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White-rumped Vulture's Habitat Suitability Prediction using MaxEnt in Arunachal Pradesh

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Authors' contributions

This work was carried out in collaboration among all authors. Authors ATK and DM framed the research design, conducted the data analysis, and wrote the manuscript. Authors ATK, JN and TB carried out the field survey and collected the data. All authors read and approved the final manuscript.

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ABSTRACT

Few reports showed that White-rumped vulture is present in Arunachal Pradesh. However, they were reported from a few places only. Such sightings suggest that either the region is not explored completely or the habitats are not suitable for the species. Therefore, knowing and predicting the habitat suitability of WRV and revealing the relative contribution of environmental variables determining such distribution can be important for their protection and conservation. The present study was based on the current distribution of WRV in Arunachal Pradesh that we had surveyed from 2016 to 2020. We followed the road count and point count methods to obtain primary occurrence data. Also, secondary data on occurrence records and data on environmental variables (landscape variables, anthropogenic variables, and climatic variables) were obtained and used. The data were processed using ArcMap. 29 occurrence records (filtered) and 11 environmental variables were used to build the prediction model using maximum entropy (MaxEnt). The MaxEnt predicted model showed high accuracy with area under the receiver operating characteristic curve value equals to 0.95 and True Skill Statistics value equals to 0.87. Of the total area, only 2629.63 km^2 (3.20 %) is suitable for WRV while the majority of the area is unsuitable (79542.84 km^2) (96.79 %). The elevation (32.2%), land use land cover (31.7%), and normalized difference vegetation index of November (26.7%) were the most influencing variables impacting the distribution of WRV. Among bioclimatic variables, the mean temperature of the warmest quarter and precipitation of the wettest quarter had the highest contribution. This work is the first attempt to understand the

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spatial distribution of WRV and the environmental factors associated with their distribution in the state. The findings can be relevant for designing conservation efforts to conserve this species in the state.

Keywords: White-rumped vulture; SDM; habitat; MaxEnt; Arunachal Pradesh.

1. INTRODUCTION

White-rumped Vulture *Gyps bengalensis* is a medium-sized raptor with wide distribution range throughout the South-Asian countries, including India, and precisely to the tropical and sub-tropical regions [1,2]. They perform a crucial and commendable job of clearing the carrion, and thereby prevent the advent of any adverse consequences. They were once regarded as one of the most abundant raptor species in the world [3]. However, by the 1990s they have undergone unprecedented population decline and by 2000, they have been recognized as a critically endangered species by IUCN [4,5]. Their population decline can have serious impacts on the health of the environment [6]. They are observed mostly in the plains and less frequently in hilly regions, mostly below 1000 m amsl [7,8]. However, they have been also recorded in higher regions up to 3100 m amsl in Nepal [9]. They prefer grasslands, scattered forest areas, semi-deserts, riverine forests, and regions near human habitation such as agricultural areas, dump yards, etc. [4]. They are colonial breeder and primarily nests on tall trees [10].

Despite their wide geographic range in India, White-rumped Vultures (WRV) have been reported only from a few places in Arunachal Pradesh (study area), which suggested that they are found in patches, showing disjunct distribution. They were reported from Siang valley [11,12], Mehao wildlife sanctuary [12], Seijusa [13], Namsai [13], Pakke tiger reserve [14], D'Ering memorial wildlife sanctuary [15–18], and Dehang-Debang biosphere reserve [19]. These meager sightings suggested that either majority of the area in the state is unexplored or has unsuitable habitats for WRV. Also, these sightings of WRV in few areas indicated that the regions have favorable environments for WRV to survive. Complete information on distribution, habitat suitability, and habitat preferences is lacking and is necessary for the protection and conservation of the WRV population in the state.

Species survivability depends on the ability of the species to access and exploit the resources of the habitat. The habitat quality and habitat suitability of any species can be related to the contribution of prevailing environmental factors. Habitat suitability depends on the assemblage of required features of environmental factors such as optimal climate and landscape conditions. Species distribution modeling (SDM) is an effective tool to understand the habitat requirements of any species. It can help in predicting the habitat suitability, potential distribution of species, and importance of environmental variables in species distribution [20–25]. It uses georeferenced occurrence data and spatial environmental data related to climate, topography, vegetation, soil type, etc., and predicts the distribution of species and their suitable habitat. With the advancement in recent technologies, various tools and techniques have been developed to generate SDMs [20,26,27]. MaxEnt is a widely used and popular SDM tool that builds the prediction model based on species presence data only [22]. The output of MaxEnt gives a probabilistic map of habitat suitability, where each pixel value indicates the degree of habitat suitability of the species under study [22,28]. The suitability of the habitats for vultures was greatly influenced by land use-land cover (forest and waterbodies), isothermality, and precipitation seasonality in Madhya Pradesh [29]; altitude, mean temperature of the wettest quarter, precipitation of the warmest quarter, and mean diurnal range in Nepal [30]. Habitat suitability or distribution of WRV and other vultures were strongly influenced by the food availability [31–33], elevation [34,35], climate [35–38], vegetation [39,40], and land use pattern [29,40,41].

Arunachal Pradesh has a landscape ranging from lowland plains to high mountainous regions thus, exhibits wide range of climatic conditions and topography, which may have a significant role in determining the distribution of WRV in Arunachal Pradesh. However, detailed information on WRV's occurrence points and suitable habitat is lacking from the state. Considering the above-mentioned research gap and research significance, the present study aimed to predict the habitat suitability of WRV and determine the relative contribution of environmental variables in the distribution of

WRV in the state. The findings will help in understanding the biogeography of WRV and contribute as baseline information for future studies in the state. The findings can also help us to identify potential sites of the WRV, where the reintroduction of WRV can be carried out in the state.

2. METHODOLOGY

2.1 Study Area

The surveys were carried out throughout the landscape of Arunachal Pradesh (26°28' - 29°30' North to 91°30' - 97°30' East), covering an area of 83,743 km^2 (Figure 1). The state is bestowed with rich terrestrial biodiversity [42], which is supported by the state's rich forest covers, topographical elevation gradient, and varied climate regimes. The state has a forest cover of 66,687.78 km^2, which is 79.63 % of the state's total geographical area [43]. In terms of vegetation types, the state includes tropical forests, sub-tropical forests, pine forests, temperate forests, alpine forests, degraded forests, and grasslands. Topographically, based on 30 m resolution SRTM-DEM, the average elevation of the state ranges from 67 m to 6853 m. Depending upon the elevation, the state displays different climatic zones, and these ranges from sub-tropical to temperate climate. The lower regions of the state experience hot and humid climates, while the northern part experiences cold and dry climates. In the foothills, the maximum temperature can be up to 40°C during the summer. The average temperature ranges from 0° to 21°C and 22° to 31°C, during the winter and monsoon months, respectively. Moreover, the annual temperature varies from below 0°C to 31°C. The state receives overall rainfall from May to early October. The annual rainfall ranges from 2,000 mm to 8,000 mm [43].

2.2 WRV Occurrence Data and Processing

Occurrence data were collected from surveys made during the study period from January 2016 to May, 2020. We followed the road count method [44] and point count method [45] to record the occurrence of WRV in the state. 27 routes were laid on the state's motorable roadways (Fig. 1) and a vehicle's speed approximately of 20-30 km/h was maintained throughout the survey. The literature review suggested that D'Ering memorial wildlife sanctuary (DEMWLS) has high potential for WRV's sighting. However, the sanctuary lacks motorable roadway, therefore we followed point count method inside the sanctuary. 10 point count stations were fixed along the forest trails and a minimum of 30 minutes stay at each point was followed. For both methods, surveys were carried out from 0800 hours in the morning to 1600 hours in the evening. A total of 28 georeferenced points (locations) of WRV occurrence were recorded by the end of the survey period. The coordinates were recorded using Garmin GPS. Since the study aims to predict the habitat suitability of WRVs in the state; occurrence records of WRVs from other sources were also used. We collected 10 occurrence records from Global Biodiversity Information Facility (GBIF) (https://www.gbif.org/) and four occurrence records from a published paper [16]. Altogether, we have a total of 42 occurrence records. However, recording of points that are too close may result in sampling biases and cause overfitting of the models [46] and thereby affecting the model performance (i.e., accuracy and precision). Therefore, we used "spatially rarefy occurrence data for SDMs" tool from the SDMToolbox in ArcMap to filter the occurrence point. Points with distances less than one km between the two points were removed randomly [34]. Finally, after filtering only 29 occurrence points were left to be used in MaxEnt operation (Fig. 2).

2.3 Environmental variables and Processing

SDM estimates the relationship between the species and its environment and predicts the habitat suitability of the species using the spatial information attached to the environmental variables [20]. The selection of the environmental variables is very much species-oriented and prefer to consider those with restrictive effect on species distribution. For this study, environmental variables such as elevation, vegetation, land use land cover, human population density, livestock density, and climate were considered. Digital elevation model (DEM) data were obtained from SRTM data (https://earthexplorer.usgs.gov/). Normalised Difference Vegetation Index (NDVI) estimates the density of greenness of an area on the land surface. It can be used as a proxy for ungulate forage availability [40]. NDVI data were obtained from MODIS data (https://lpdaac.usgs.gov/products/mod13a3v006/). Land use land cover (LULC) data were obtained from ESRI data (https://livingatlas.arcgis.com/landcover/) (Figure 3). Human population density (HPD) data was obtained from SEDAC data (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11). Livestock census data was obtained from Livestock census, 2019, Directorate of Animal Husbandry & Veterinary, Government of Arunachal Pradesh. The livestock census data was then converted to livestock density (LD). Climatic data were obtained from WorldClim data (https://www.worldclim.org/). WorldClim provides the averaged weather data over 30 years (1970 to 2000) and among the data, we considered bioclimatic variables. Bioclimatic variables are derived from monthly temperature and rainfall values [47] and thus can act as more biologically meaningful variables. There were 19 bioclimatic variables, but we chose only 4 variables for the study namely, mean temperature of warmest quarter, mean temperature of coldest quarter, precipitation of wettest quarter, and precipitation of driest quarter. These were chosen on the basis that they can cover the average extreme temperature and precipitation of summer and winter. Moreover, for any regional study with species that has wide distribution, the overall temperature and precipitation won't affect much, in compare to the landscape/ habitat and anthropogenic factors. We then used variance inflation factor (VIF) test with cutoff threshold greater than 10 (VIF>10) [24] in r software (R version 4.1.1) to see any collinearity between the 4 bioclimatic variables. The 4 input variables have no collinearity problem. Therefore, finally, we have 11 environmental variables (one DEM, three NDVIs, one LULC, one HPD, one LD, and four bioclimatic variables).

To run an SDM, every layer of the environmental variables undertaken must have same spatial resolution and projection. The bioclimatic layer has "0.0083333333 x 0.0083333333" spatial resolution and "GCS_WGS_1984" projection. The DEM layer has "0.00027777778 x 0.00027777778" spatial resolution and "GCS_WGS_1984" projection. The NDVIs layers have "926.6254331 x 926.6254331" spatial resolution and "sinusoidal grid" projection. The LULC layer has "10 x 10" spatial resolution with "WGS_1984_UTM_Zone" projection. HPD layer and LD layer have spatial resolution of "0.0083333333 x 0.0083333333" and GCS_WGS_1984 projection. Therefore, all the layers were resampled to "0.0083333333 x 0.0083333333" spatial resolution and GCS_WGS_1984 projection. Then, were clipped to the shapefile of study area and were converted to "ascii" format files. These processings were carried out in ArcMap 10.4. Furthermore, in many studies, a bias layer has been used to prevent sampling bias and to restrict the selection of background points during MaxEnt operation. So, we created a bias layer that has the same extent and resolution as the processed bioclimatic layer using the minimum convex polygon (MCP) and a buffer distance of 20 km in ArcMap.

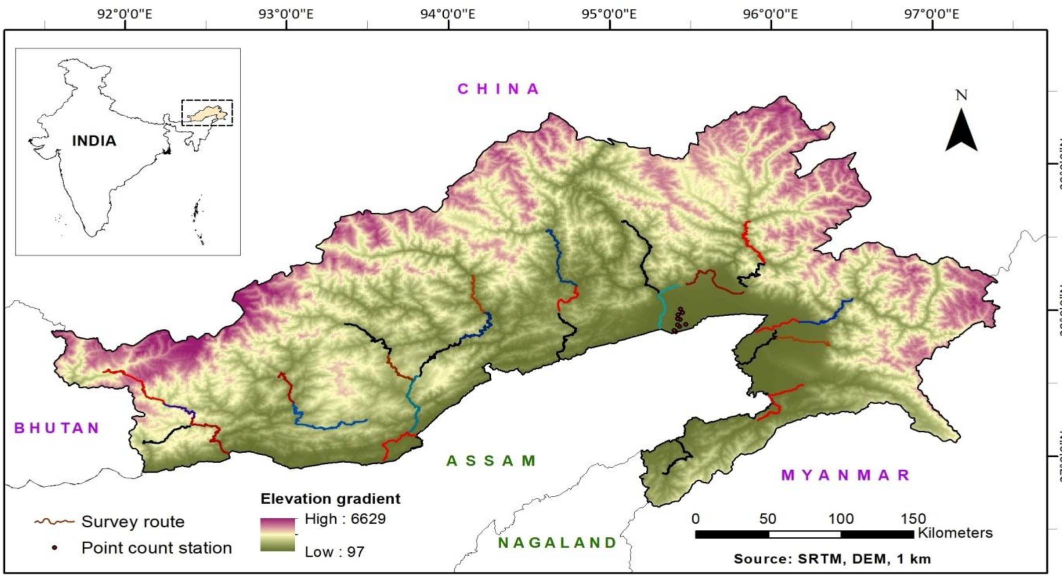


Fig. 1. Study area map (Arunachal Pradesh) with survey routes and point count stations (Different colors of polylines are used to distinguish and show different survey routes)

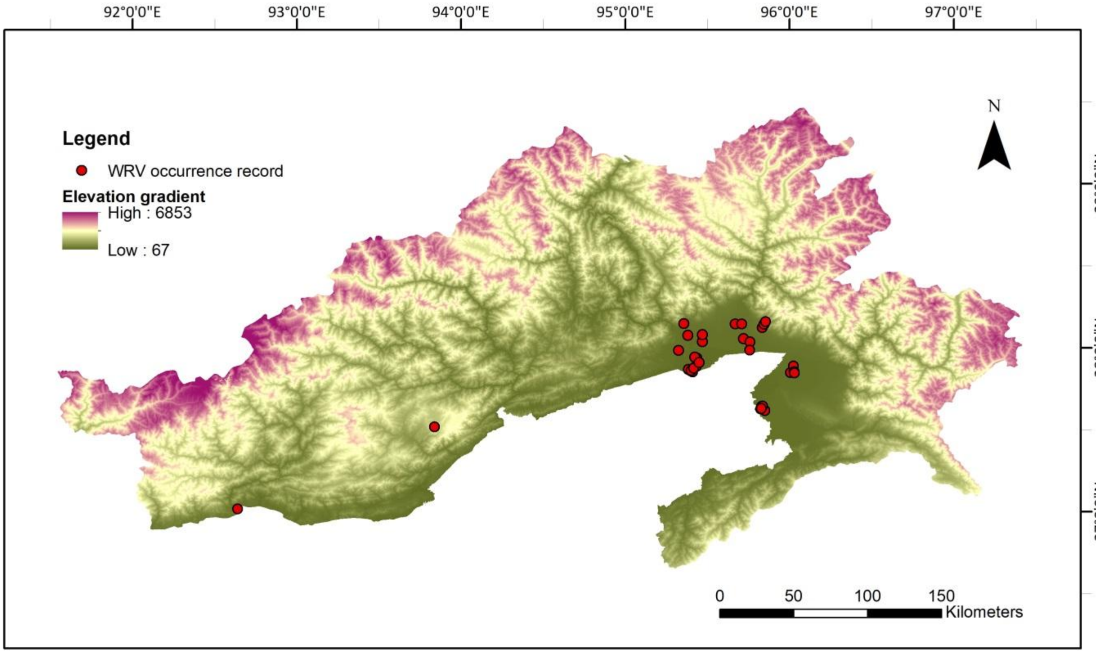


Fig. 2. Occurrence records of WRV (red dots) in Arunachal Pradesh

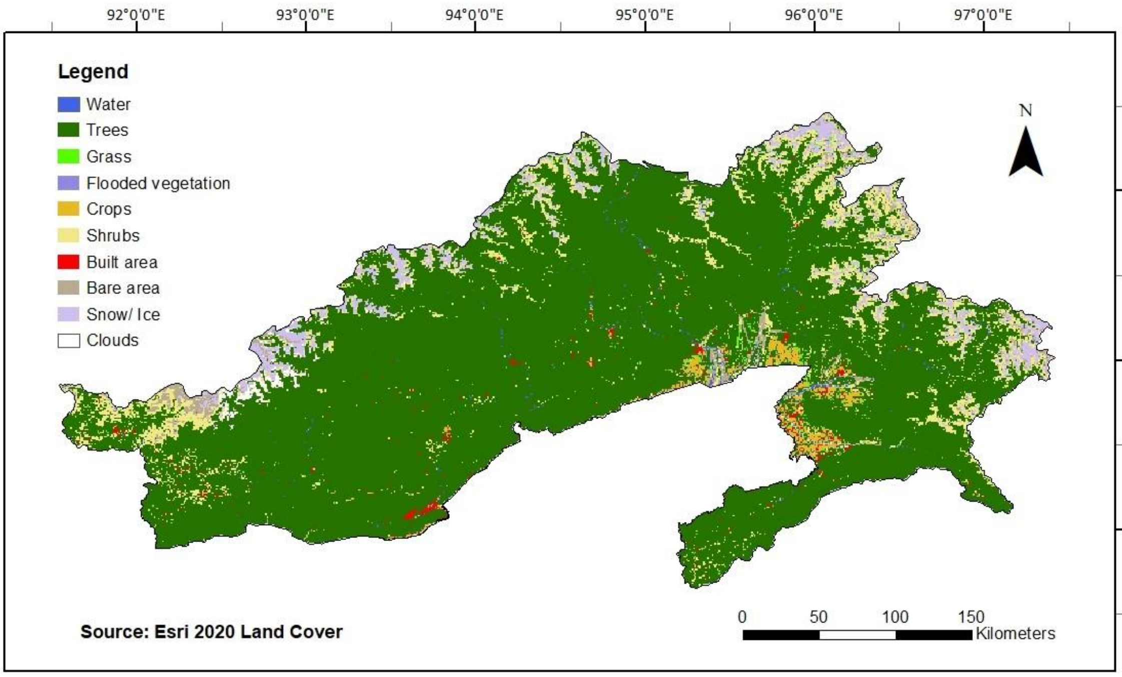


Fig. 3. LULC map of Arunachal Pradesh (Rescaled to 1km resolution)

2.4 Modeling Approach and Procedure

For the present study, we chose maximum entropy (MaxEnt) for predicting habitat suitability of WRV in Arunachal Pradesh. The output quality of MaxEnt depends on the optimization or adjustment in different parameters of MaxEnt settings [48]. Akaike's information criterion (AIC) determines the fitness of the model statistically and the model with the lowest delta AIC_c (should equal zero) is the best fit model. Therefore, the delta AIC_c value was estimated using "ENMevaluate" command in r software [49,50] and the values of other parameters associated with the lowest delta AIC_c were selected and used in MaxEnt setting. In MaxEnt interface, we combined five parameters (linear, quadratic, product, threshold, and hinge features) under the features combination and selected “cloglog” output format. Additionally, other setting parameters were optimized: random test percentage set to 25%, regularization multiplier set to 4, and maximum iteration set to 5000 times. Bootstrap replication run type was selected with replicates set to 10. Area Under the Receiver operating characteristic curve (AUC) (threshold independent) and True Skill Statistics (TSS) (threshold dependent) coefficient were used to evaluate the accuracy of the predicted model. Percentage contribution of variables table and jackknife analysis were used to evaluate each variable's relative importance.

3. RESULTS

3.1 Model Performance

Area Under the Receiver operating characteristic curve (AUC) was considered to evaluate the accuracy of the model. The average AUC of the predicted model for habitat suitability of WRV in Arunachal Pradesh was greater than 0.9, which indicates that the prediction result has high accuracy ($AUC_{training}$ = 0.95, AUC_{test} = 0.95) (Fig. 4). Also, the threshold-dependent validation test of the predicted model indicated high predictive accuracy of the model (TSS= 0.87).

3.2 Habitat suitability of WRV in Arunachal Pradesh

The predicted map of habitat suitability of WRV is continuous data with values ranging from 0 to 1 (lowest to highest probability of distribution). Therefore, we classified the output of MaxEnt into four classes of habitat suitability based on maximum training sensitivity plus specificity cloglog threshold (=0.49): unsuitable (< 0.49), Low suitable (0.49 - 0.6), moderate suitable (0.6 - 0.8), and high suitable (> 0.8). The suitable habitat of White-rumped vulture is predicted to cover 2629.63 km^2 which is only 3.20 % of the total area of Arunachal Pradesh. Further, only 0.67 % of the area has high suitability of habitat. A large portion of the area (79542.84 km^2) is found to be unsuitable for the WRV (Table 1, Fig. 5). The model result shows that the areas with high suitability for WRVs are distributed in the regions of East Siang, Namsai, Lower Dibang Valley, Lohit, Changlang, Lower Siang, West Siang, Upper Subansiri, and Papumpare districts in Arunachal Pradesh.

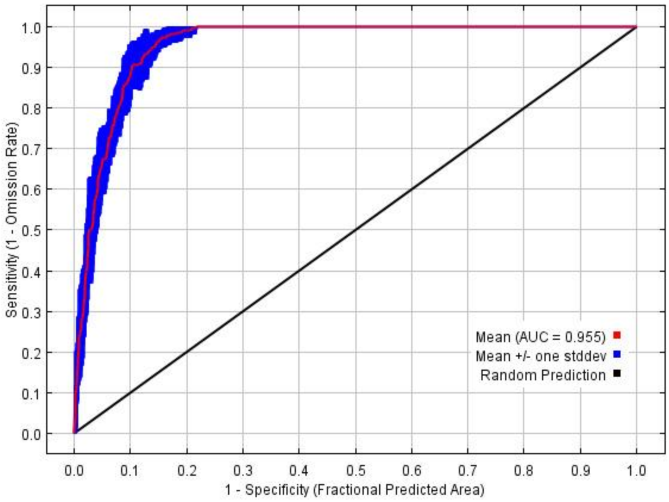


Fig. 4. AUC report of training model prediction

Table 1. Habitat suitability class based on predictive probability range with area (km^2, %)

Habitat suitability class	Area (km^2)	% Area
Unsuitable (< 0.49)	79542.84	96.79
Low suitable (0.49 - 0.6)	865.41	1.05
Moderate suitable (0.6 - 0.8)	1209.97	1.47
High suitable (> 0.8)	554.24	0.67

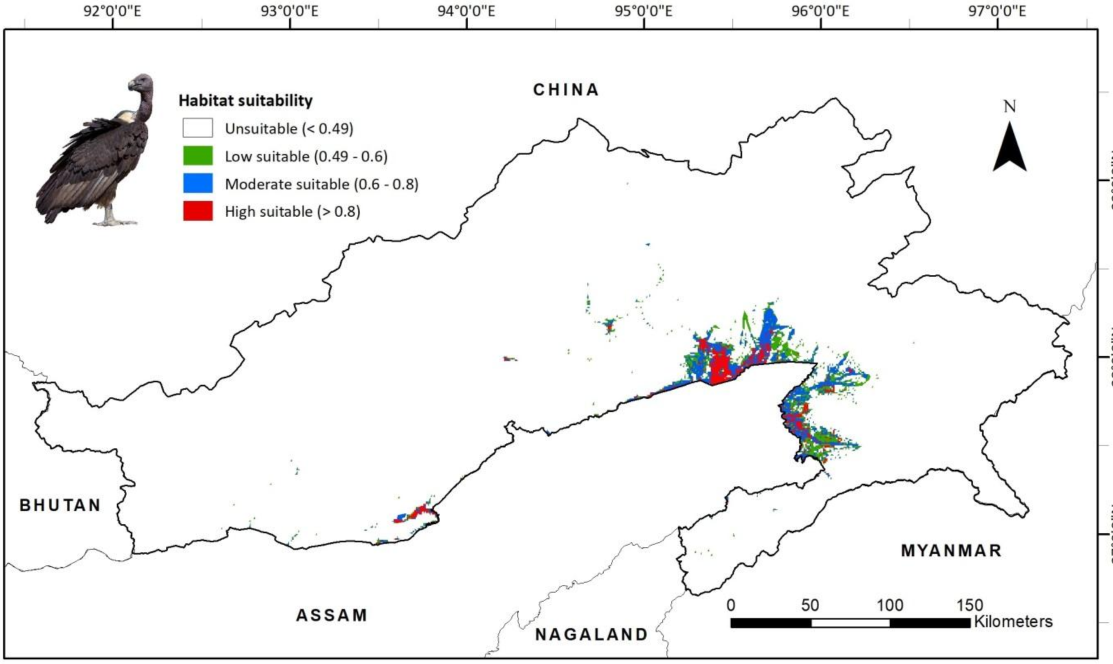


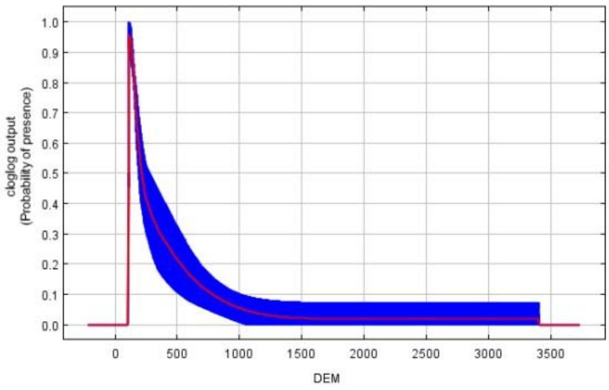
Fig. 5. Habitat suitability prediction of White-rumped vulture in Arunachal Pradesh

3.3 Relative Contribution of Environmental Variables in Distribution of WRV

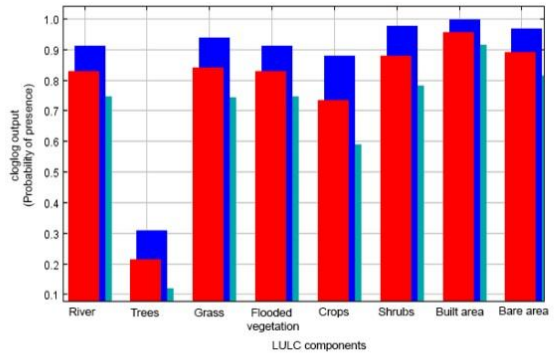
Analysis of variable contributions table of model prediction showed that DEM is the most significant variable with 54.2% contribution in the distribution prediction. Followed by LULC (31.7%) and NDVI11 (26.7%). Rest of the variables showed little contribution (Bio10-2.2%, Bio16- 2.1%, HPD- 1.9%, Bio17- 1%, LD- 0.9%, NDVI2- 0.8%, NDVI6- 0.5%, and Bio11- 0.2%) (Table 2). Among the land use land cover components, built area, shrub, and bare area are found to be the most influential ones (Fig. 6). The response curves of the predicted model showed that DEM and NDVIs are negatively correlated (Fig. 6). Bio10, Bio11, Bio16, and Bio17 are positively correlated, whereas HPD and LD didn't show a clear response to the distribution of this vulture. Adding to this, the Jackknife analysis (of regularised training gain) showed that NDVI11, DEM, NDVI2, LULC, and Bio10 are the five most influencing variables for the distribution of WRV in Arunachal Pradesh. The variable with the highest gain, when used in isolation, is NDVI11, and the variable that decreases the gain the most when it is omitted, is LULC (Fig. 7).

Table 2. Relative contribution of the environmental variables to the MaxEnt model

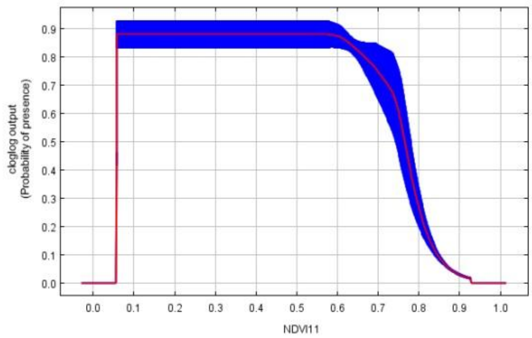
Code	Environmental variable	% contribution
DEM	Digital elevation model	32.2
LULC	Land use land cover	31.7
NDVI11	Normalized difference vegetation index, November	26.7
Bio10	Mean temperature of warmest quarter	2.2
Bio16	Precipitation of wettest quarter	2.1
HPD	Human population density	1.9
Bio17	Precipitation of driest quarter	1.0
LD	Livestock density	0.9
NDVI2	Normalised difference vegetation index, February	0.8
NDVI6	Normalised difference vegetation index, June	0.5
Bio11	Mean temperature of coldest quarter	0.2



(a)



(b)



(c)

Fig. 6. Response curves showing the correlation between WRV's distribution and the three most influencing variables: (a) Digital elevation model, (b) Land use land cover, and (c) Normalised difference vegetation index, November. (The curves show the mean response of the 10 replicate Maxent runs (red) and the mean +/- one standard deviation (blue, two shades for categorical variables)

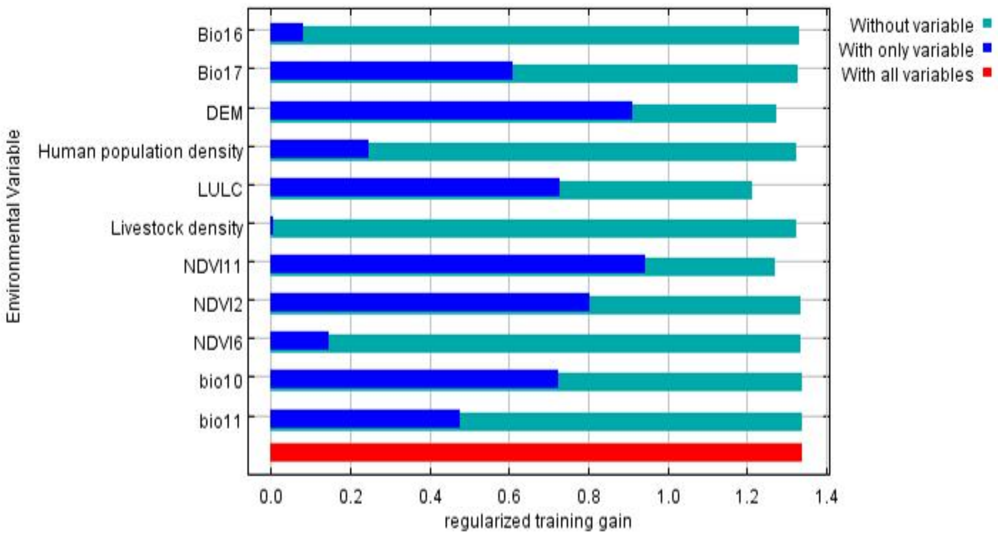


Fig. 7. Jackknife test of variable importance (regularised training gain)

4. DISCUSSIONS

4.1 Model Performance

The performance of the model was evaluated using AUC and TSS. Our predicted model has an AUC value greater than 0.9 ($AUC_{training}$ = 0.95) and TSS value = 0.87. In both the measures, a value nearer to 1 indicates that the model is more accurate and is good to consider [22,51]. Also, TSS coefficient value ranges from −1 to +1. The value +1 indicates perfect agreement and values of zero or less indicate a performance no better than random [52].

4.2 Habitat suitability of WRV in Arunachal Pradesh

The predicted model shows that a very small portion, 2629.63 km^2 (3.20 %) of the total area is suitable for WRV under the present climatic conditions and landscape features. Such findings suggest that the WRV has very specific requirements for habitat preference in the state. Generally, WRVs are found in regions with lower altitude ranges (below 2700m amsl), nearby human settlements (built-up areas), open forests, and wooded savannah [1,4]. Our prediction reflects the same characteristics of the areas of suitable habitats. Suitable habitats are found to be concentrated in the areas with lower elevation ranges, open forests, built-up areas, and waterbody availability in the state. In addition to the actual recording sites of WRV, other areas where there were no observations have also been predicted as suitable habitats. This indicates that maybe those regions have similar climatic and other environmental variables envelope in the state. A large portion of the geographic area of the state is predicted unsuitable for WRV and this is supported by the fact that the majority of the areas in the state are covered with forests (Very dense forests (25.19 %), and moderately dense forests (36.49 %)) [43]. The non-preference of the dense forests by WRV is due to the fact that they need a clearer ground cover, where they can easily detect their food (carcass) on the ground. The availability of suitable habitats in the state is a good sign for the conservation of WRV and with proper investigations and management of those habitats, reintroduction of WRV in occupied or unoccupied suitable habitats can be carried out, if required.

4.3 Relative Contribution of Environmental Variables in Distribution of WRV

Environmental factors (variables) not only affect the growth and reproduction of vultures but also the behavior of the species. Among 11 selected variables, the analysis of variables contribution shows that the most important variables are the DEM (54.2%), LULC (31.7%), and NDVI11 (26.7%). The elevation can affect the distribution of WRV by determining the availability of their food resources [34]. Also, the elevation is related to the climatic condition of the area as there will be a decrease in temperature with the increase in altitude and this can impact the reproduction success of vultures (endotherms). Our predicted model shows that all the potential areas fall within the range of average elevation of 67 m to 1047 m amsl. The response curve of DEM and WRV (probability of occurrence) showed a negative correlation (Fig. 6). Thus the finding suggests that the preferable habitats of WRV are the areas under lower elevation range. In support of this, it was found that elevation has greatly impacted the distribution of WRV in Nepal [30]. However, in contrast to this, elevation was found one of the least influencing factors for distribution of WRV in Madhya Pradesh [29]. The land use-land cover can be a key determinant in influencing the distribution of vultures across their range. Habitats that are in or nearby built areas and nearby waterbody are more preferred by the WRVs [29,53]. This may be because these areas can provide good opportunities for food sources in the form of cattle stock [9,33,54] and dumpsites [55–57]. Our model response curve of LULC shows that the built area, shrubs, and bare area are the three most influencing variables which determine the WRV distribution in the state (Fig. 6). In Fig. 7, the regularised training gain of the model without LULC was less than that of the models without other single variables, thus the LULC is found to be a more useful variable in determining the WRV distribution in the state. Further, WRV being an old-world vulture has a highly developed vision and is the only primary tool to find food sources in vast landscapes. Hence, an ideal habitat where they can find food should be open areas with scattered trees and grasses which can support relatively good numbers of ungulates. The normalized difference vegetation index (NDVI), indicates the degree and extent of greenness thus, is related to vegetation cover and can have a significant role in presence of ungulates [39,40], thereby influencing the distribution of WRV in the state. In our predicted model, we observed that NDVI11 has a good contribution to WRV distribution in compare to NDVI6 and NDVI2 (Fig. 6). On comparing three NDVIs, we observed a lesser extent of greenery in NDVI11 to all the occurrence points. This suggests that there is sparse vegetation cover in November, and thus less forage cover for ungulates which in turn increases the chance of more dead ungulates. The response curve of NDVI11 and WRV (probability of occurrence) showed a negative correlation (Fig. 6). This indicates that areas with lower NDVI values (i.e. lower greenery) support more WRV or more numbers of WRV have been observed when there has been a reduction in the greenery of that area. Temperature and precipitation can also influence both, the growth and reproduction of vultures [34,37,58]. However, in our predicted model, we observed a very small contribution percentage of temperature and precipitation in WRV distribution. This may be because for species like WRV which has a wide distribution range, the temperature and precipitation may have the least influence on their distribution at the regional level (i.e., Arunachal Pradesh). Among the 4 bioclimatic variables, the Mean temperature of warmest quarter and precipitation of wettest quarter have the highest contribution with 2.2% and 2.1%, respectively (Table 2). However, in contrast to this, the precipitation (of wettest quarter) and temperature (of warmest month) were found as important influencing factors for WRV distribution in Nepal [30]. WRV, being obligate scavengers are directly influenced by the availability of food sources, mainly ungulates [31–33]. For this study, livestock density and human population density were considered to represent the availability of food. However, in our predicted model, both of the variables don't show any strong correlation with distribution of WRV and its contribution percentage to WRV distribution was least. These suggest that along with food availability, other factors may have synergistically impacted the occurrence of WRV in the state.

5. CONCLUSION

We used MaxEnt and sets of environmental variables to evaluate the suitable habitat distribution of WRV in Arunachal Pradesh. The model reveals that a very small portion of the area 2647.07 km^2 (3.22 %) of the total area is suitable for WRV. Though it is a small portion, it still has enough space and requirements for the improvement of threatened status (globally recognized) and conservation of WRV in the state. Interestingly, within these suitable regions, there is an obvious lack of overlap between the predicted model and observed occurrence recording of WRV, which suggests that there may be some factors that are inhibiting the expansion of WRV distribution or might have been responsible for the local extinction. Therefore, it is worth considering identifying those influencing factors so that, the right management can be carried out. If so, then these predicted suitable habitats can be utilized for reintroduction programs. Our results showed that the DEM, LULC, and NDVI11 have more contributions than other variables in the distribution of WRV in the state. As a whole, the HPD and LD don't show any strong positive or negative correlation with the distribution of WRV. But it is also evident that all the distributed areas of WRV have a good number of human populations and livestock populations. This work is the first attempt to understand the spatial distribution of WRV and the environmental factors associated with their distribution in the state. The findings can act as baseline information for further analysis of WRV distribution and reintroduction programs in the state.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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