



# Habitat suitability mapping for migratory and resident vultures: A case of Indian stronghold and species distribution model

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Received: 16 February 2020 / Revised: 17 May 2020 / Accepted: 17 May 2020 / Published online: 12 June 2020. Ministry of Sciences, Research, and Technology, Arak University, Iran.

## Abstract

The vulture, an immensely invaluable service provider, has been reported to have plummeted to its lowest numbers in the recent past, causing serious concerns. Hence, a habitat study has become imperative for planning the conservation and recovery of this endangered species. Central India (Madhya Pradesh), one of the strongholds of the vulture and the study site, supports numerous vulture locations and individuals belonging to seven vulture species. MaxEnt based species distribution modeling was chosen for the prediction of habitat suitability, to identify the prediction-impacting environmental variables, and to compare the area expanse of different species. Predicted potential habitat distribution maps of all vultures together and seven vulture species have been prepared. The performance accuracy of all the models was in a very high range (average AUC= 0.938). Though 77% - 89% area is negligibly suitable to different species, Himalayan Griffon, Cinereous and Egyptian vultures had larger areas as compared to Long-billed, Eurasian Griffon, White-rumped and Red-headed vultures. Out of 23 variables used in the modeling, landuse-land cover (forest and waterbody), isothermality, and precipitation

seasonality were the prominent determinants of the distribution of all the species. Agriculture and elevation played a minimal role. The data generated in the study could be used for the planning of vulture recovery by conservation and reintroduction. The less suitable areas could also be used for the management of ecologically plastic species by modifying such landscape into agroforestry, including animal husbandry.

**Keywords:** Environmental predictors, landscape management, MaxEnt model, vulture distribution maps

## Introduction

Vultures have been in peril in different parts of the world in general, and in the Indian subcontinent in particular, in the recent past (Garbett *et al.* 2018, McLure *et al.* 2018) to the extent that they are among the most threatened animal taxa in the world (Birdlife International 2018, Ogada *et al.* 2012, Badia-Boher *et al.* 2019). The ecological implications of vulture decline could be extensive because vultures consume substantial amounts of dead animal matter, without which the functioning of the ecosystem would be disturbed (Hill *et al.* 2018). Several Indian provinces support vulture population, including Central India (CI  $\equiv$  Madhya Pradesh), which is considered to be a vulture stronghold, being supportive of the maximum number of vulture locations, species, and individuals (Jha 2018). Out of nine vulture species reported in India (Ali and Ripley 1987, Jha 2015), only four species breed here, and three species spend time as a result of winter migration in CI (Jha 2017). The Indian *Gyps* vultures were under severe threat of extinction, probably due to diclofenac

use (Prakash *et al.* 2007, Cuthbert *et al.* 2014) and faced fierce competition for food resources from the migratory species. Another essential reason is habitat loss due to various anthropogenic activities (Baral *et al.* 2013, Pande *et al.* 2013). However, Prakash *et al.* (2012, 2017) reported a slowing down of the decline leading to the stabilization of the vulture population in India. Further, vulture monitoring in MP indicated increases in vulture individuals in recent times (office record of vulture censuses 2016 and 2019; MP Forest Department). This highlights the importance of habitat in the recovery of vultures. To encourage such recovery further and to regain the lost vulture glory, the knowledge of habitat expanse and its quality becomes very important in the scientific management of vulture.

Habitat characterization depends on environmental factors, like landuse-landcover (LULC), human influence on resources, and climatic conditions of the area, which finally decide the distribution of the population. This could be achieved by indexing the habitat or developing the habitat suitability index (HSI), which is a probability of species presence inferred from ecological niche modeling by relating the occurrence of a species at a given location to environmental features (Guisan and Thuiller 2005). The output of species distribution models (SDMs) based on such niche modeling is considered as a measure of the suitability of environmental features for the occurrence of the target species (VanDerWal *et al.* 2009). In recent years, significant advances have been made in the statistical tools and techniques used to generate SDMs (Guisan and Zimmermann 2000, Guisan and Thuiller 2005, Elith and Leathwick 2009). SDMs predict species occurrence using mathematical models based on field data and environmental variables (Phillips *et al.* 2006), which can indicate the suitability of habitats for developing populations of a particular species or community (Ferrier 2002). Statistical methods employed for formulating

SDMs include those requiring presence/absence data. One such model - maximum entropy (MaxEnt) based only on presence data (Phillips *et al.* 2006, Phillips and Dudík 2008) was used in habitat distribution range studies mostly in threatened plants and animals (Angelieri *et al.* 2016, Hernandez-Baz *et al.* 2016, Qin *et al.* 2017, Abolmaali *et al.* 2018, Corovic *et al.* 2018, Esfanzani *et al.* 2018). Still, it lacks in most important scavengers like endangered vultures. Therefore, this paper is aimed at (1) mapping habitat suitability of vulture species in Central India (2) determining the relative contribution of environmental variables to species habitat suitability (3) identifying and comparing the habitat expanse of different vulture species and (4) exploring some management implication.

## Material and methods

### Study area

The Central Indian province (Madhya Pradesh, 308252 km<sup>2</sup>), was chosen for habitat suitability or niche-based modeling since it has high richness and abundance of vultures. This province is situated between 21°6' - 26°30' North latitude and 74°00' - 82°51' East longitude in the tropical and sub-tropical climate. The temperature varies between 1°C and 47°C from winter to summer. The average rainfall is about 1370 mm, which decreases from east (2150 mm) to west (1000 mm). The state falls in three climatic regions of India – Semi-arid in the northwest, Tropical wet and dry in the southwest, and Sub-tropical wet and dry in the remaining, much larger part. It has hilly tracts, valley, and plateau with sylvan and agriculture landscapes. Waterbodies, including rivers, lakes, and streams, are interspersed throughout the state. Approximately 52% and 28% area of the state has agriculture and forest LULC, respectively. Different types of forests by density cover are as follows: 2.15% Very dense, 11.35% Moderately dense, 11.7% Open, and 2.08% Scrub (ISFR 2011). These forests mostly belong to Tropical dry deciduous and moist deciduous types.

### Species occurrence data

Vulture presence data was taken from field observation recorded during the vulture census of the state, which was done during winter and summer 2016 following a specific protocol (Jha 2017). Single-day point count by a two-member team (covering 3 to 4 locations) of nesting/roosting (sitting not flying) vultures in the morning hours (between 06:00 and 10:00 h) in the whole state was done. Of a total of recorded 1510 presence locations (species-wise), there were 761 and 749 location (sighting) in these two seasons, respectively. Coordinates of these locations were taken by Garmin GPS and were used as sample input (spatial data) in SDM software MaxEnt after processing.

### Environmental variables

Locational information on environmental factors associated with the species is used in SDMs. Such models estimate the relationship between a species and its environment and then predict a distribution based on the occurrence of the identified environmental variables across the landscape under study (Guisan and Zimmerman 2000, Guisan and Thuiller 2005). A suite of environmental variables was used, which are acronymed / coded in the literature (Tytar and Nekrasova 2016, Prockow *et al.* 2018) as given in Table 1. Depending on the relationship with the species, other variables were also used. Vultures are known to use cliffs and tall trees which provide safe shelter for nesting. Vegetation cover is reported to influence the distribution of an animal species more than any other factor since it determines the land's ability to supply food and/or shelter to animals. In other words, it may be a limiting factor for the spread of a species (Herrero *et al.* 2006, Bosch *et al.* 2014). Studies have included elevation (Angelieri *et al.* 2016, Qin *et al.* 2017), LULC (Yang *et al.* 2013), and vegetation as the driving factors for species distribution. Quite a few reports (Zhao *et al.* 2015, Lu *et al.* 2017, Janssen *et al.* 2018, Li *et*

*al.* 2018, Liang 2018) have shown some relationship between Normalized Differentiated Vegetation Index (NDVI) and vegetation parameter (forest cover and land cover change). Santangeli *et al.* (2018) advocated that NDVI can be used as a proxy for ungulate forage availability, which is inversely correlated with their mortality. The increased ungulate mortality resulting from below-average forage availability (i.e., low NDVI) likely leads to increased carrion availability for vultures. The model prediction was found to be improved after the inclusion of land cover in pheasant distribution (Dunn *et al.* 2015). Therefore, elevation, LULC, and NDVI were included along with the above climatic variables. Landuse-land cover data was procured from the State Organization, MP Council of Science and Technology, Bhopal. This included different layers like forests, water bodies, built-up area, wasteland, agriculture, and wasteland scrub. Thus, there were a total of 23 variables or covariates (19 Bioclim variables, two NDVI layers, one LULC layer, and one elevation layer) to be used in the models (Table 1). However, the literature review (Yang *et al.* 2013, Fourcade *et al.* 2014, Ashraf *et al.* 2016, Keya *et al.* 2016, Abolmaali *et al.* 2018) suggested the examination of cross-correlations among the variables to account for multicollinearity, since ignoring the spatial autocorrelation and multicollinearity may lead to false ecological conclusions in modeling the spatial distribution of a species (Heikkinen *et al.* 2006, de Frutos *et al.* 2007). We used the Pearson correlation test and  $r > 0.8$  as the cut-off threshold to determine highly correlated variables (Khanum *et al.* 2013, Ashraf *et al.* 2016, Cao *et al.* 2016). This led to the decision to remove certain variables from the current climate data used over the period 1950–2000.

### Data file preparation

The Bioclim variables were downloaded from [www.worldclim.org/bioclim](http://www.worldclim.org/bioclim). The downloaded file had “0.00833 \* 0.00833” cell size spatial

resolution with “GCS\_WGS\_1984” projection. NDVI data was downloaded from [www.earthexplorer.usgs.gov](http://www.earthexplorer.usgs.gov). MODIS (Moderate Resolution Imaging Spectroradiometer) data was downloaded for January and May in the year 2016 because the actual survey was done in the same months, and the canopy of the forests also varied contrastingly. These data had a spatial resolution of “231.6563583 \* 231.6563583” with undefined projection. Elevation data was also downloaded from [www.earthexplorer.usgs.gov](http://www.earthexplorer.usgs.gov) with spatial resolution “0.00833 \* 0.00833” and GCS\_WGS\_1984 projection. Fifty-four tiles were downloaded, mosaicked together, and

clipped with CI shapefile.

All the layers were projected to WGS\_1984\_UTM\_Zone\_43N, and cell size was changed with reference to the MODIS data because it had the smallest cell size or highest spatial resolution. The files were masked with the shapefile after re-projecting and checked every layer had the same spatial resolution and processing extent. The layers had to be re-projected again to the GCS\_WGS\_1984 system because the software did not accept the files with WGS\_1984\_UTM\_Zone\_43N projection. The GPS data of vulture presence were pooled and used in the CSV format as per the requirement of the software.

**Table 1.** Variables used in the current vulture habitat prediction

Climatic				Environmental			
Temperature			Precipitation				
Variable		Acronym	Variable		Acronym		
(i) Annual Mean Temperature		bio1	(xii) Annual Precipitation		bio12	LULC (Forest, water, rural and urban built-up area, agriculture, wasteland, scrubland) NDVI (May and June 2016)	
(ii) Mean Diurnal Range (Mean of monthly (max temp - min temp))		bio2	(xiii) Precipitation of Wettest Month		bio13		
(iii) Isothermality (bio2/bio7) (* 100)		bio3	(xiv) Precipitation of Driest Month		bio14	Elevation	
(iv) Temperature Seasonality (standard deviation *100)		bio4	(xv) Precipitation Seasonality (Coefficient of Variation)		bio15		
(v) Max Temperature of Warmest Month		bio5	(xvi) Precipitation of Wettest Quarter		bio16		
(vi) Min Temperature of Coldest Month		bio6	(xvii) Precipitation of Driest Quarter		bio17		
(vii) Temperature Annual Range (bio5-bio6)		bio7	(xviii) Precipitation of Warmest Quarter		bio18		
(viii) Mean Temperature of Wettest Quarter		bio8	(xix) Precipitation of Coldest Quarter		bio19		
(ix) Mean Temperature of Driest Quarter		bio9					
(x) Mean Temperature of Warmest Quarter		bio10					
(xi) Mean Temperature of Coldest Quarter		bio11					

### Species distribution modeling

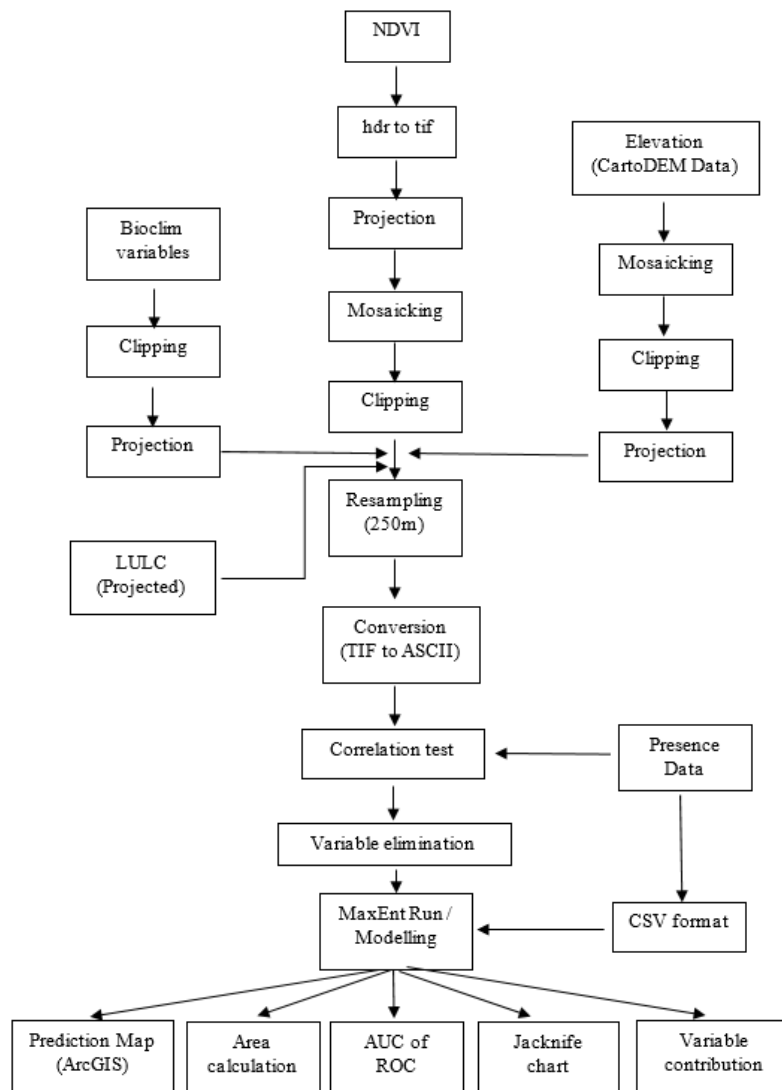
MaxEnt (4.3.1) was chosen for the present study among many SDMs (GARP, ENFA, BIOCLIM, DOMAIN) frequently used for

habitat prediction (Cao *et al.* 2016, Qin *et al.* 2017), since this algorithm is highly precise, is ranked among the best when absence data for the species are not available, and seems to

outperform other modeling methods in quality and predictive power when the number of geographic records is scarce (Elith *et al.* 2006, Phillips *et al.* 2006, Phillips and Dudik 2008, Wisz *et al.* 2008, Corovic *et al.* 2018). While running the model, the model output chosen was logistic, model testing data selected was 25%, and the replicated run type was bootstrap. Jackknife analysis was performed to determine variables, and Area Under the Receiving Operator Curve (AUC) was taken into account for model evaluation. The model with the highest AUC value was considered the best performer.

MaxEnt models predicting the presence of

vultures were imported to ArcGIS 10.3 for display maps and further analysis like area calculation, file export for correlation, etc. Yang *et al.* (2013) and Qin *et al.* (2017) were consulted for classifying the prediction range for suitability of habitat. Prediction range (0–1) was divided into five HSI classes of potential habitats. They were arbitrarily regrouped as Negligibly suitable habitat (0–0.2); Slightly suitable habitat (0.2–0.4); Moderately suitable habitat (0.4–0.6); Highly suitable habitat (0.6–0.8); Extremely suitable habitat (0.8–1.0). Schematic representation of MaxEnt input preparation and the expected output is presented in figure 1.



**Figure 1.** Abstract of the methodology adopted in the present study, which includes MaxEnt based modeling, preceding steps, and model output. Flow chart modified from Ashraf *et al.* (2016)

## Results

Pooled summer and winter vulture location points of 2016 in CI are depicted in Figure 2. Using coordinates of these points and different variables, we ran 8 test models having high AUC values. Subsequently developed the same number of final models for all vulture species together and seven different species found in central India (Cinereous Vulture, Eurasian Griffon and Himalayan Griffon; the migratory species coming from European, and other Asian countries and Egyptian Vulture, Long-billed Vulture, Red-headed Vulture, and White-rumped Vulture; the resident species). AUC of different models varied among themselves, but the average was 0.943 (Test run), and 0.938 (Final run). None of the AUC was lower than 0.899 (Test) and 0.889 (Final). The Pearson correlation test ( $r > 0.8$ ) with bioclimatic and other variables showed a high correlation among some of them (Table 2). Therefore, a set of such five variables like bio1 (Annual Mean Temperature), bio7 (Temperature Annual Range), bio10 (Mean Temperature of Warmest Quarter), bio12 (Annual Precipitation), bio16 (Precipitation of Wettest Quarter) was eliminated to reduce collinearity effect from the modeling and to improve prediction.

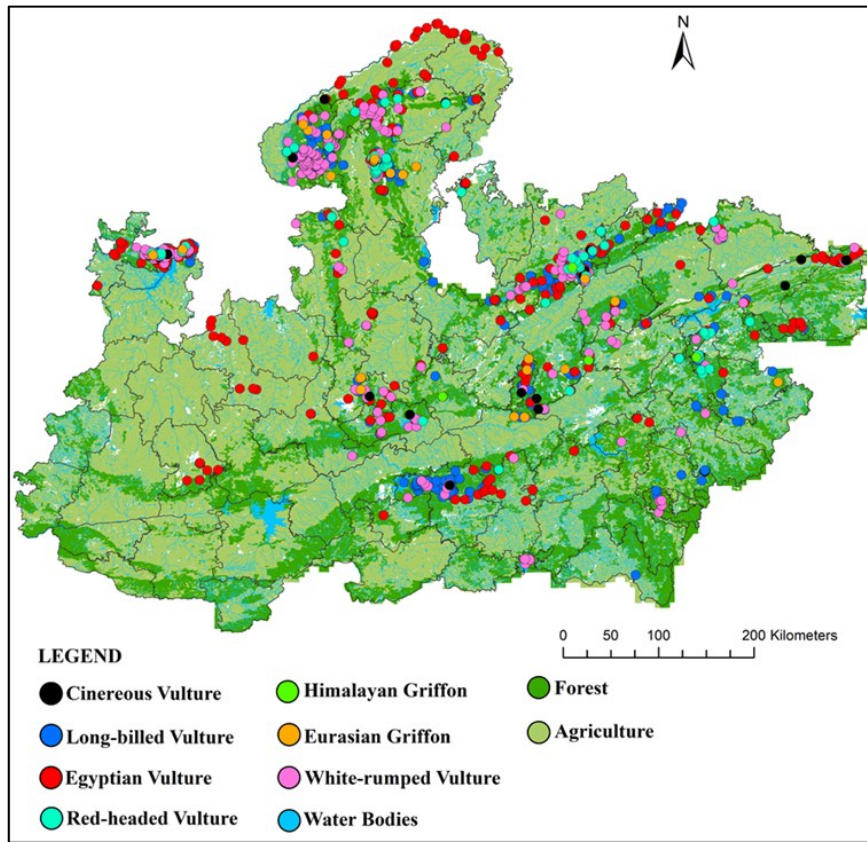
Among all the variables used for habitat prediction, LULC was found to be the most important variable impacting the distribution model. Analysis of the variable contribution table of MaxEnt models showed the average contribution of LULC across all the models to the quantum of 54.9%. Different species were influenced by this variable in the following order of decrement: Himalayan Griffon (74.2) > Cinereous Vulture (59.9) > Eurasian Griffon (57.3) > Long-billed Vulture (54.7) > Red-headed Vulture (52.0) > Egyptian Vulture (51.1) > White-rumped Vulture (35.5). However, within this categorical parameter, forest, waterbody, and rural-urban built-up area influenced the scavenger's distribution the most. Agriculture, wasteland, and scrubland were found to be the least impactful

(Fig. 3). It is evident from the LULC response chart that for all vulture species, the two most important components were forest and water. Out of these two components, migratory species and Egyptian vulture showed a preference for forest over water in habitat selection while other resident vultures preferred water.

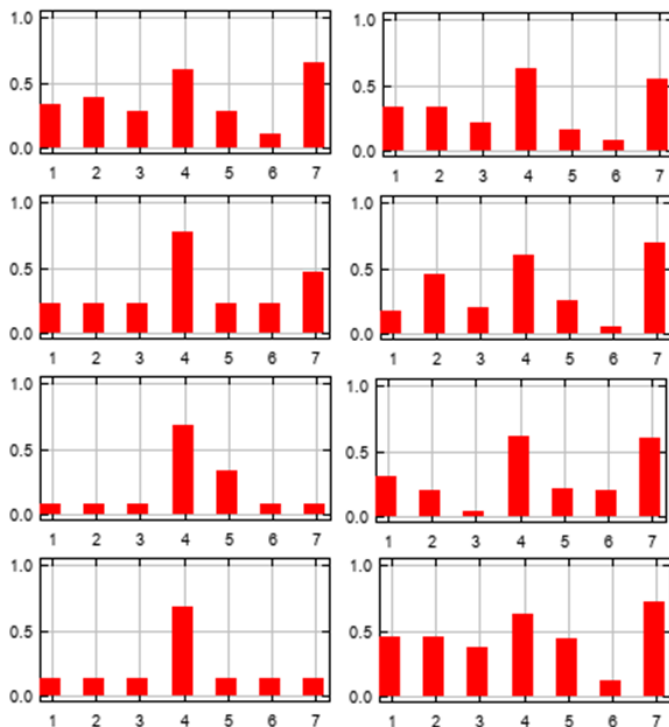
Jackknife diagram predicting the contribution of variables to the construction of the model is presented in Figures 4 and 5. The dark blue bars show the value of the variable independent of others, the light-blue bars show the result of excluding the variable from the prediction across the entire set of variables, and the red bar demonstrates the total contribution of all the variables. This chart indicates that across all species the five most important variables apart from LULC were bio3 (Isothermality), bio15 (Precipitation Seasonality), bio18 (Precipitation of Warmest Quarter), bio4 (Temperature Seasonality) and bio11 (Mean Temperature of Coldest Quarter) which played a significant role in habitat quality determination or species distribution. Isothermality (bio3) and Precipitation Seasonality (bio15) were the top contributors in almost all the models. Other lesser essential variables were bio8 (Mean Temperature of Wettest Quarter), bio2 (Mean Diurnal Range of temperature), and January NDVI. Elevation, in this case, had very little or practically no impact on distribution.

Vulture habitat suitability maps are presented in Figures 6 and 7. Non-suitable (Negligibly suitable) and potentially suitable habitat (slightly, moderately, highly, and extremely suitable) area of different species of vultures derived from the model maps are presented in Table 3. A majority of the area of Central India is found to be negligibly or not suitable (77.3% to 89.3%) for vultures under current climatic conditions and natural resources. However, the potentially suitable area available for different vultures in decreasing order is 22.7% (Himalayan Griffon), 18.6% (Long-billed Vulture), 17.4% (Egyptian

vulture), 16.6% (Cinereous Vulture), 13.6% (Eurasian Griffon), 12.7% (White-rumped Vulture) and 10.7% (Red-headed Vulture).



**Figure 2.** Combined location map of different species of vultures with respect to major landuse-landcover in Central India during the winter and summer survey of 2016. This presence only record was used in Species Distribution Model, MaxEnt, as sample input. Map: Adopted from Jha (2018)



**Figure 3.** Contribution of different LULC components in model prediction. 1 Rural and Urban built-up, 2 Road and Mine built-up, 3 Agriculture, 4 Forest, 5 Wasteland, 6 Scrubland, and 7 Waterbody. Charts in the left column: top to bottom - All vultures, Cinereous Vulture, Eurasian Griffon, Himalayan Griffon. Charts in the right column: top to bottom – Egyptian, Long-billed, Red-headed, and White-rumped vultures

**Table 2.** Correlation matrix among environmental and natural resource variables (Elev'n = Elevation, ndvij = NDVI January, and ndvim = NDVI May).

	Elev'n	ndvij	ndvim	bio1	bio2	bio3	bio4	bio5	bio6	bio7	bio8	bio9	bio10	bio11	bio12	bio13	bio14	bio15	bio16	bio17	bio18	bio19	LULC	
Elev'n	1.00																							
ndvij	0.33	1.00																						
ndvim	0.50	0.71	1.00																					
bio1	-0.68	-0.54	-0.66	1.00																				
bio2	-0.52	-0.16	-0.37	0.20	1.00																			
bio3	0.25	-0.15	-0.14	0.09	0.27	1.00																		
bio4	-0.73	-0.17	-0.32	0.25	0.75	0.37	1.00																	
bio5	-0.82	-0.39	-0.65	0.74	0.68	0.04	0.68	1.00																
bio6	0.35	-0.11	0.01	0.24	0.80	0.17	0.83	0.34	1.00															
bio7	-0.65	-0.10	-0.32	0.17	0.91	0.14	0.93	0.72	0.89	1.00														
bio8	-0.84	-0.50	-0.60	0.80	0.47	0.15	0.71	0.77	0.26	0.55	1.00													
bio9	-0.31	-0.07	-0.23	0.25	0.08	0.48	0.20	0.31	0.03	0.13	0.20	1.00												
bio10	-0.87	-0.45	-0.66	0.86	0.56	0.13	0.67	0.95	0.24	0.63	0.89	0.35	1.00											
bio11	0.19	-0.20	-0.17	0.46	0.53	0.38	0.73	0.07	0.91	0.70	0.12	0.03	0.00	1.00										
bio12	0.59	0.52	0.54	0.67	0.48	0.17	0.52	0.57	0.20	0.42	0.82	0.15	-0.67	0.06	1.00									
bio13	0.56	0.51	0.52	0.62	0.45	0.15	0.49	0.54	0.19	0.40	0.78	0.11	-0.62	0.07	0.97	1.00								
bio14	0.51	0.46	0.50	0.74	0.31	0.19	0.29	0.55	0.04	0.24	0.68	0.10	-0.65	-0.22	0.75	0.64	1.00							
bio15	-0.32	-0.37	-0.35	0.53	0.28	0.27	0.23	0.33	0.02	0.17	0.52	0.23	0.46	0.14	-0.67	-0.50	-0.79	1.00						
bio16	0.60	0.49	0.51	0.62	0.51	0.14	0.56	0.58	0.26	0.47	0.82	0.14	-0.66	0.13	0.99	0.98	0.67	-0.56	1.00					
bio17	0.41	0.53	0.54	0.74	0.24	0.31	0.18	0.48	0.15	0.12	0.63	0.07	-0.59	-0.32	0.77	0.69	0.92	-0.82	0.68	1.00				
bio18	0.45	0.45	0.47	0.62	0.32	0.10	0.37	0.49	0.08	0.29	0.66	0.10	-0.60	-0.06	0.80	0.72	0.75	-0.77	0.73	0.78	1.00			
bio19	0.02	0.44	0.27	0.46	0.00	0.55	0.20	0.04	0.36	0.24	0.31	0.47	-0.15	-0.44	0.63	0.57	0.66	-0.72	0.54	0.79	0.60	1.00		
LULC	-0.09	-0.18	-0.04	0.09	0.10	0.04	0.05	0.03	0.13	0.08	0.04	0.07	0.03	0.10	-0.09	-0.09	-0.08	0.09	-0.08	-0.09	-0.09	-0.09	-0.15	1.00



**Table 3.** Habitat area (km<sup>2</sup>) of different categories for the use of vulture species in Central India

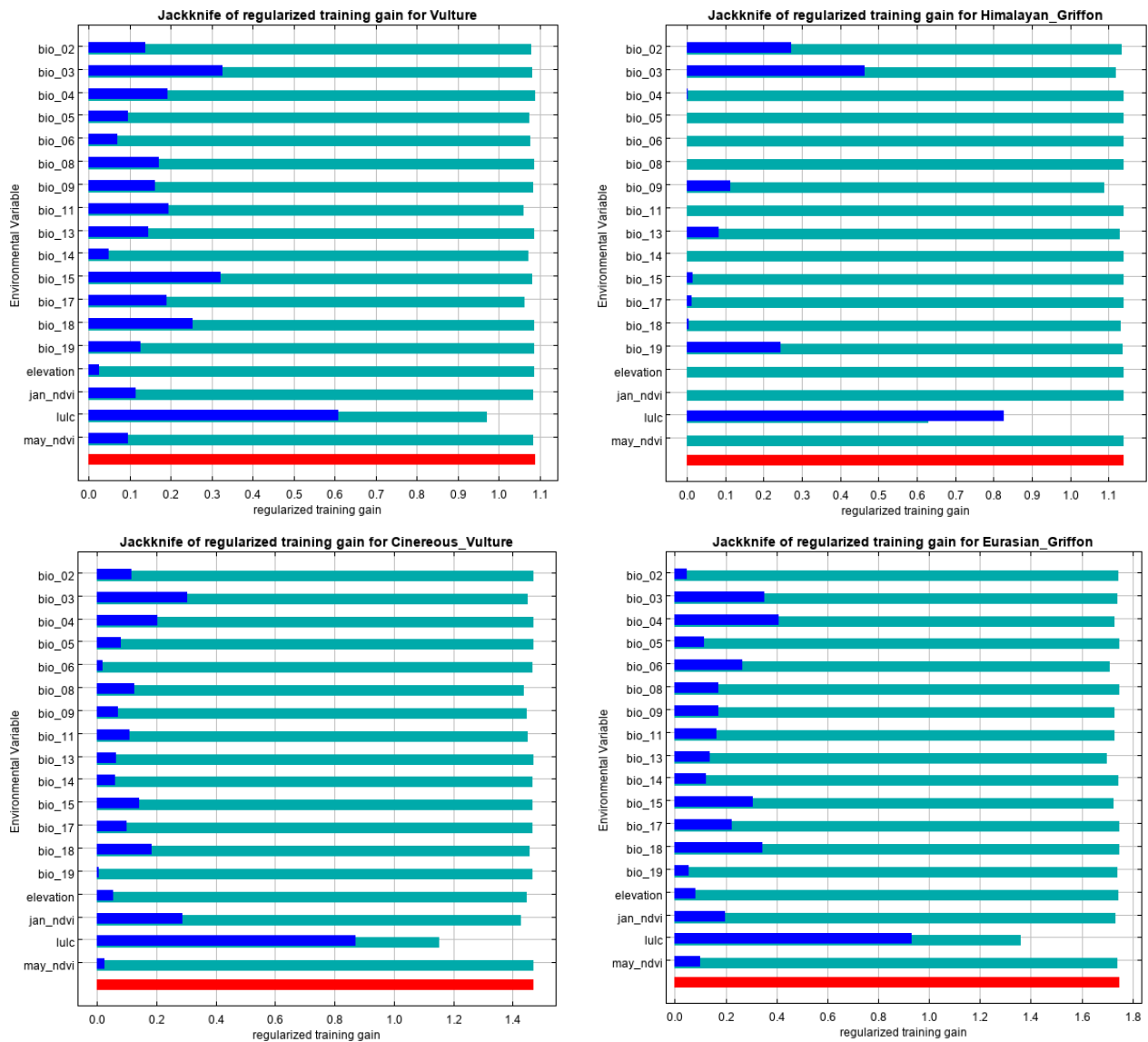
Vulture species	Suitability parameter	Negligibly Suitable	Slightly Suitable	Moderately Suitable	Highly Suitable	Extremely Suitable
Cinereous Vulture	Area km <sup>2</sup>	254281.4	17048.4	20228.2	12517.8	704.7
	% area	83.4	5.6	6.6	4.1	0.2
Eurasian Griffon	Area km <sup>2</sup>	263208.6	20819.9	13228.8	6562.9	960.2
	% area	86.4	6.8	4.3	2.2	0.3
Himalayan Griffon	Area km <sup>2</sup>	235672.5	27074.7	19284.0	22570.5	178.7
	% area	77.3	8.9	6.3	7.4	0.1
Egyptian Vulture	Area km <sup>2</sup>	251722.5	25258.3	21690.3	5430.9	678.5
	% area	82.6	8.3	7.1	1.8	0.2
Long-billed Vulture	Area km <sup>2</sup>	248034.6	26250.6	22521.7	7639.4	334.2
	% area	81.4	8.6	7.4	2.5	0.1
Red-headed Vulture	Area km <sup>2</sup>	272021.1	17079.2	9900.7	5346.1	433.4
	% area	89.3	5.6	3.2	1.8	0.1
White-rumped Vulture	Area km <sup>2</sup>	266116.0	22749.0	10590.9	4827.5	497.2
	% area	87.3	7.5	3.5	1.6	0.2
All vultures	Area km <sup>2</sup>	239455.5	31139.0	25382.8	8709.4	93.7
	% area	78.6	10.2	8.3	2.9	0.03

## Discussion

In recent years, the development of habitat distribution models has increased with the rise of GIS tools and statistical techniques in ecology. Such models relate the geographical distribution of the species and the features of their present environment. They are static and probabilistic (Guisan and Zimmermann 2000). Nevertheless, they can identify additional localities where the target species may already exist but have not yet been detected, recognize the localities where it can spread, and help prioritize the selection of area for conservation of rare species (Qin *et al.* 2017). In the present study, potential suitable habitat area was identified by using MaxEnt species distribution modeling for current climatic scenario, and mapping was done. The evaluation of the performance of the models, and the impact of environment variables on vulture habitat and habitat extent suitability have been discussed in the following paragraphs which can be used for addressing conservation problems of the vultures (Brotons *et al.* 2004, Linkie *et al.* 2006, Rodriguez *et al.* 2007).

## Model performance

Area Under Curve of ROC (Receiver Operating Characteristic) curve, a preferred technique to evaluate models, was used to estimate the accuracy of the final models (Stockwell and Peters 1999, Bosch *et al.* 2014) in the present study as well. The closer the AUC value to 1, the greater is the accuracy of the model, while the values of 0.5 suggested that the model performs no better than random (Bosch *et al.* 2014). Such a high AUC value (0.938) of final models in the present study fell in the very good category of model performance as suggested (i.e., AUC: >0.9 = very good; AUC: 0.7–0.9 = good, AUC: <0.7 = uninformative) by Swets (1988), Baldwin *et al.* (2009), Lv *et al.* (2012) etc. Other studies (Pearce and Ferrier 2000, Newbold *et al.* 2009, Hernandez-Baz *et al.* 2016) also indicated values above 0.9 as the highest accuracy of the model. Simple implication of this result is that model prediction level is very high which can be used with higher degree of confidence in planning and execution of the conservation project.



**Figure 4.** The relative predictive power of different environmental variables based on the jackknife of regularized training gain in MaxEnt models for all and migratory vultures. The dark blue bars show the value of the variable independent of others. All the species combined and the other three migrant species show that the LULC is the essential variable. Elevation was among the least important variables

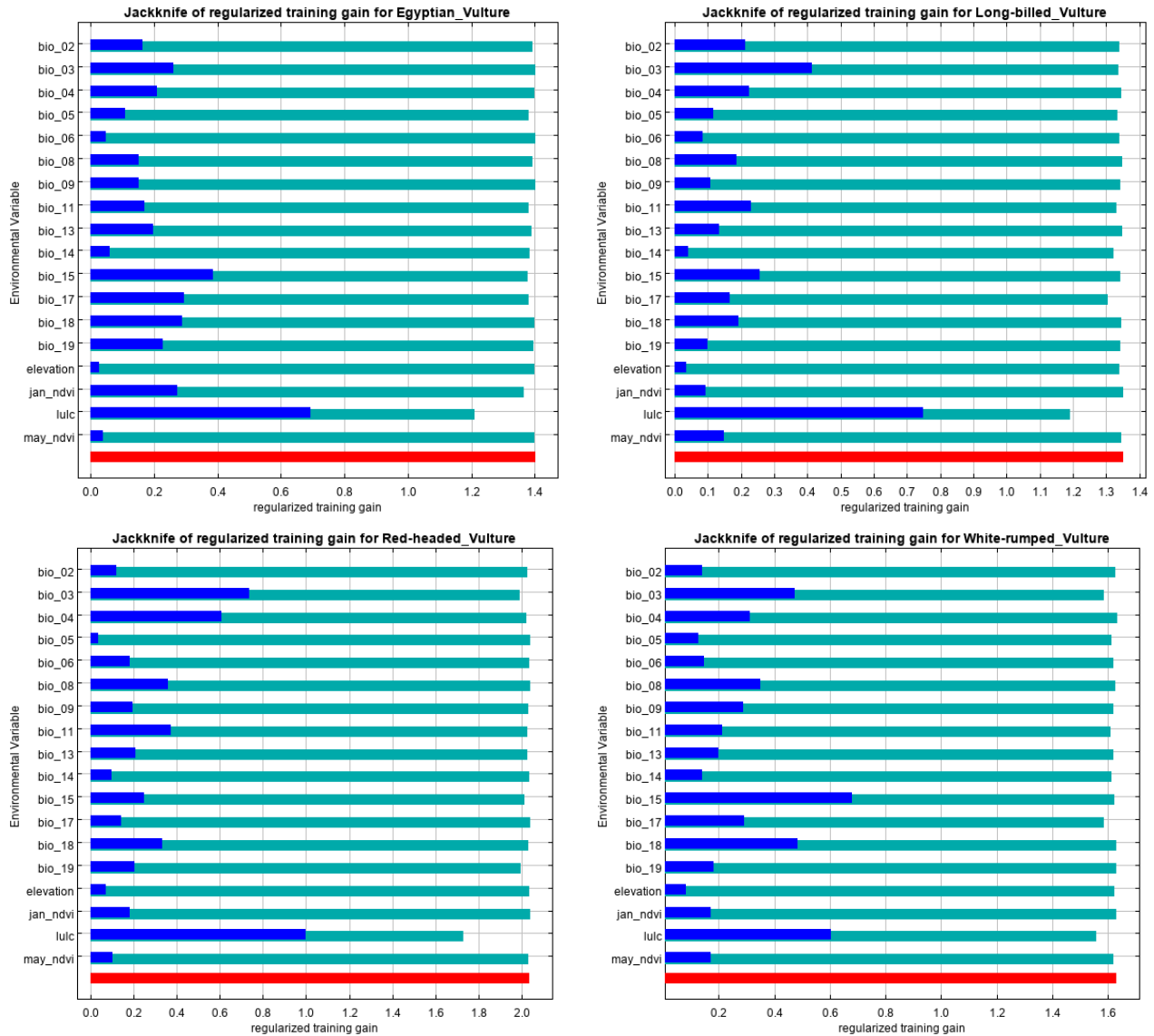
**Environmental predictors**

Of all environmental layers used in the model, LULC had the most considerable influence on suitable habitat prediction. However, among them, the forest was the most important determinant, like other reports of vegetation (Howard *et al.* 2012, Hernandez-Baz *et al.* 2016). The presence of the water body was the next equally important factor governing habitat suitability as also reported heuristically by Kanaujia and Kushwaha (2014) in the case of vultures. This is in line with another reporting in waterbird metapopulations that geographic

parameters such as the prevalence of water bodies and forested land are critical predictors for the distribution of species (Sheehan *et al.* 2016). The urban and rural built-up areas provide some of the vulture species opportunities for food. Vultures are seen exploiting garbage dumps, bone meal, and solid waste processing factories in urban areas (Buechley *et al.* 2018, Angelov *et al.* 2020) as well as setting up colonies near villages (Jha 2015, Henriques *et al.* 2018). Other than natural resources, climatic variables also played their role in habitat suitability. Abiotic factors

such as temperature, precipitation, and humidity may have a more considerable influence on the distribution of some organisms or biodiversity (Hawkins and Porter 2003a, b, Begon *et al.* 2006, Whittaker *et al.* 2007, Corovic *et al.* 2018). There is evidence that rainfall patterns influence the success of vulture

breeding (Bridgeford and Bridgeford 2003, Virani *et al.* 2012). Temperature change also governs the reproduction of vultures, causing stress directly to the animal (Chaudhry 2007 and Schultz 2007 in Phipps *et al.* 2017, Bamford *et al.* 2009, Midgley and Bond 2015).



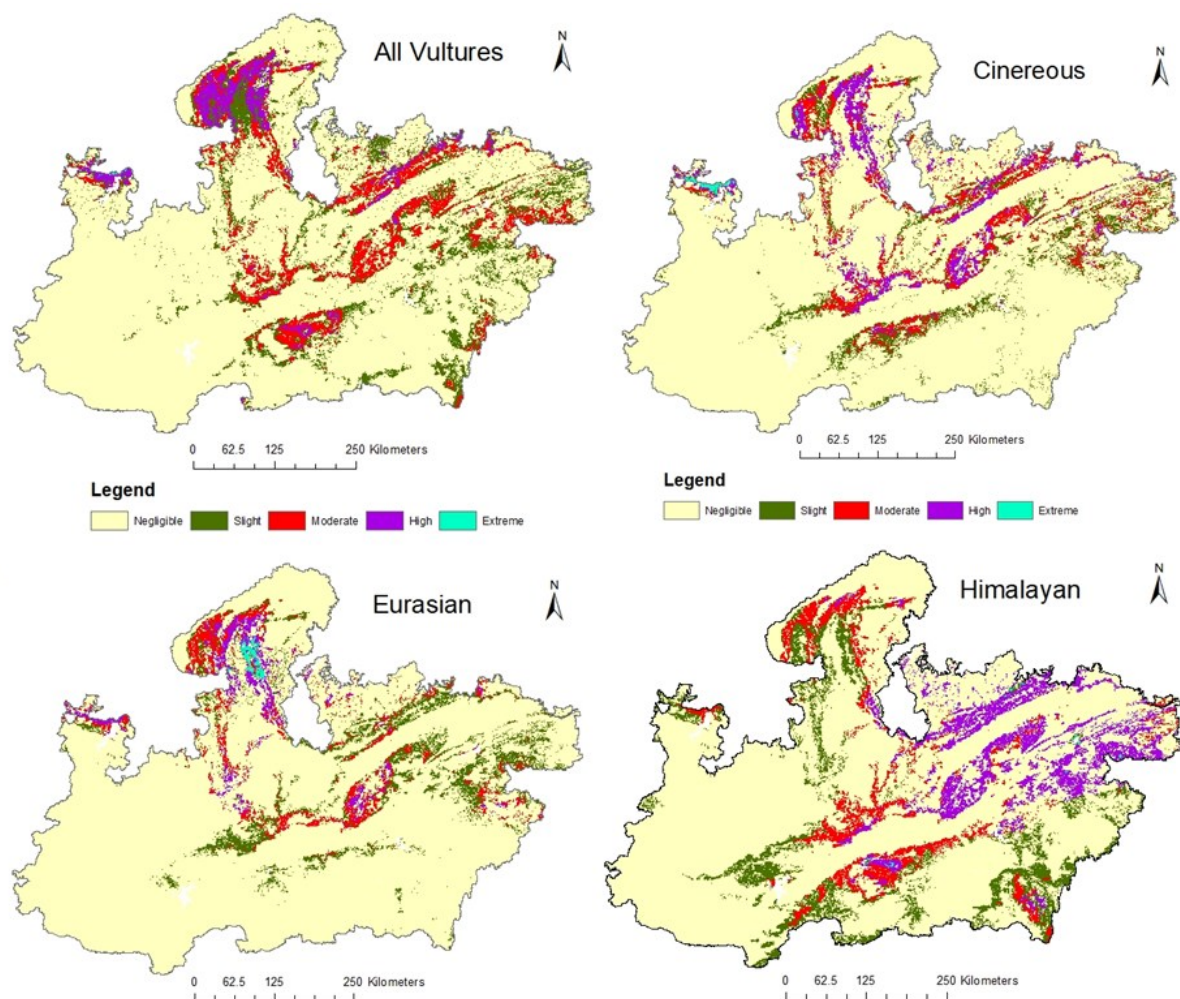
**Figure 5.** The relative predictive power of different environmental variables based on the jackknife of regularized training gain in MaxEnt models for resident vultures. The dark blue bars show the value of the variable independent of others. In all the three resident vultures (Egyptian, Long-billed and Red-headed) the LULC (land use-land cover) was the most crucial variable except White-rumped Vulture, where it was second most important after bio 15. Elevation was among the least important variables

Agreeing with these findings, our models also emphasized particularly on temperature (isothermality, temperature seasonality, and mean temperature of the coldest quarter) and precipitation (precipitation seasonality and

precipitation of warmest quarter) variables as important contributors of habitat suitability. The two top contributors in almost all the species were isothermality and precipitation seasonality. The very low contribution of

agriculture may be due to the inability of the agriculture landscape to meet the primary requirement of safe nesting and roosting as it lacks tall trees and high cliffs. Elevation also has a low contribution as it generally controls the edapho-climatic conditions which do not significantly impact vultures, unlike in the case of plants. Moreover, the plateau and hills in central India are low on elevation (average <500m, maximum 1000m). The insignificant role of NDVI, which was used as a proxy for food availability appears to be contradictory

since food availability is the significant and limiting component of vulture habitat. Therefore, the inclusion of livestock and wildlife providing carrion as direct input in the model should be included to get better results. More parameters characterizing the habitat like disturbance causing factors (proximity to traffic, settlement, etc.), aspect of the slope, etc. may help in the robustness of model prediction as they influence vulture population (Vlachos *et al.* 1998, Liberatori and Penteriani 2001, Marinkovic *et al.* 2012, Sen *et al.* 2017).



**Figure 6.** Habitat suitability maps of all and migratory vultures. Classified area differences could be marked for different species. Colour other than yucca yellow indicates a suitable area of varying degrees for different species

### Area Suitability

The least potential area was mostly covered by agriculture and wasteland scrub, while other potential areas were covered by forests and hilly tracts. Variation in the suitable area

seemed to be linked with habitat availability, requirement, and choice of the species. For example, Red-headed Vulture and White-rumped Vulture among the resident ones, have a lower area in comparison to others since they

nest almost exclusively on taller trees in forest area (Thakur and Kataria 2012, Thakur and Narang 2012, Khatri 2015, Sinha *et al.* 2017, Majgaonkar *et al.* 2018, Ahmad *et al.* 2020). Other resident species like Egyptian vultures have a more suitable habitat area since they frequent outside forests and prefer cliff-nesting as well as trees (Donazar *et al.* 2002, Milchev *et al.* 2012, Zuberogoitia *et al.* 2014). Long-billed vulture, though cliff nesters (Venkitachalam and Senthilnathan 2015), also have a more substantial area due to the availability of cliffs in undulating terrain in plenty in the state. They also nested on heritage monuments and occasionally on trees (Kushwaha and Kanaujia 2009). Himalayan Griffon and Cinereous Vultures, primarily cliff nesters (Mihoub *et al.* 2013), have a larger suitable area since they have to just roost in the region and do not have any specific requirement of cliff or trees, though can nest in both (Purohit and Saran 2013). They possibly look mostly for safety during roosting in a larger area of the state. Eurasian Griffon, another cliff-nester (Garcia-Ripolles *et al.* 2005, Marinkovic *et al.* 2012, Freund *et al.* 2017) with no nesting requirement during migration, may have lesser adaptability to varied landscapes of the state, therefore, have the lesser suitable area as compared to Cinereous Vulture and Himalayan Griffon.

Moreover, some vultures are the most selective species concerning environmental characteristics. In contrast, a few (Eurasian Griffon and the Egyptian Vulture) display a higher degree of ecological plasticity (Margalida *et al.* 2007). Nevertheless, quality-wise and species wise details of habitat area identified in the study, though overlapping, would be useful in preparing a vulture conservation action plan and incorporating it in the management plan of Forest Divisions or Protected Areas of the state.

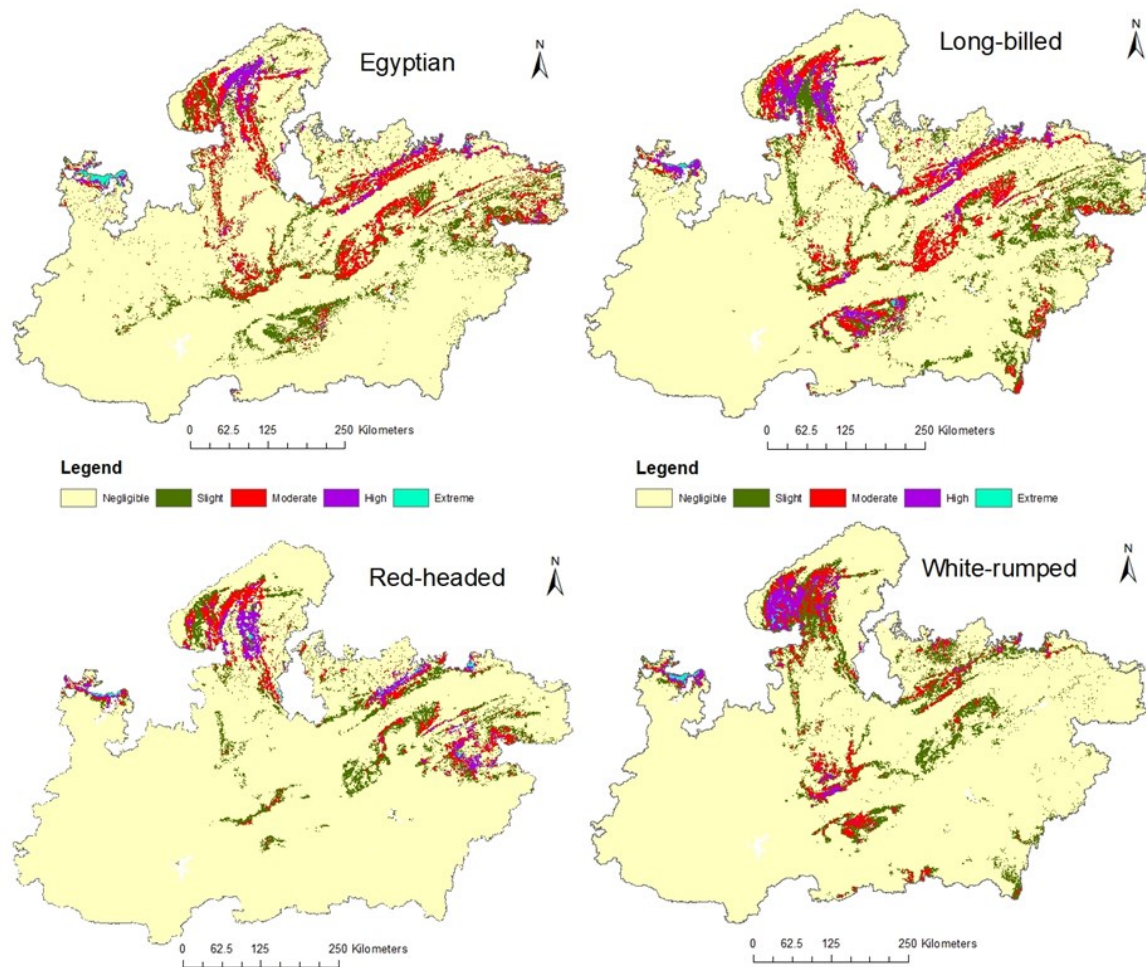
### Management implication

Detailed and reliable information about the spatial distribution of a species provides essential information for species management, especially in the case of rare species of conservation interest (Qin *et al.* 2017). Our study, based on highly accurate MaxEnt models, provided the first predicted potential habitat distribution map for an obligatory scavenging group of species, vultures, in Central India, which supports a considerable population of dwindling vultures.

Prediction and mapping of potentially suitable habitat for threatened and endangered vultures are critical for monitoring and restoration of declining populations in their natural habitat. This could be achieved by artificial introduction, selection of conservation sites, and rehabilitation of the native habitat itself (Gaston 1996, Kumar and Stohlgren 2009). Since the suitable area, especially of the resident vultures, is limited and they are in the threatened stage, proper planning and landuse management around the existing population and further expansion within the predicted habitat is essential for the stabilization and recovery of the numbers from the pre-diclofenac era.

Highly suitable and extremely suitable areas could be used for in situ conservation and reintroduction of the species in the wild (Khosravi *et al.* 2016), and the least suitable and moderately suitable area could be used for population expansion by improving habitat conditions. If required, a negligibly suitable area could also be used for highly plastic species by altering the agriculture landscape to agroforestry use since vultures are reported to nest on smaller trees in rural setups (Kambale 2011, Khatri 2013, Jha 2015) in the absence of larger ones. Incorporation of animal husbandry will further strengthen the cause by increasing the chances of food availability. This appears in line with the expected landuse change in the future with an increase in the requirement for

livestock products (Mateo-Tomas and Olea 2015).



**Figure 7.** Habitat suitability maps of resident vultures. Classified area differences could be marked for different species. Colour other than yucca yellow indicates a suitable area of varying degrees for different species

## Conclusion

Vulture distribution models developed in Central India on the maximum entropy principle were of high-performance accuracy and prediction was in consonance with other studies. Forest and waterbody contributed most among environmental factors within LULC, which in itself had a significant share in model development. The agriculture landscape had minimal impact on vulture distribution. The two most important climatic variables influencing the model were isothermality and precipitation seasonality. Elevation had a minimum contribution.

Nevertheless, the inclusion of food availability, disturbance causing factors, aspect of the slope, vegetation density etc. which have been the limitation of this study, may help in further improvement of the model prediction. Potentially suitable area for species distribution varied among migratory and resident groups of vultures as well as within the species. However, such predicted area in different categories could be used for the improvement of the threatened status of vultures by doing in situ conservation in highly suited areas and facilitating population expansion in less suited areas. The large chunk of a negligibly suitable area in the state could also be turned in favor of

vulture conservation by modifying the landuse and landcover.

### Acknowledgment

The authors are thankful to the Principal Chief Conservator of Forests, and the Chief Wild Life Warden, Madhya Pradesh, Forest Department, Member Secretary, Madhya Pradesh State Biodiversity Board, and the Director, Indian Institute of Forest Management for supporting the Vulture Census Project in Madhya Pradesh. Miss Amreesh Bhullar deserves thanks for her initial support in performing the task.

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