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ORIGINAL ARTICLE

Projected future of slender-billed vulture: Habitat distribution modelling and population study in Northern India

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Abstract

Slender-billed vulture is an Old-world vulture classified as critically endangered, yet insufficiently studied on account of future habitat and population trends. This is a narrow ranging, forest confined species found in the moist deciduous Tarai region of Northern India along Himalayan foothills. In the wake of a decreasing population trend and impact of climate change, we made model predictions to study suitable habitat area dynamics. Though the Ensemble model predicted better results than other models (GBM, GLM, MARS, CTA, ANN, MaxEnt, RF and SVM), independent Maxent prediction was found equally good. Suitable area was mainly determined by two vital climatic variables. Rising mean temperature of the driest quarter, 16 ºC onwards, and falling precipitation of the wettest month, 700 mm downwards, lowered the habitability of this vulture in Tarai ecozone. The projected suitable habitat showed spatiotemporal dynamics and a general trend of net gain in the expanse in different emission scenarios of near and distant future. However, the predicted population status was not encouraging. It is suggested that considerable attention and quick recovery management practices should be enforced proactively by total warding off of the population from diclofenac, followed by intensive breeding in captivity, habitat improvement and habitat construction/reconstruction for further spread.

Keywords Ensemble · Habitat dynamics · Model choice · Model contributors · Species distribution models

Introduction

Vultures, invaluable ecosystem service providers, are threatened across the world (Straub et al. 2015; McClure et al. 2018). Four Old-world vultures residing in India are critically endangered (Jha et al. 2023). Though other three are broader range species, the slender-billed vulture (= SBV, *Gyps tenuirostris* Gray, 1844) has a relatively narrow range across the Himalayan foothills, Tarai, in India. This range extended from Himachal Pradesh to Arunanchal Pradesh (Naoroji 2006; Jha and Jha 2023). The geographical extension of this range also lies in adjoining Nepal, Bhutan, and Bangladesh. Earlier reports recorded the SBV presence in Myanmar, Laos and Cambodia too (BirdLife International 2021). This species has a very low global population (Hla et al. 2011; DNPWC 2015; MoEF 2016; Sum and Loveridge 2016; Prakash et al. 2019) which is declining further (BirdLife International 2021). This is due to several natural and anthropogenic threats, especially in Indian subcontinent which was affected by the diclofenac crises[1]. Zero sightings during a survey in 2019 in Uttar Pradesh (UPFD and BNHS 2021), though not an indicator of total disappearance, definitely indicate a severe decline in the population. Additionally, narrow-ranging species living under very specific environmental conditions are also predicted to be particularly vulnerable to climate change (Dubos et al. 2022a). Forest confined species such as the SBV, are affected by wildfire and drought which is linked to climate change (Abatzoglou and Williams 2016; van Wees et al. 2021). The

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[1] A sharp decline in vulture population in a short period was reported in the Indian subcontinent during late 1990s and early 2000s. This was attributed to unrestricted use of a non-steroidal anti-inflammatory drug, diclofenac, in cattle. This was transferred to vultures on carcass consumption proving fatal.

SBV population and habitat are also understudied in India. All these necessitate immediate monitoring and management interventions for earliest possible recovery of such an imperiled species.

Successful management requires measurement of some ecological parameters of the biological entity such as richness and abundance of the species, spatial and temporal distribution, and habitat requirement. In the case of the SBV, this would initiate the determination of its presence, numbers, and spatiotemporal distribution (Jha 2018). Temporal distribution, especially of the future, would require the study of the impact of changing climate, well known to impact habitat distribution (Jiao et al. 2016; Liu et al. 2017). There are several species distribution models (SDM) and global circulation models (GCM) which could be used in habitat predictions (Jha and Jha 2021a) for monitoring and management. Population could also be projected using semi-algorithmic model (Zeng et al. 2015).

With the above background, the present study is aimed at assessing and analyzing current and future habitats distribution and populations with the help of species distribution modelling in west-central Tarai region which forms the part of Uttar Pradesh or Northern India. It is also aimed at ascertaining suitable species distribution models and vital model predictors for the SBV habitat in this region so that some conservation measures could be suggested.

Materials and methods

Study area

Uttar Pradesh (UP), a north Indian province, (Fig. 1) was selected for the present study. Due to prevalence of the SBV in Tarai ecozone, northern districts and adjoining areas were focused upon. The Tarai region in UP shares its northern boundary with Nepal and spreads between 28°45′–26°15′ N and 79°51′–84°24′ E as a 30–50 km wide and ca. 1,670 km long strip with the elevation ranging between 100 and 300 m a.s.l. It has a monsoon type of climate. The mean minimum temperature varies from 4−5 °C in December–January and maximum 40−45 °C in May–June. The average annual rainfall varies from 1085 to 1228 mm (Bajpai et al. 2015). This region has tropical moist deciduous type of vegetation (Champion and Seth 1968) which can be further divided into following forest types: Sal forest, miscellaneous forest, teak plantation and savannah grasslands. Outside forests, agriculture landscapes also form foraging grounds for vultures.

Population assessment

Transect survey

After consulting literature and vulture experts, we decided on transect routes for the SBV occurrence data collection (Fig. 1). We selected reserve forests and protected areas of the Tarai ecozone and adjoining agriculture landscapes of these forests. Motoring and trekking routes were also decided with the help of frontline forest workers and locals to cover potential / historical sites. Vehicle speed was maintained at 40 km h^{-1} and 20 km h^{-1} on the pucca road outside the forest and kuchcha motorable road inside the forests, respectively. We used binoculars and covered the visible distance on both sides of the roads. Inside the forest compartments, we walked briskly but approached the presence locations slowly. The survey was conducted during March and December 2020.

Area-density method

Since we did not encounter any SBV during our surveys, we used area-density method suggested by Zeng et al. (2015). Density was calculated using the data available in literature: occupancy and vulture population of 2010 2.7% (Jha 2022) and 516 individuals (Jha 2015), respectively. Projected suitable habitats of 2020, 2050 and 2070 in the present study yielded the possible population using the density.

Habitat projection

Ensemble modelling

Since several SDM are available to project habitat/environmental suitability and no single model is considered the best for particular species or landscape, an ensemble, a combination of better performing models, is suggested (Marmion et al. 2009; Valavi et al. 2022). This prediction presents a viable approach for unravelling the differences between various models and overcoming uncertainties in individual models (Hao et al. 2019). Therefore, various algorithms like, regression models (GBM, GLM, MARS), classification techniques (CTA), and machine learning (ANN, MaxEnt, RF, SVM), as recognized by a few researchers (Bucklin et al. 2015; Fruh et al. 2018), were run to make Ensemble model in this study. All the model runs were at default setting.

MaxEnt modelling, input and output

Ensemble models are influenced by constituent algorithms and sometimes may overpredict the results (Jha 2022). On

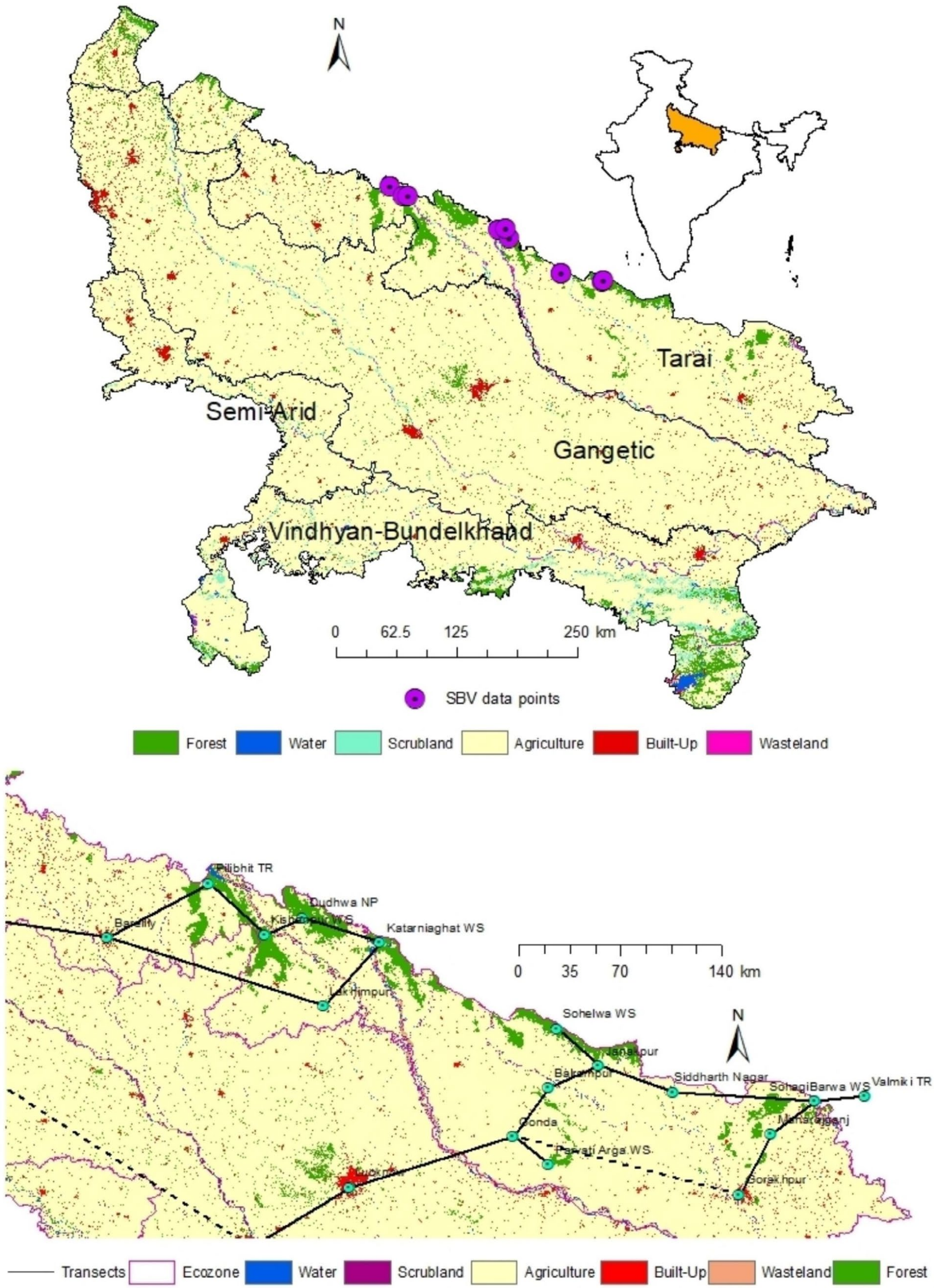

Fig. 1 Study area location map (inset) with land-use landcover and the slender-billed vulture (SBV) occurrence data points (left), and transect survey routes in Tarai ecozone (right). Solid lines were covered by vehicle and on foot, dashed lines indicate railway transect

the other hand, stand-alone MaxEnt algorithm is capable of producing distribution maps of comparable accuracy to Ensemble method and is heavily favoured by the scientific community (Kaky et al. 2020). Therefore, for spatiotemporal habitat dynamics determination, MaxEnt model was run at default settings with a change in the run type bootstrap with 10 replicates per prediction and a random test percentage of 25. Feature type used for model training was auto features and the number of background points was 10,000.

All SDMs needed occurrence and bioenvironmental data as the input for habitat to analyze features of a set of geographic locations that together represent a known niche of an organism of interest, with the goal of predicting its distribution across a defined geographic region (Beeman et al. 2021). Since the 2020 survey could not detect the SBV locations, citizen science data [records from eBird (www.ebird.org) (Sullivan et al. 2009)] and published records were used for the same purpose. Standard processes of uncertainty reduction namely, duplicate removal and spatial rarefication (Brown et al. 2017) was done. As a result, ten occurrence points were reduced to seven. Bioenvironmental raster layers namely, bioclimatic variables were downloaded from www.worldclim.org (Fick and Hijmans 2017), elevation data from Earth Resources Observation and Science (EROS) Center (USGS EROS 2018), two sets of Normalized Differentiated Vegetation Index (NDVI) data of winter (January) and summer (June) seasons (Didan 2015) from www.earthexplorer.usgs.gov, and land use and land cover (LULC) from www.land.copernicus.eu (Buchhorn et al. 2020).

Selection of the above environmental and climatic factors was guided by the published records. Fourcade et al. (2018); Dubos et al. (2022b) suggested that causal relationship between selected predictors and the biology of the species is needed for proper modeling. The vegetation cover presence, a biotic factor, determines the land's ability to supply food and/or shelter to animals and becomes a limiting factor to spread of a species (Herrero et al. 2006; Bosch et al. 2014). Vultures use cliffs and tall trees for safe shelter for nesting and inhabit higher altitude (Jha and Campbell 2023). The SBV, in particular, is found in moist forests and reported to use up to 1800 m altitude and is a specialized tree nester (Naoroji 2006). Carcasses available in forests are safe for vulture consumption which can be determined through NDVI as proxy (Campbell 2015; Santangeli et al. 2018). Abiotic factors like the rainfall patterns influence the success of vulture breeding (Bridgeford and Bridgeford 2003; Virani et al. 2012) and temperature change also governs the reproduction of vultures, causing stress directly to the animal (Chaudhry 2007; Schultz 2007 in Phipps et al. 2017; Bamford et al. 2009; Midgley and Bond 2015). Additionally, Luoto et al. (2006) reported that species could rapidly respond to climatic change resulting into altered distribution. However, before plugging in, bioenvironmental data were subjected to Pearson collinearity test at ±0.7 threshold for removing collinearity effect.

For the current predictions eight SDMs (GBM, GLM, MARS, CTA, ANN, MaxEnt, RF and SVM) were generated in R using Stacked Species Distribution Modelling package (Schmitt et al. 2017) at default setting followed by the Ensemble. Model strength was evaluated using Area Under Curve (AUC), Kappa and True Skill Statistics (TSS) values. The AUC scale was categorized as excellent (0.91-1.0), good (0.81–0.9), fair (0.71–0.8), poor (0.61–0.7) and fail (< 0.6) (Swets 1988; Heikkinen et al. 2006). The Kappa values were classified as excellent (0.81-1.0), good (0.61–0.8), fair (0.21–0.4) and fail (< 0.2) (Landis and Koch 1977; Heikkinen et al. 2006). The TSS values were graded as: excellent (0.81-1.0), good (0.61–0.8), fair (0.41–0.6), poor (0.21–0.4) and fail (< 0.2) (Allouche et al. 2006; Rew et al. 2020). Failed models were excluded from the Ensemble. For future projections, MaxEnt was the SDM of choice. All the future models are climatic only and without LULC, elevation and NDVI. Three Global Circulation Models (GCMs): CCSM4, HadGEM2A and MIROC5 were further selected for future projection. Model derived continuous index heatmaps were reclassified into four categories: unsuitable (0.0-0.25), low suitability (0.25–0.50), moderate suitability (0.50–0.75) and high suitability (0.75-1.00) as suggested for raptors and vultures (Zhang et al. 2019; Jha and Jha 2021a; Jha et al. 2022b). With the help of this categorization, habitat /environmental suitability maps were prepared using ArcGIS 10.5. The whole process of modelling is depicted in Fig. 2.

Results

Multiple SDMs and ensemble prediction

Eight algorithm-based (ANN, CTA, GBM, GLM, MARS, MaxEnt, RF and SVM) and one Ensemble environmental suitability modelling results are presented in Fig. 3 along with model evaluators in Table 1. While GBM did not predict anything (failure due to insufficient data), MARS predicted just 1% total suitable area (low, moderate and high) in the state and SVM predicted 36% total suitable area against background area of 240,928 km^2. Prediction by other models (ANN, CTA, GLM, MaxEnt, and RF) fell within this range. For Ensemble prediction MARS and CTA were eliminated due to poor performance but ANN, GLM, MaxEnt, RF and SVM formed the constituent components as two out of three evaluators performed fair to excellent. Ensemble was found to be influenced more by ANN and SVM, since it also predicted suitable area as a prominent patch like constituent models in west-central region of the

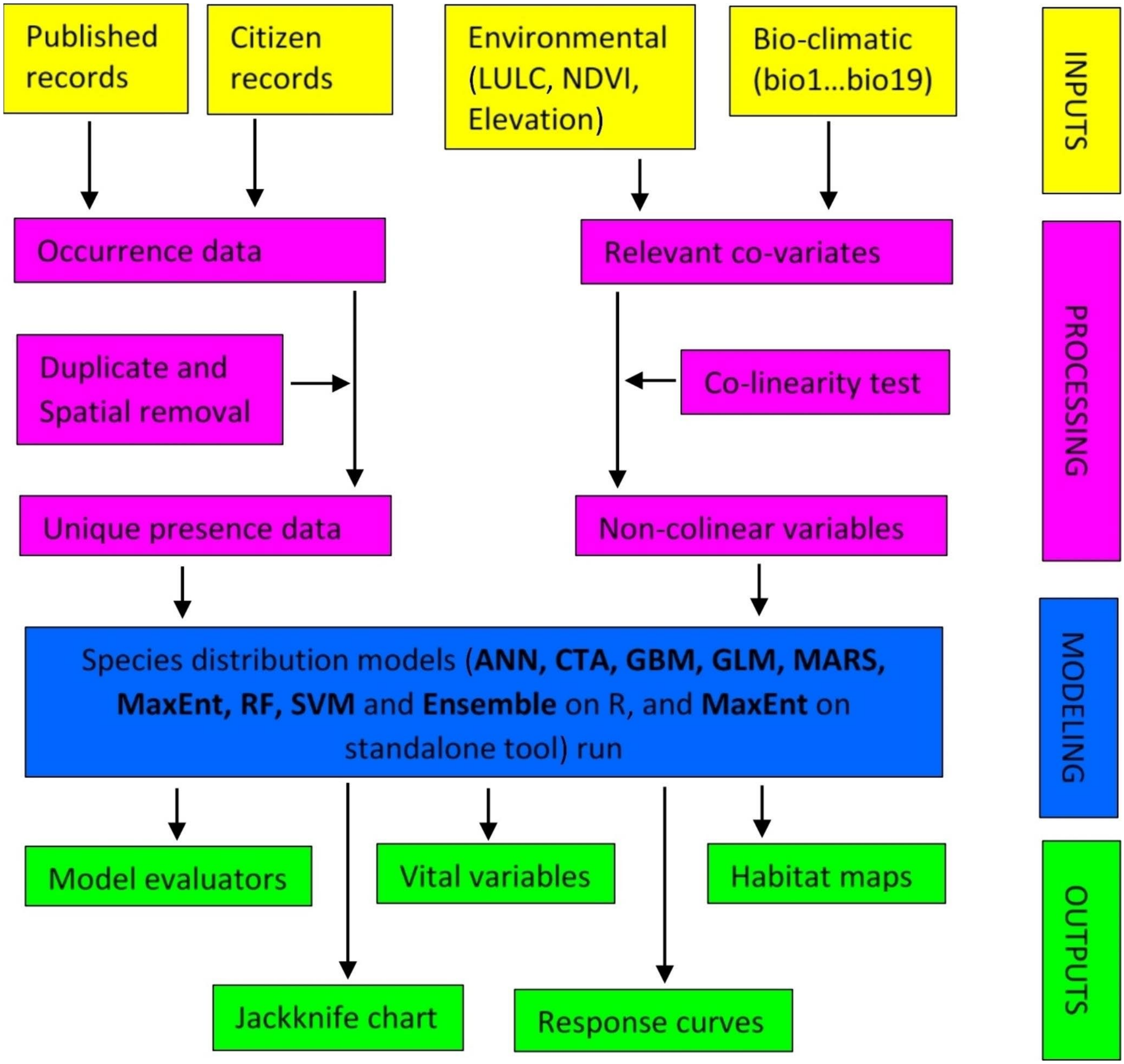

Fig. 2 Flow chart showing different steps involved in modelling done for the slender-billed vulture's habitat projection. Modified from Jha et al. (2022b)

state. However, GLM, MARS, RF and MaxEnt did not predict such unnatural patch of suitable area.

Model determining vital variables

Mean temperature of driest quarter (bio9) and precipitation of wettest month (bio13) were the vital variables (*sensu* Zhang et al. 2020) which contributed the most in both the current models without LULC (69% and 14%, respectively) and with LULC (67% and 12%, respectively). All other non-colinear variables (bio1, bio2, bio8, bio9, bio14, bio15; and LULC, NDVI, Elevation) played a minor role in habitat determination. Nevertheless, LULC which contributed just 10% in model prediction, showed that presence of waterbody was the most important component. In future predictions also bio9 and bio13 remained vital in all the scenarios and contributed in model prediction > 70% and > 10%, respectively while all other climatic variables remained minor contributors (Table 2). The charts of habitat determining variables are given in Fig. 4.

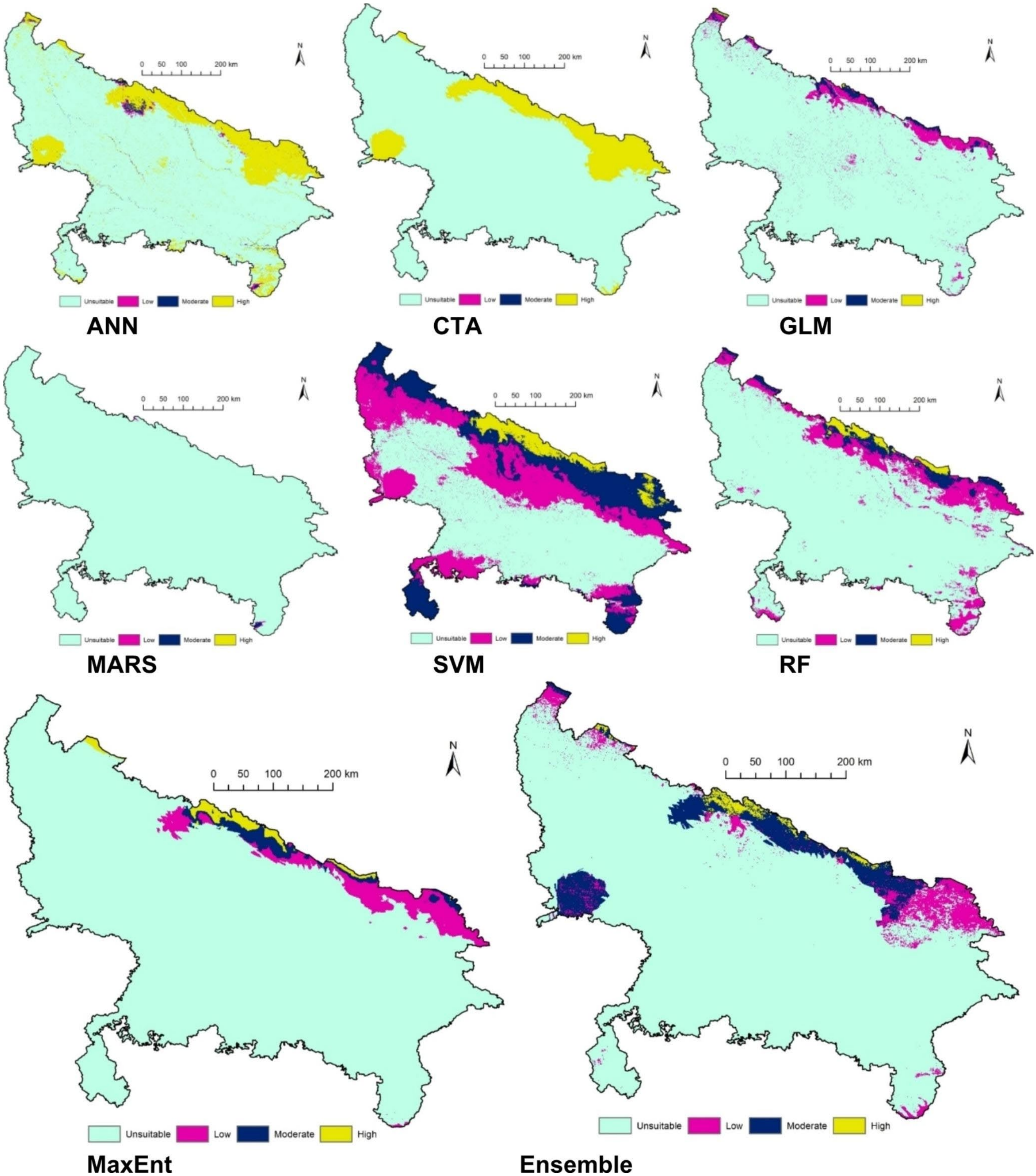

Fig. 3 Various environmental suitability prediction maps of slender-billed vulture for the present with LULC scenario. A distinctive near circular patch (western-central region of the state) of suitable area prediction by ANN, CTA, SVM and Ensemble may be noticed

Table 1 Model performance using three model indicators. Colours indicate the performance classes' similarity and number in parentheses are indicator values

Model/Indicator	AUC	TSS	Kappa
ANN	Excellent (1.0)	Excellent (1.0)	Excellent (1.0)
CTA	Good (0.8)	Fair (0.5)	Fair (0.5)
GLM	Excellent (1.0)	Excellent (0.9)	Poor (0.2)
MARS	Good (0.8)	Poor (0.2)	Poor (0.0)
RF	Excellent (1.0)	Excellent (1.0)	Excellent (1.0)
SVM	Excellent (1.0)	Excellent (1.0)	Excellent (1.0)
MaxEnt	Excellent (1.0)	Excellent (1.0)	Poor (0.1)
Ensemble	Good (0.8)	Good (0.7)	Fair (0.5)

Habitat projection and area dynamics

As per current projection models the suitable habitats for the SBV in UP (Table 3) was around 3% of the available study area (240,928 km^2) under both the conditions: (i) prediction with LULC (6331 km^2) and (ii) without LULC (5924 km^2). The suitable area in patches, showing marginal difference of 407 km^2, are totally confined in northern part of UP (Fig. 5) falling exclusively in the Tarai ecozone and Tropical moist deciduous forest. Comparing with the present projection without LULC, total suitable area in all future scenarios increased irrespective of the timeframe and emission pathways (3 −5% suitable area) except RCP2.6 of 2070 (only 2% suitable area). It is interesting to note that both the extreme scenarios (RCP2.6 and RCP8.5) would have highest suitable area and moderate scenarios (RCP4.5 and RCP6.0) would have relatively lower suitable area in near future. However, the case would be reverse in distant future (Figs. 6 and 7).

Area dynamics showed partial conversion of suitable area to unsuitable area and vice versa (Figs. 5, 8 and 9) which could be appreciated numerically in Table 4 in the form of gain and loss categories. The loss in area ranged from 1 km^2 to 610 km^2 and gain ranged from 882 km^2 to 6234 km^2. The loss in suitable area is offset by gain in all the cases and a net gain was seen with the exception of RCP2.6 of 2070.

Population estimation

As per area-density method, projected current population ranged between 178 and 190. Considering all the emission scenarios together, after short term it could range between 204 and 365 showing marginal rise over the current population. In long-term, this range went down to 159–263.

Discussion

Choice of SDM

In the present study, different SDMs projected area suitability in the range of 1–36% of the study area which could be either under estimation (e.g., MARS) or over estimation (e.g., SVM) when compared among themselves. Such variations are reported earlier also (Ghareghan et al. 2020; Rew et al. 2020). Ensemble along with ANN, GLM, RF, MaxEnt and SVM were good category models (Table 1). However, ensemble prediction showed suitable area in Semi-Arid ecozone (Fig. 3) turning out to be over prediction when verified in the field (ravenous landscape devoid of moist deciduous forests, large size trees, insufficient prey and predators). Experts also confirmed absence of the SBV in semi-arid ecozone. Such scrutinizing finds support in Mi et al. (2017)'s observation also that modelers should not depend fully on model evaluating metrics, but also should base their assessments on the combined use of visualization and expert knowledge. Other researchers (Hertzog et al. 2014; Lannuzel et al. 2021; Dubos et al. 2022b) have also

Table 2 Species wise variable contribution in habitat suitability prediction for future scenarios

Scenario	RCP2.6		RCP4.5		RCP6.0		RCP8.5	
	Variable	Average % contribution	Variable	Average % contribution	Variable	Average % contribution	Variable	Average % contribution
2050	bio09	78.8	bio09	73.6	bio09	72.9	bio09	72.4
	bio13	10.7	bio13	11.6	bio13	15.1	bio13	14.6
	bio15	5.1	bio15	6.8	bio15	5.1	bio02	5.3
	bio02	3.7	bio02	6.5	bio02	4.2	bio15	5.0
	bio14	0.6	bio14	0.7	bio14	0.8	bio01	1.0
	Others	0.9	Others	0.9	Others	1.9	Others	1.7
2070	bio09	71.4	bio09	71.8	bio09	74.6	bio09	73.8
	bio13	15.5	bio13	13.5	bio13	12.5	bio13	15.7
	bio02	7.0	bio02	6.6	bio15	6.6	bio15	5.3
	bio15	3.1	bio15	5.0	bio02	4.1	bio02	2.6
	bio08	1.4	bio08	1.8	bio01	1.1	bio01	1.0
	Others	1.6	Others	1.3	Others	1.1	Others	1.6

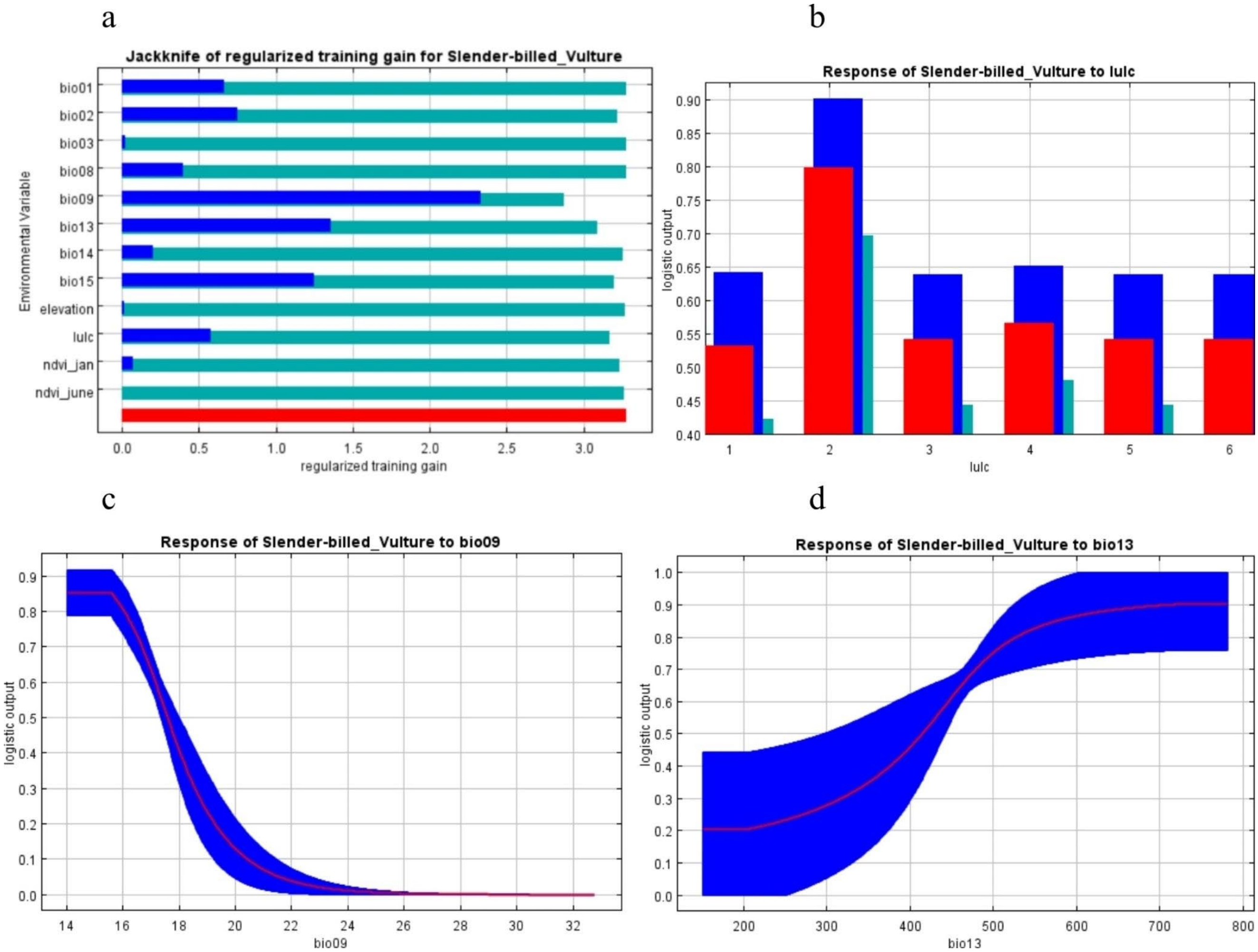

Fig. 4 Charts of habitat determining variables. **a** Jackknife chart of variables' importance, **b** categorial variables of LULC (1 = forest; 2 = water; 3 = scrubland; 4 = agriculture; 5 = built-up area; and 6 = wasteland) and at the bottom response curves, **c** bio9 and **d** bio13 showing the relationship of presence probability in the habitat by the slender-billed vulture

emphasized on the importance and utility of field validation for prediction accuracy. Existing range maps (Botha et al. 2017) showed presence of the SBV in Tarai and Gangetic plain only, not in Semi-Arid ecozone. However, MaxEnt prediction appeared closer to the ground reality. Kaky et al. (2020) also suggested that MaxEnt model's performance is comparable to the ensemble approach. This is further supported by Yates et al. (2018)'s hypothesis that although an ensemble model tends to be more accurate than individual models, an optimal single model for prediction analysis may yield better results than an ensemble model. This further guided us to model current and future habitats for the SBV to see the impact of climate change on the habitat distribution using only MaxEnt algorithm. Valavi et al. (2022) has also evaluated MaxEnt as one of the best performing SDMs.

Habitat predictors

All the MaxEnt projections/models having strong predictability showed marginal difference in (of 400 km^2) suitable habitats for present between the models with and without LULC. But the larger area expanse in LULC model is contrary to earlier findings of Jha and Jha (2021 a, b) who concluded that inclusion of LULC limits the suitable habitat availability. The most important LULC component also differed from these two findings. Built-up area was the most important instead of waterbody as suggested by these researchers. It could be speculated that interaction between the SBV and water had higher significance. On account of around 80% contribution (Table 4; Fig. 9), mean temperature of driest quarter (bio9) and precipitation of wettest month (bio13) were the deciding features of the habitat. This is in contradiction with Jha and Jha (2023) reporting built-up and other dominating covariates (bio18, bio1, bio14). This

Table 3 Projected habitat / environmental suitability area under different terms: (a) variable category wise for present and (b) concentration pathways wise for future (% decimal digits are rounded off)

(a)	Current prediction								
Prediction period	Area suitability class	Environmental		Climatic					
		km^2	%	km^2	%				
2020	Unsuitable	234,596	97	235,004	98				
	Low	4906	2	4245	2				
	Medium	1330	1	1602	1				
	High	95	0	77	0				
	Suitable (L+M+H)	6331	3	5924	3				
(b)	Future scenario (Climatic)								
Prediction period	Area suitability class	RCP2.6		RCP4.5		RCP6.0		RCP8.5	
		km^2	%	km^2	%	km^2	%	km^2	%
2050	Unsuitable	228,771	95	233,697	97	234,124	97	233,445	97
	Low (L)	9436	4	5408	2	5255	2	5697	2
	Medium (M)	2626	1	1805	1	1538	1	1756	1
	High (H)	95	0	18	0	11	0	31	0
	Suitable (L+M+H)	12,157	5	7231	3	6804	3	7483	3
2070	Unsuitable	235,614	98	233,885	97	232,153	96	233,923	97
	Low	3716	2	5448	2	6478	3	4933	2
	Medium	1525	1	1559	1	2220	1	2019	1
	High	73	0	35	0	77	0	54	0
	Suitable (L+M+H)	5314	2	7043	3	8775	4	7005	3

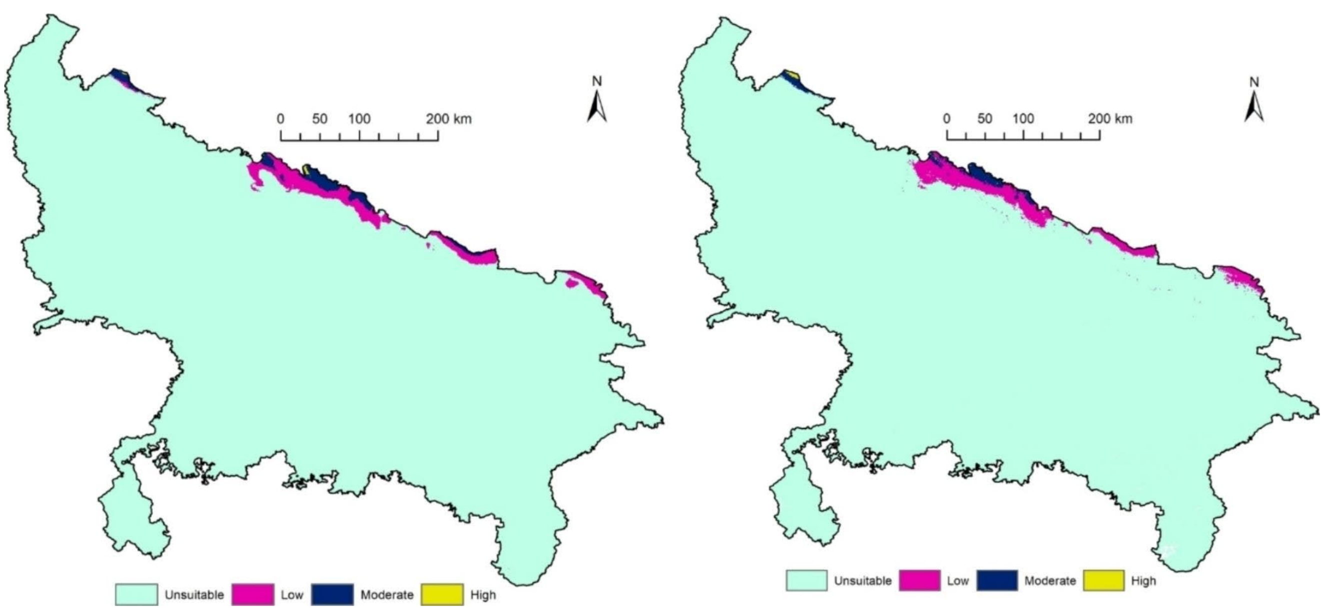

Fig. 5 Present day habitat /environmental suitability maps of the slender-billed vulture (MaxEnt modelling). Projections without LULC (left) and with LULC (right)

could possibly be due to larger study area covering varied climatic factors in the case of latter. However, considering a single variable in isolation may be also misleading as the species choose their habitat based on the interaction of several factors (Jha and Jha 2021b). The rising mean temperature of driest quarter, 16 ºC onwards (bio9), and falling precipitation of wettest month, 700 mm downwards (bio13), limited the habitat in the present case. It also indicated that beyond 22 ºC (bio9) and 200 mm (bio13) conditions could be intolerable. Therefore, it was evident that the SBV preferred wetter area with moderate temperature. This finding disagrees with Jha and Jha (2021b) where combined vulture species preferred drier areas. This could possibly be due to the adaptability of other vulture species found in wider range of climatic factors. However, the SBV seems to be a habitat specialist when compared with other resident vulture species (Jha and Jha 2023). Though it is difficult to disentangle climate and habitat on the basis of the present study,

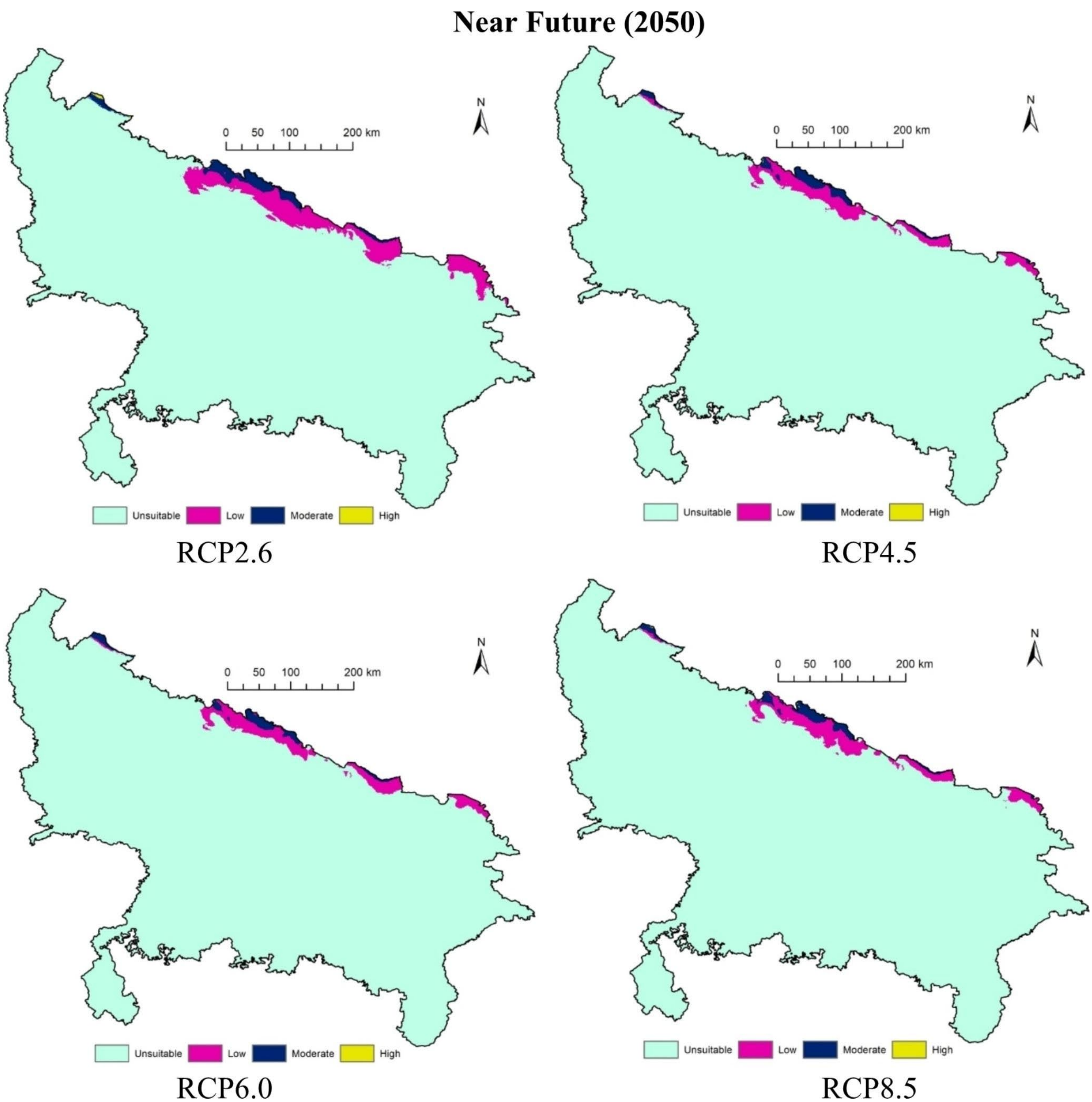

Fig. 6 Habitat suitability maps of the slender-billed vulture in short term (2050) under all representative concentration pathways

climate played a very important role in habitat prediction. Therefore, to our understanding, there is a combined effect of climate and habitat variables on the distribution of SBV in its range.

Spatiotemporal habitat changes

Comparison within present predictions and between present and future scenarios showing minor variation in suitable habitat area indicated influence of additional variable (LULC) in the case of former while climate change in the latter. It has already been reported that additional predictors have relatively minor effects on the accuracy and spatial predictions of climate-based SDMs (Bucklin et al. 2015). However, increasing suitable area in the SBV (except RCP2.6 of 2070) contradicted Saenz-Jimenez et al. (2020) but concurred earlier report in birds and vultures (Bender et al. 2019; Phipps et al. 2017). This is a positive sign for the conservation managers since they would face lesser challenge due to non-reduction of suitable area in future. However,

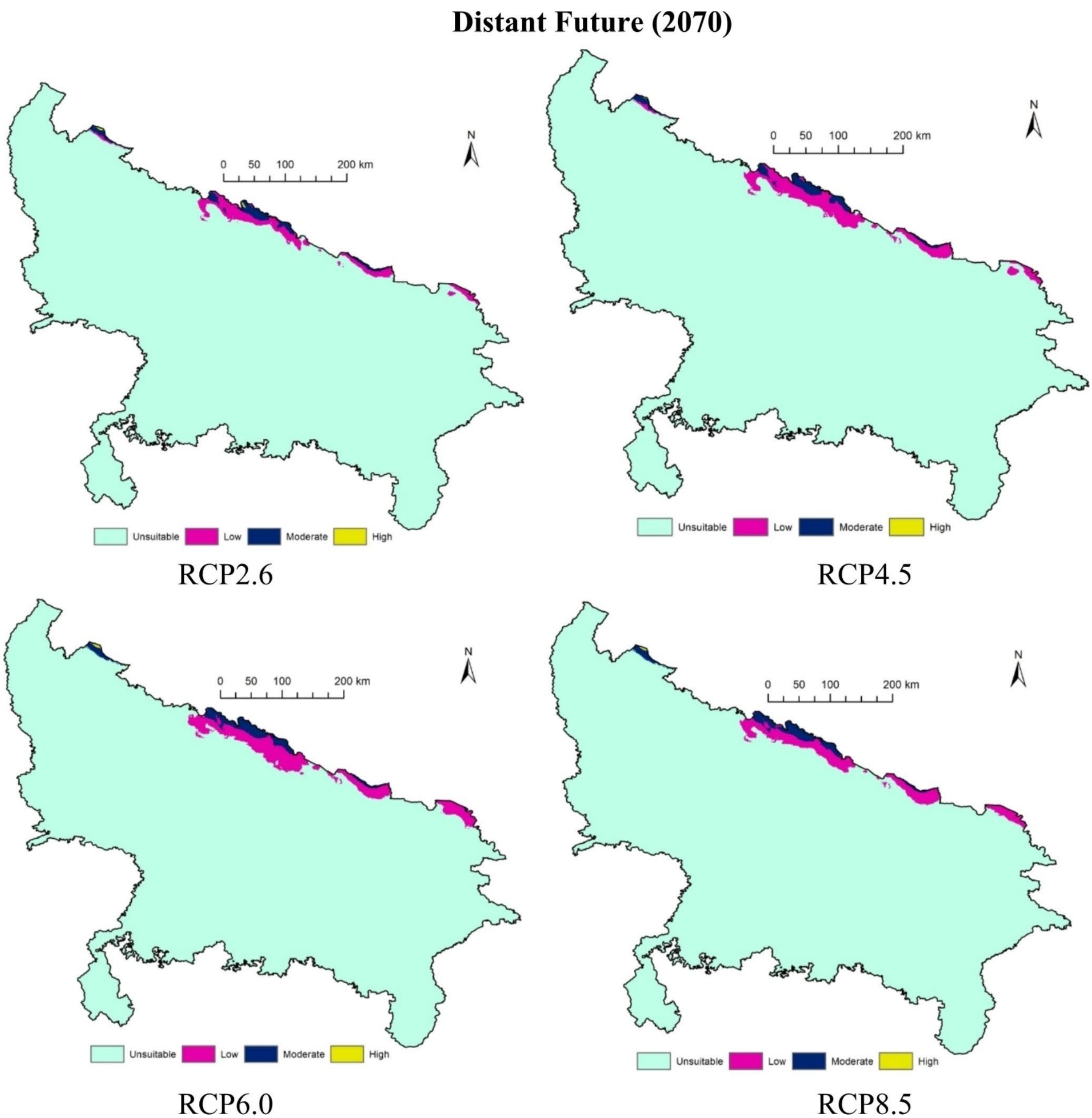

Fig. 7 Habitat suitability maps of the slender-billed vulture in long term (2070) under all representative concentration pathways

Jha and Jha (2023) working on pan India level reported that Tarai of Uttar Pradesh has only moderately suitable area for the SBV while Assam Tarai/plain has both moderately and highly suitable area, indicating that UP has relatively inferior habitat with negative implication on the SBV residency. Conversely, Assam could be a superior prospect for focusing on the SBV conservation.

Population dynamics

A sharp drop (63-66% decline) within ten years from reference population of 2010 (Jha 2015) could be due to continued use of diclofenac (Galligan et al. 2020; Jha et al. 2021) and climatic anomalies, since forest fire, flash flood, devastating storms affected the habitat during the period (Jha et al. 2022a). An assumption in our population estimation is that within this decade climate had not changed significantly.

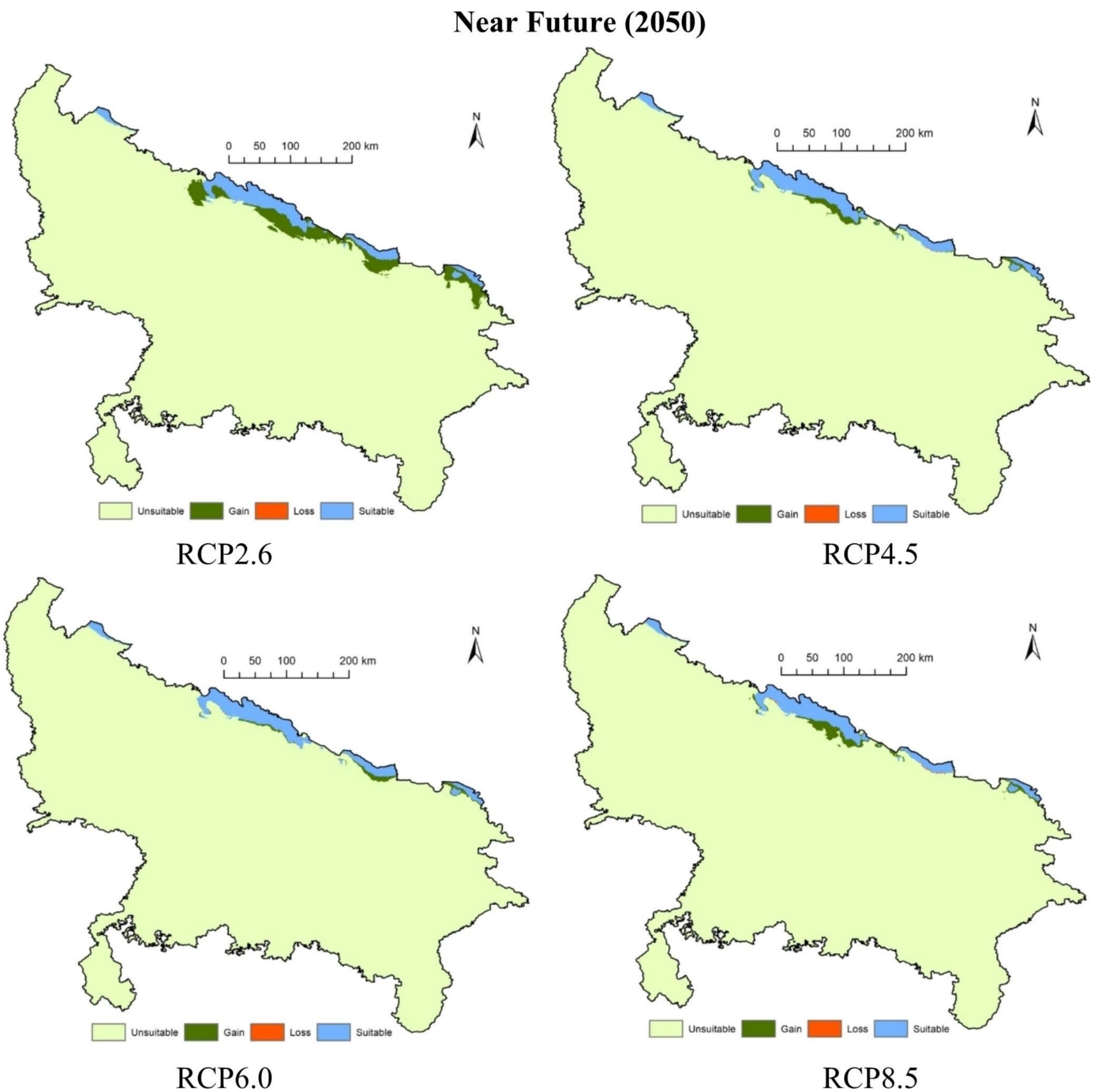

Fig. 8 Habitat dynamics maps of the slender-billed vulture in short term (2050) under all representative concentration pathways

Irrespective of the actual reason of fall in the SBV population, this accelerated slump finds corroboration in survey result of no sighting of the SBV even in those areas where it was unmissable ten years ago. In a recent survey of 2019 by the Forest Department of UP and BNHS, Mumbai also, the SBV was not detected during transect survey. Our results did not agree with reported recovery in the SBV population in adjoining Nepal (Bhusal et al. 2019). This could be due to varying conditions of the surroundings on either side of the border. It is noteworthy that Nepal has emphasized vigorously on the creation of vulture safe zones in the last decade (Bhusal et al. 2019).

A population rise in thirty years and fall in fifty years could be indicative of the impact of climate change in future, since models did not consider diclofenac or any other threat conditions. However, both the future populations being lower than the present warrant expeditious attention and quick recovery management practices to be enforced in proactive manner. Such activities could be (i) total warding off of the population from diclofenac, (ii) intensive breeding in

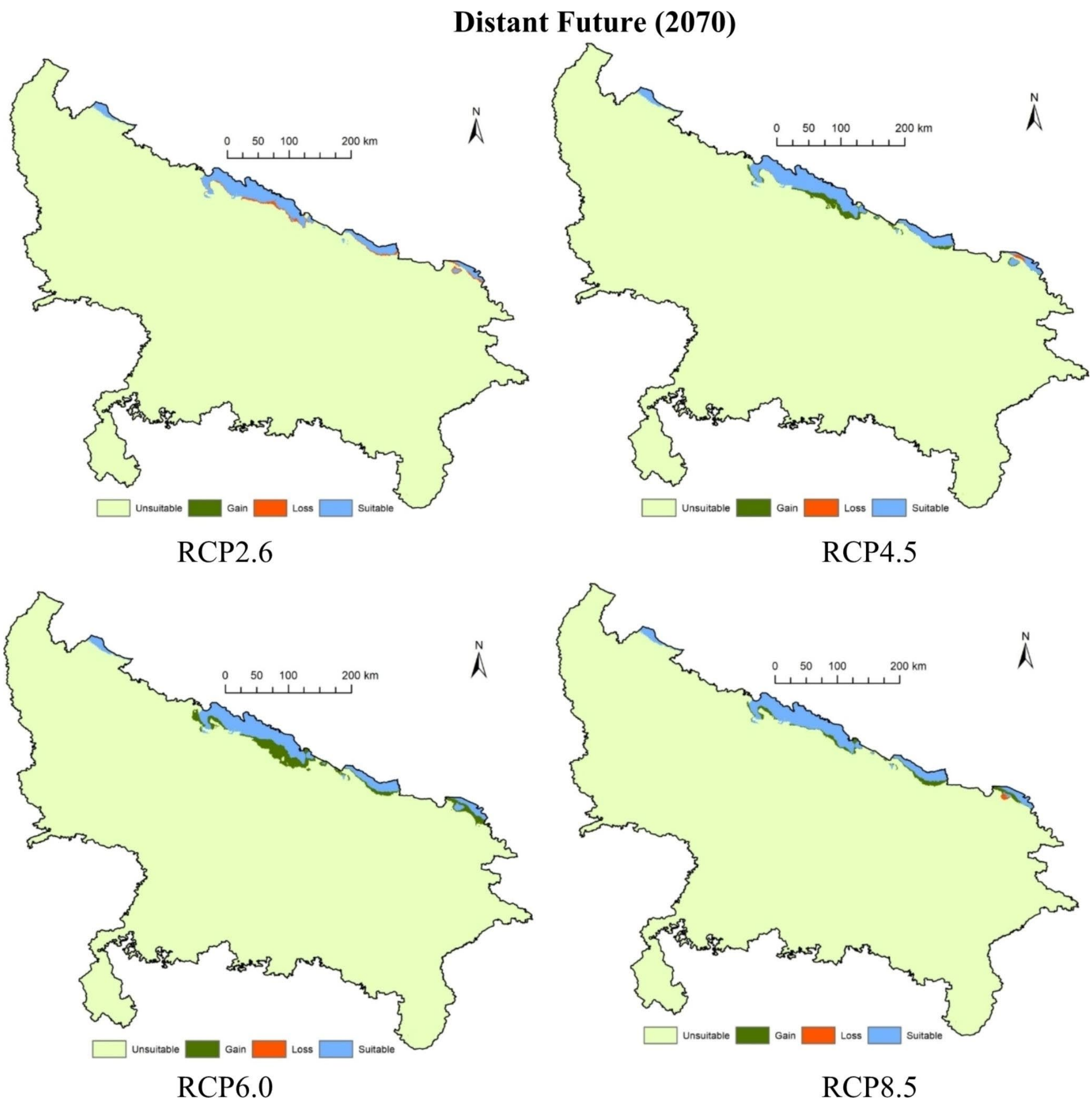

Fig. 9 Habitat dynamics maps of the slender-billed vulture in long term (2070) under all representative concentration pathways

Table 4 Projected habitat area dynamics under different terms and concentration pathways (% decimal digits are rounded off)

Future Scenario	Area category	RCP2.6		RCP4.5		RCP6.0		RCP8.5	
		km^2	%	km^2	%	km^2	%	km^2	%
2050	Unsuitable	228,770	95	233,685	97	234,122	97	233,385	97
	Gain	6234	3	1319	1	882	0	1619	1
	Loss	1	0	12	0	2	0	60	0
	Suitable	5923	2	5912	2	5922	2	5865	2
2070	Unsuitable	235,003	98	233,805	97	232,152	96	233,848	97
	Gain	1	0	1199	0	2852	1	1156	0
	Loss	610	0	80	0	1	0	75	0
	Suitable	5314	2	5844	2	5923	2	5849	2

captivity for future release, (iii) habitat improvement like mudflat restoration, fire prevention, zero logging of tall trees and (iv) habitat construction/reconstruction in unstable areas in the form of planting of nesting and roosting trees. For habitat management, the managers should focus on the area predictions of moderate scenario (RCP4.5 and RCP6.0) since it is believed that a sharp cut in CO_2 emission (RCP8.5) will not happen (Lane 2018) and lower emission scenarios (RCP2.6) will be unlikely (Manning et al. 2010).

Conclusion

Species distribution modelling for habitat suitability and dynamics for vultures in India and elsewhere had been done earlier, but the SBV has been attempted regionally for the first time in this study. This brought out suitable habitat prediction, influence of climatic factors in habitat determination and influence of climate change on suitable habitat and population in this critically endangered species with low population going further down. Out of several modelling algorithms, MaxEnt was found preferable over ANN, CTA, GBM, GLM, MARS, RF, SVM and even Ensemble due to its accuracy and other inbuilt advantages. Current population, already suffering from sharp decline did not show any bright future but there is a ray of hope of population expansion due to increase in suitable area impacted by climate change in future. This study is pertinent, especially due to the extreme conservation status of the species, and will contribute to stimulate and guide urgent conservation actions. Among some suggested measures for conservation of the SBV, captive breeding and safe zone creation, though in progress in the country, need intensified effort for early supplementing of existing populations and their safety. However, keeping in view considerably small size of suitable area for the SBV in India (including Assam and other states), a major home, it is imperative that an urgent study of this kind should be taken up in other Asian countries (Nepal, Bhutan, Bangladesh, Myanmar, Laos and Cambodia) with historical and existing records of the vulture, for planning extended conservation management.

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Declarations

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References

Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. Proc Natl Acad Sci USA 113:11770–11775. https://doi.org/10.1073/pnas.1607171113

Allouche O, Tsoar A, Kadmon R (2006) Assessing the accuracy of species distribution model: prevalence, kappa and the true skill statistic (TSS). J Appl Ecol 43:1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Bajpai O, Kumar A, Srivastava AK, Kushwaha AK, Pandey J, Chaudhary LB (2015) Tree species of the Himalayan Terai region of Uttar Pradesh, India: a checklist. Check List 11(4):1718. https://doi.org/10.15560/11.4.1718

Bamford AJ, Monadjem A, Hardy IW (2009) Nesting habitat preference of the African white backed vulture *Gyps africanus* and the effects of anthropogenic disturbance. Ibis 151(1):51–62

Beeman SP, Morrison AM, Unnasch TR, Unnasch RS (2021) Ensemble ecological niche modeling of West Nile virus probability in Florida. PLoS ONE 16(10):e0256868. https://doi.org/10.1371/journal.pone.0256868

Bender IMA, Kissling WD, Böhning-Gaese K, Hensen I, Ingolf K, Nowak L, Topfer T, Wiegand T, Matthais Dehling D, Schleuning M (2019) Projected impacts of climate change on functional diversity of frugivorous birds along a tropical elevational gradient. Sci Rep 9:17708. https://doi.org/10.1038/s41598-019-53409-6

Bhusal KP, Chaudhary IP, Dangaura HL, Rana DB, Joshi AB (2019) Nesting of critically endangered Slender-billed vulture *Gyps tenuirostris* more than decade in Nepal. Vulture Bull Annual Newsl Special Issue 8:25–27

BirdLife I (2021) *Gyps tenuirostris*. The IUCN red list of threatened species 2021 eT22729460A204781113. Accessed on 16 November 2022 https://doi.org/10.2305/IUCN.UK.2021-3.RLTS.T22729460A204781113.en

Bosch J, Mardones F, Perez A, Torre AL, Munoz MJ (2014) A maximum entropy model for predicting wild boar distribution in Spain. Span J Agricul Res 12(4):984–999. https://doi.org/10.5424/sjar/2014124-5717

Botha AJ, Andevski J, Bowden CGR, Gudka M, Safford RJ, Tavares J, Williams NP (2017) Multi-species action plan to conserve African-Eurasian vultures. CMS raptors mou technical publication no. 5. CMS technical series no. 35. Coordinating unit of the CMS raptors MOU, Abu Dhabi, United Arab Emirates

Bridgeford P, Bridgeford M (2003) Ten years of monitoring breeding Lappet-faced vultures *Torgos tracheliotos* in the Namib-Naukluft Park, Namibia. Vulture News 48:3–11

Brown JL, Bennett JR, French CM (2017) SDM tollbox 2.0: the next generation python-based GIS toolkit for landscape, genetic, biogeographic and species distribution model analysis. PeerJ 5:e4095. https://doi.org/10.7717/peerj.4095

Bucklin DN, Basille M, Benscoter AM, Brandt LA, Mazzotti FJ, Romanach SS, Speroterra C, Watling JI (2015) Comparing species distribution models constructed with different subsets of environmental predictors. Divers Distrib 21:23–35. https://doi.org/10.1111/ddi.12247

Campbell M (2015) Vultures: their evolution, ecology and conservation. CRC Press, Taylor and Francis Group, London and New York

Champion HG, Seth SK (1968) A revised survey of the forest types of India. Publication Division, Government of India, New Delhi

Chaudhry MJI (2007) Are Cape vultures (*Gyps coprotheres*) feeling the heat? Behavioural differences at north and south facing colonies in South Africa. University of Cape Town, Cape Town, South Africa

Didan K (2015) MOD13A3 MODIS/Terra vegetation indices monthly L3 global 1km SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. https://doi.org/10.5067/MODIS/MOD13A3.006. Accessed 08th August 2019

DNPWC (2015) Vulture Conservation Action Plan for Nepal (2015–2019). Kathmandu: Department of National Parks and Wildlife Conservation, Ministry of Forests and Soil Conservation, Government of Nepal

Dubos N, Montfort F, Grinand C, Nourtier M, Deso G, Probst J-M, Razafimanahaka JH, Andriantsimanarilafy RR, Rakotondrasoa EF, Razafindraibe P, Jenkins R, Crottini A (2022a) Are narrow-ranging species doomed to extinction? Projected dramatic decline in future climate suitability of two highly threatened species. Perspect Ecol Conserv 20:18–28. https://doi.org/10.1016/j.pecon.2021.10.002

Dubos N, Préau C, Lenormand M, Papuga G, Monsarrat S, Denelle P, Le Louarn M, Heremans S, May R, Roche P, Luque S (2022b) Assessing the effect of sample bias correction in species distribution models. Ecol Indic 145:109487. https://doi.org/10.1016/j.ecolind.2022.109487

Fick SE, Hijmans RJ (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int J Climatol 37: 4302–4315. https://doi.org/10.1002/joc.5086

Fourcade Y, Besnard AG, Secondi J (2018) Paintings predict the distribution of species, or the challenge of selecting environmental predictors and evaluation statistics. Glob Ecol Biogeogr 27:245–256. https://doi.org/10.1111/geb.12684

Früh L, Kampen H, Kerkow A, Schaub GA, Walther D, Wieland R (2018) Modelling the potential distribution of an invasive mosquito species: comparative evaluation of four machine learning methods and their combinations. Ecol Modell 388:136–144. https://doi.org/10.1016/j.ecolmodel.2018.08.011

Galligan TH, Mallord JW, Prakash VM, Bhusal KP, Alam ABMS, Anthony FM, Dave R, Dube A, Shastri K, Kumar Y, Prakash N, Ranade S, Shringarpure R, Chapagain D, Chaudhary IP, Joshi AB, Paudel K, Kabir T, Ahmed S, Azmiri KZ, Cuthbert RJ, Bowden CGR, Green RE (2020) Trends in the availability of the vulture-toxic drug, diclofenac, and other NSAIDs in South Asia, as revealed by covert pharmacy surveys. Bird Conserv Int 1–17. https://doi.org/10.1017/S0959270920000477

Ghareghan F, Ghanbarian G, Pourghasemi HR, Safaeian R (2020) Prediction of habitat suitability of *Morina persica* L. species using artificial intelligence techniques. Ecol Indic 112:106096. https://doi.org/10.1016/j.ecolind.2020.106096

Hao T, Elith J, Guillera-Arroita G, Lahoz-Monfort JJ (2019) A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. Divers Distrib 25:839–852. https://doi.org/10.1111/ddi.12892

Heikkinen RK, Luoto M, Araújo MB, Virkkala R, Thuiller W, Sykes MT (2006) Methods and uncertainties in bioclimatic envelope modelling under climate change. Prog Phys Geogr 30(6):1–27. https://doi.org/10.1177/0309133306071957

Herrero J, Garcia-Serrano A, Couto S, Ortuno V, Garcia-Gonzalez R (2006) Diet of wild boar *Sus scrofa* L. and crop damage in an intensive agroecosystem. Eur J Wildl Res 52:245–250. https://doi.org/10.1007/s10344-006-0045-3

Hertzog LR, Besnard A, Jay-Robert P (2014) Field validation shows bias-corrected pseudo-absence selection is the best method for predictive species-distribution modelling. Divers Distrib 20:1403–1413. https://doi.org/10.1111/ddi.12249

Hla H, Shwe NM, Htun TW, Zaw SM, Mahood S, Eames JC, Pilgrim JD (2011) Historical and current status of vultures in Myanmar. Bird Conserv Int 21:376–387

Jha KK (2015) Distribution of vultures in Uttar Pradesh, India. J Threat Taxa 7(1):6750–6763. https://doi.org/10.11609/JoTT.o3319.6750-63

Jha KK (2018) Mapping and management of vultures in an Indian stronghold. In: Campbell MO (ed) Geomatics and conservation biology. Nova Science Publishers, New York, pp 45–75

Jha KK, Campbell MO (2023) Vultures of India: ecological development, problems and prospects. Nova Science Publishers, New York

Jha KK, Jha R (2021a) Study of vulture habitat suitability and impact of climate change in Central India using MaxEnt. J Resour Ecol 12(1):30–42. https://doi.org/10.5814/j.issn.1674-764x.2021.01.004

Jha KK, Jha R, Campbell MO (2021) The distribution, nesting habits and status of threatened vulture species in protected areas of Central India. Ecol Quest 32(3):7–22. https://doi.org/10.12775/EQ.2021.20

Jha R (2022) Sociocultural aspects, Spatial distribution, Decadal change in population and Impact of climate crisis on habitat of vultures in Uttar Pradesh. Ph D Dissertation, University of Lucknow, India

Jha R, Jha KK (2021b) Habitat prediction modelling for vulture conservation in Gangetic–Thar–Deccan region of India. Environ Monit Assess 193(8):532. https://doi.org/10.1007/s10661-021-09323-4

Jha R, Jha KK (2023) Environmental factors shaping habitat suitability of *Gyps* vultures: climate change impact modelling for conservation in India. Ornithol Res 31:119–140. https://doi.org/10.1007/s43388-023-00124-6

Jha R, Jha KK, Kanaujia A (2022a) Humans and vultures: socioculture and conservation perspectives in Northern India. Hum Ecol 51:107–118. https://doi.org/10.1007/s10745-022-00377-7

Jha R, Jha KK, Kanaujia A (2023) Notable changes in conservation status of vultures in Uttar Pradesh, India: a study based on occupancy and habitat modelling. Proc Zool Soc. https://doi.org/10.1007/s12595-023-00496-z

Jha R, Kanaujia A, Jha KK (2022b) Wintering habitat modelling for conservation of Eurasian vultures in northern India. Nova Geod 2(1):22. https://doi.org/10.55779/ng2122

Jiao S, Zeng Q, Sun G, Lei G (2016) Improving conservation of cranes by modeling potential wintering distributions in China. J Resour Ecol 7(1):44–50. https://doi.org/10.5814/j.issn.1674-764X.2016.01.006

Kaky E, Nolan V, Alatawi A, Gilbert F (2020) A comparison between Ensemble and MaxEnt species distribution modelling approaches for conservation: a case study with Egyptian medicinal plants. Ecol Inf 60:101150. https://doi.org/10.1016/j.ecoinf.2020.101150

Landis J, Koch G (1977) The measurement of observer agreement for categorical data. Biometrics 33:159–174

Lane JE (2018) Climate crisis and the we: an essay in deconstruction. Int J Manage Stud Res 6(7):34–43

Lannuzel G, Balmot J, Dubos N, Thibault M, Fogliani B (2021) High-resolution topographic variables accurately predict the distribution of rare plant species for conservation area selection in a narrow-endemism hotspot in New Caledonia. Biodivers Conserv 30:963–990. https://doi.org/10.1007/s10531-021-02126-6

Liu L, Zhao Z, Zhang Y, Wu X (2017) Using MaxEnt model to predict suitable habitat changes for key protected species in Koshi

Basin, Central Himalayas. J Resour Ecol 8(1):77–87. https://doi.org/10.5814/j.issn.1674-764x.2017.01.010
Manning MR, Edmonds J, Emori S, Grubler A, Hibbard K, Joos F, Kainuma M, Keeling RF, Kram T, Manning AC, Meinshausen M, Moss R, Nakicenovic N, Riahi K, Rose SK, Smith S, Swart R, van Vuuren DP (2010) Misrepresentation of the IPCC CO2 emission scenarios. Nat Geosci 3:376–377
Marmion M, Parviainen M, Luoto M, Heikkinen RK, Thuiller W (2009) Evaluation of consensus methods in predictive species distribution modelling. Divers Distrib 15:59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x
McClure CW, Westrip JS, Johnson JA, Schulwitz SE, Virani MZ, Davies R, Symes A, Wheatly H, Thorstrom R, Amar A, Buij R, Jones VR, Williams NP, Buecheley ER, Butchart SHM (2018) State of the world's raptors: distributions, threats, and conservation recommendations. Biol Conserv 227:390–402. https://doi.org/10.1016/j.biocon.2018.08.012
Mi C, Huettmann F, Guo Y, Han X, Wen L (2017) Why choose Random Forest to predict rare species distribution with few samples in large under sampled areas? Three asian crane species models provide supporting evidence. PeerJ 12:5e2849. https://peerj.com/articles/2849/
Midgley GF, Bond WJ (2015) Future of African terrestrial biodiversity and ecosystems under anthropogenic climate change. Nat Clim Change 5:823–829
MoEF (2016) Bangladesh Vulture Conservation Action Plan 2016–2025. Ministry of Environment and Forests, Government of the People's Republic of Bangladesh, Dhaka
Naoroji R (2006) Birds of prey of the Indian subcontinent. Om Books International, NOIDA, India
Phipps WL, Diekmann M, MacTavish LM, Mendelsohn JM, Naidoo V, Wolter K, Yarnell RW (2017) Due South: a first assessment of the potential impacts of climate change on Cape vulture occurrence. Biol Conserv 210:16–25. https://doi.org/10.1016/j.biocon.2017.03.028
Prakash V, Galligan TH, Chakraborty SS, Dave R, Kulkarni MD, Prakash N, Shringarpure RN, Ranade SP Green RE (2019) Recent changes in populations of critically endangered *Gyps* vultures in India. Bird Conserv Int 29:55–70. https://doi.org/10.1017/S0959270917000545
Rew J, Cho Y, Moon J, Hwang E (2020) Habitat suitability estimation using a two-stage ensemble approach. Remote Sens 12:1475. https://doi.org/10.3390/rs12091475
Saenz-Jimenez F, Rojas-Soto O, Perez-Torres J, Martinez-Meyer E, Sheppard JK (2020) Effects of climate change and human influence in the distribution and range overlap between two widely distributed avian scavengers. Bird Conserv Int 1–19. https://doi.org/10.1017/S0959270920000271
Santangeli A, Spiegel O, Bridgeford P, Girardello M (2018) Synergistic effect of land-use and vegetation greenness on vulture nestling body condition in arid ecosystems. Sci Rep 8:13027. https://doi.org/10.1038/s41598-018-31344-2
Schmitt S, Pouteau R, Justeau D, de Boisseu F, Birnbaum P (2017) SSDM: an R package to predict distribution of species richness and composition based on stacked species distribution models. Methods Ecol Evol 8:1795–1803. https://doi.org/10.1111/2041-210X.12841
Schultz P (2007) Does bush encroachment impact foraging success of the critically endangered Namibian population of the Cape Vulture *Gyps coprotheres*? University of Cape Town, Rondebosch, South Africa. http://hdl.handle.net/20.500.11892/49885
Straub MH, Kelly TR, Rideout BA, Eng C, Wynne J, Braun J, Johnson CK (2015) Seroepidemiologic survey of potential pathogens in obligate and facultative scavenging avian species in California. PLoS ONE 10(11):e0143018. https://doi.org/10.1371/journal.pone.0143018
Sullivan BL, Wood CL, Iliff MJ, Bonney RE, Fink D, Kelling S (2009) eBird: a citizen-based bird observation network in the biological sciences. Biol Conserv 142:12282–12292. https://doi.org/10.1016/j.biocon.2009.05.006
Sum P, Loveridge R (2016) Cambodia vulture action plan 2016–2025. Phnom Penh, Cambodia
Swets K (1988) Measuring the accuracy of diagnostic systems. Science 240:1285–1293. https://www.science.org/doi/10.1126/science.3287615
UPFD BNHS (2021) Determination of the status and distribution of vultures in Uttar Pradesh. Uttar Pradesh Forest Department, Lucknow; Bombay Natural History Society, Mumbai
USGS EROS (2018) Shuttle Radar Topography Mission 1 Arc-Second Global. https://doi.org/10.5066/F7PR7TFT
Valavi R, Guillera-Arroita G, Lahoz-Monfort JJ, Elith J (2022) Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. Ecol Monogr 92(1):e01486. https://doi.org/10.1002/ecm.1486
van Wees D, van der Werf GR, Randerson JT, Andela N, Chen Y, Morton DC (2021) The role of fire in global forest loss dynamics. Glob Chang Biol 27:2377–2391. https://doi.org/10.1111/gcb.15591
Virani MZ, Monadjem A, Thomsett S, Kendall C (2012) Seasonal variation in breeding Ruppell's vultures *Gyps rueppellii* at Kwenia, southern Kenya and implications for conservation. Bird Conserv Int 22:260–269. https://doi.org/10.1017/S0959270911000505
Yates KL, Bouchet PJ, Caley M, Mengersen K, Randin CF, Parnell S et al (2018) Outstanding challenges in the transferability of ecological models. Trends Ecol Evol 33:790–802. https://doi.org/10.1016/j.tree.2018.08.001
Zeng Q, Zhang Y, Sun G, Duo H, Wen L, Lei G (2015) Using species distribution model to estimate the wintering population size of the endangered Scaly-sided Merganser in China. PLoS ONE 10(2):e0117307. https://doi.org/10.1371/journal.pone.0117307
Zhang J, Jiang F, Li G, Qin W, Li S, Gao H, Cai Z, Lin G, Zhang T (2019) MaxEnt modeling for predicting the spatial distribution of three raptors in the Sanjiangyuan National Park, China. Ecol Evol 9:6643–6654. https://doi.org/10.1002/ece3.5243
Zhang K, Zhang Y, Jia D, Tao J (2020) Species distribution modeling of *Sassafras tzumu* and implications for forest management. Sustainability 12:4132. https://doi.org/10.3390/su12104132