect of increase in annual temperature on the habitat suitability of *Rucervus eldii eldii* (Sangai). Precipitation in the wettest quarter is of serious concern. A higher amount of rainfall during the monsoon period leads to flooding due to increase in the water level of Loktak Lake. Due to the increase in the water level of Loktak Lake, swampy phumdis plays an important role in the ecosystem of

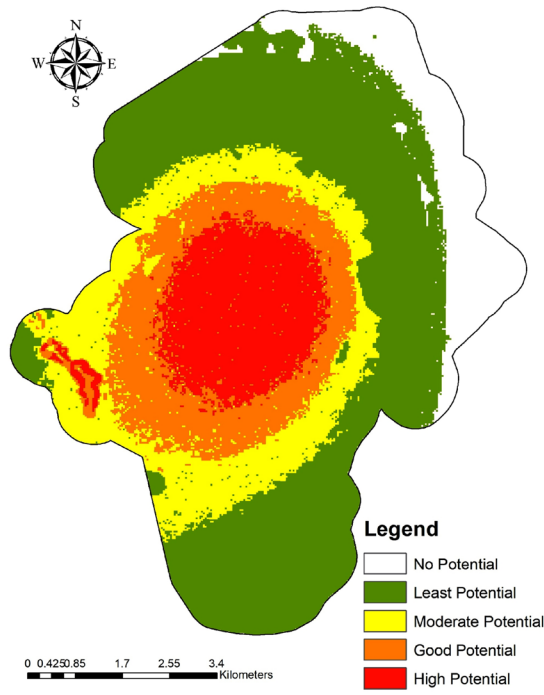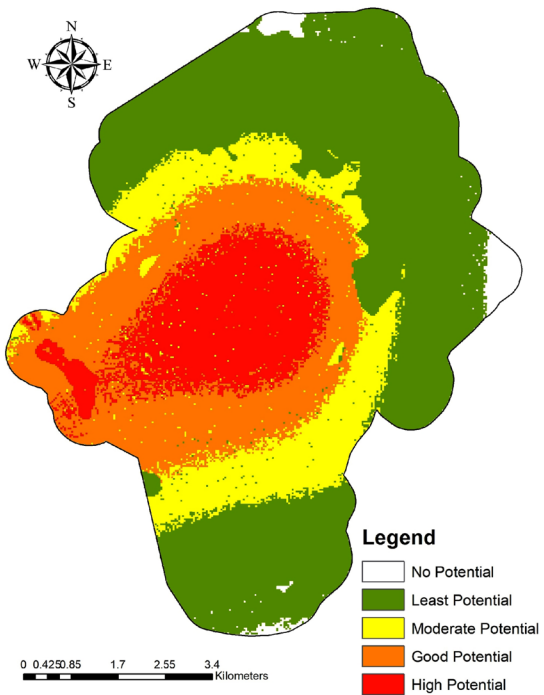### HABITAT SUITABILITY FOR 2050 UNDER RCP 2.6

HABITAT SUITABILITY FOR 2070 UNDER RCP 2.6

(a)

HABITAT SUITABILITY FOR 2050 UNDER RCP 8.5

HABITAT SUITABILITY FOR 2070 UNDER RCP 8.5

(b)

◀ **Fig. 7 a** Projected habitat suitability for 2050 and 2070 under RCP 2.6. **b** Projected habitat suitability for 2050 and 2070 under RCP 8.5

the deer can take rest and shelter, which makes the suitability zone very confined especially during monsoon.

Table 4 Spatial coverage of habitat suitability potential under current and future scenarios according to suitability classes

Suitability	Current area (km^2)	2050 (RCP 2.6) area (km^2)	2050 (RCP 8.5) area (km^2)	2070 (RCP 2.6) area (km^2)	2070 (RCP 8.5) area (km^2)
No potential	0.45	4.07	2.09	4.03	6.28
Least potential	29.25	22.21	25.64	21.05	25.12
Moderate potential	8.29	9.09	8.70	7.30	9.33
Good potential	9.21	12.56	12.36	16.45	8.49
High potential	8.82	8.09	7.23	7.19	6.80

the park, as it provides suitable feeding, bedding, and breeding ground of the Sangai (Shamungou, 2010) which gets affected during the south-west monsoon season. During this period, three hillocks of the 100–200-m wide area called Thangbral-yangbri (locally) stretching from west to east are the only hard grounds in the entire park on which

History and future dynamic trend of suitability under climate change

Once distributed throughout Southeast Asia, extending from Indo-China to Manipur, the *Rucervus eldii* deer are now curbed in patches in Manipur,
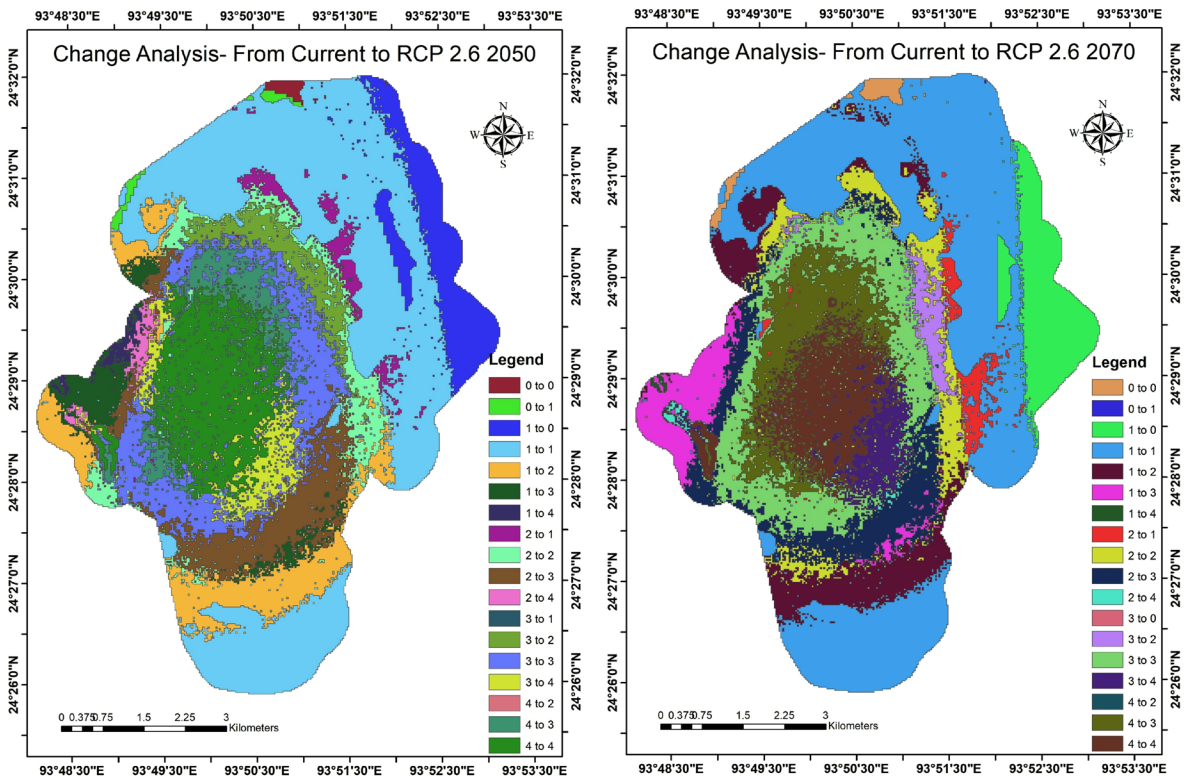

Fig. 8 Changes in the current potential distribution to future distribution under RCP 2.6 for 2050 and 2070 ("0" indicates no suitability potential, "1" indicates least suitability potential,

"2" indicates moderate suitability potential, "3" indicates good suitability potential, and "4" indicates high suitability potential)
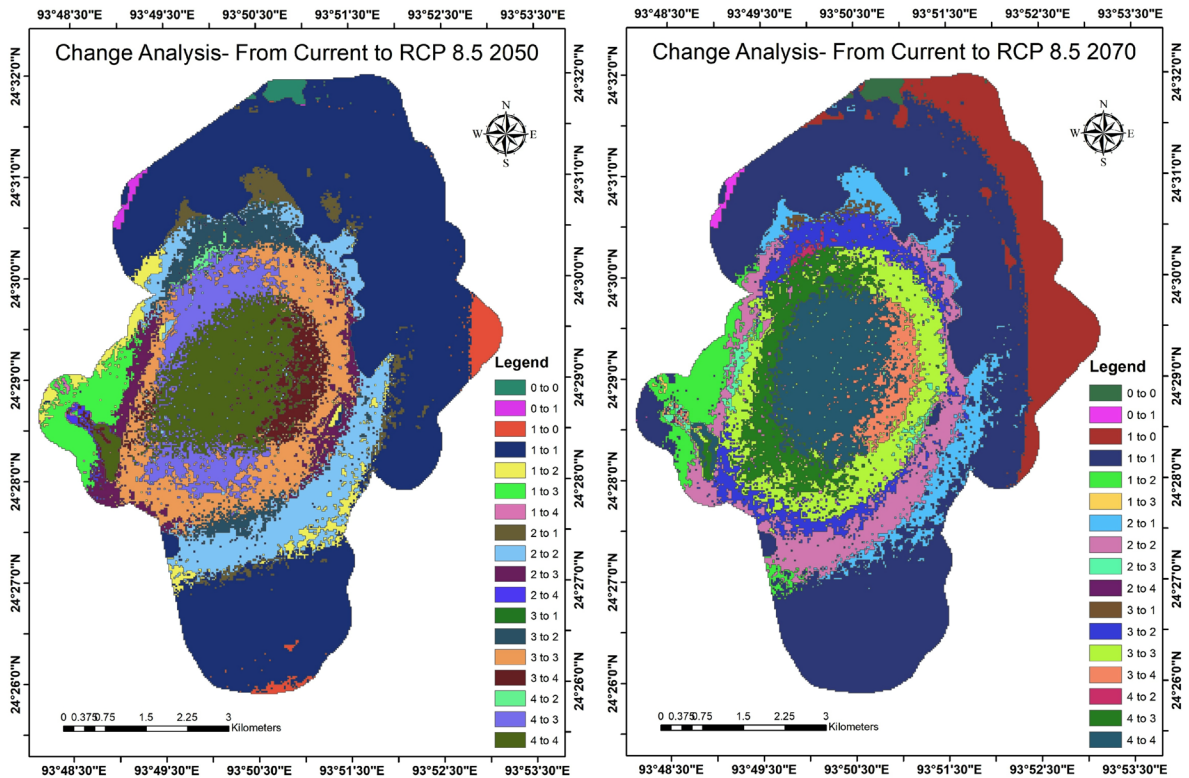
Fig. 9 Changes in the current potential distribution to future distribution under RCP 8.5 for 2050 and 2070 ("0" indicates no suitability potential, "1" indicates least suitability potential,

"2" indicates moderate suitability potential, "3" indicates good suitability potential, and "4" indicates high suitability potential)

Cambodia, Myanmar, Thailand, and Vietnam. Especially among all the *Rucervus eldii* groups, the *Rucervus eldii eldii* population is decreasing globally and is on the brink of extinction. *Rucervus eldii eldii* (Sangai) once thought to be extinct from India was rediscovered in 1953 on the southern fringe of Loktak Lake (Gee, 1960). Due to the intensive conservation and constant effort made by Forest Department, Manipur, the population of *Rucervus eldii eldii* has gone up to 204 in 2013 from just 14 in 1975 (Department of Forest (GoM), 2013).

But considering the model result and the impact of future climate change on the habitat of *Rucervus eldii eldii*, it can be noted that the area under high suitability potential is decreasing, whereas the area under no potential is increasing especially in the northeastern zone of KLNP adjacent to the main water body of Loktak Lake which is of major concern. The second major noted observation is a shift in the high-suitability potential zone from the western, northwestern, and southwestern peripheries

of the KLNP to the central core zone of KLNP which is very limited. From the model spatial distribution result in Fig. 7a, b, it can be observed that the high suitability potential zone from the western periphery of the KLNP to the central zone is getting shifted in the year 2050 but still the high potential patches are in minor contact with the western periphery, but in the year 2070 under both the RCPs it can be seen that the high potential zone is completely limited to the central core zone of KLNP, making the high suitability zone very limited and to be of serious concern.

Other threats

Geographic and climate factors have always been considered in the species distribution modeling, but the other factors like land use change, interspecies competition, and adaptability always play a significant role in the species distribution (Cauwer et al., 2014). This study only considers the climate

Table 5 Changes in current geographical distribution of *Rucervus eldii eldii* (Sangai) to the projected future distribution for 2050 and 2070 under RCP 2.6 and RCP 8.5

RCP 2.6				RCP 8.5			
2050		2070		2050		2070	
Change	Area (km^2)	Change	Area (km^2)	Change	Area (km^2)	Change	Area (km^2)
0 to 1	0.25	0 to 1	0.01	0 to 1	0.15	0 to 1	0.14
1 to 0	3.89	1 to 0	4.03	1 to 0	0.79	1 to 0	5.98
1 to 2	4.41	1 to 2	3.98	1 to 2	1.42	1 to 2	1.91
1 to 3	1.76	1 to 3	2.34	1 to 3	1.69	1 to 3	0.04
1 to 4	0.37	1 to 4	0.07	1 to 4	0.05	2 to 1	3.13
2 to 1	1.18	2 to 1	1.11	2 to 1	1.17	2 to 3	0.54
2 to 3	3.96	2 to 3	4.13	2 to 3	1.85	2 to 4	0.02
2 to 4	0.45	2 to 4	0.17	2 to 4	0.14	3 to 1	0.16
3 to 1	0.01	3 to 2	1.08	3 to 1	0.01	3 to 2	3.07
3 to 2	2.00	3 to 4	1.72	3 to 2	1.99	3 to 4	1.39
3 to 4	1.89	4 to 2	0.01	3 to 4	1.62	4 to 2	0.11
4 to 2	0.01	4 to 3	4.59	4 to 2	0.17	4 to 3	3.32
4 to 3	2.63			4 to 3	3.24		

and the topographic conditions in the form of elevation and slope, which indicates the decreasing trend of high suitability potential zones in the coming future. Other factors like land use change can also be one of the reasons which can impact the habitat of *Rucervus eldii eldii* (Sangai) as some of the study suggests that there can be an increase in the settlement in the eco-sensitive zones of KLNP and decrease in the herbaceous wetlands (Phumdis), one of major natural habitats of *Rucervus eldii eldii* (Sangai) (Anand & Oinam, 2020).

Conclusion

This study reveals that the future projected climate change will have adverse impacts on the habitat suitability of *Rucervus eldii eldii* (Sangai) according to the model result based on the maximum entropy algorithm, which further reveals that the suitable distribution areas will be narrower and will be limited to the central core zone of the KLNP. Two variables, isothermality (bio3) which is dependent on temperature and precipitation in the wettest quarter (bio16), were found to be the most influencing variables. Inclusion of bio3 as a significant variables hints about the adverse effect of increasing temperature in the future on the habitat of *Rucervus eldii eldii* (Sangai). As this study is based on the topographical and climate factors using the

maximum entropy principle, there is a future scope to explore the other dimension such as distance from the road, distance from settlement zones, change in land use land cover, interspecies competition, etc., which impacts the suitability using the various other algorithms like multiple-criteria evaluation (MCE), logistic regression, multiple-layer perceptron neural network approach (MLP-NNA), and Mahalanobis typicality approach. Based on the maximum entropy model results, we conclude that the population and distribution of *Rucervus eldii eldii* (Sangai) are vulnerable to climate change in future. Hence, the population and distribution of *Rucervus eldii eldii* (Sangai) should be emphasized to ex situ conservation and habitat restoration plans need to be implemented in the near future. This study can provide vital information for the protection and management of *Rucervus eldii eldii* (Sangai) and resources to address the global climate challenges.

Author contribution   BO and VA conceived the idea and designed the experiment. IHS collected and compiled the field data. Writing and editing was done by VA. Both VA and BO analyzed the result. All the authors read and approved the manuscript.

Declarations

Conflict of interest   The authors declare that they have no conflict of interest.

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