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Multi-Model Analysis to Predict the Potential Suitable Habitat for *Quercus oblongata* D. Don (Fagaceae) in the Western Himalayan Region

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ABSTRACT

Quercus oblongata D. Don is an economically and ecologically important tree species. It is distributed in the western Himalayan region of India as well as Nepal, Pakistan, Thailand, and Vietnam. The present study explored the potential distribution and habitat suitability of *Q. oblongata* using ensemble modeling. Eleven environmental variables (eight bioclimatic and three topographic), and 121 occurrence records were used in the analysis. Four algorithms: Generalized Additive Model (GAM), Generalized Linear Model (GLM), Random Forest (RF), and Maximum Entropy (MaxEnt) were used to build the ensemble model for potential suitable habitat of *Q. oblongata.* To evaluate the model performance, AUC and TSS metrics were used, which showed high AUC (>0.94) and TSS (>0.86) metrics for all the models. The environmental variables that displayed high contribution in the prediction were temperature annual range (bio7, 48.5%), precipitation of wettest period (bio13 ; 41%), and elevation (elev ; 40%). The total suitable area was 22634 km^2, including the least (12546 km^2), moderate (7935 km^2), and highly (2153 km^2) suitable areas. Habitat suitability of *Q. oblongata* is predicted in most of the regions of Nainital, Almora, central Tehri Garhwal, eastern Mussoorie and Chakrata region of Dehradun District of Uttarakhand. A sizeable wide patch was found in Southern Chamba with Northern Kangra District, including the northern region of Mandi District of Himachal Pradesh. The predicted suitable habitat can be used for future exploration for the study of genetic diversity and conservation purposes.

Keywords Ensemble model, Environmental variables, MaxEnt, Random forests, *Quercus*.

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INTRODUCTION

Quercus oblongata D. Don (Fagaceae) is a broad-leaved, evergreen and dominant tree species distributed in India, Nepal, Pakistan, Thailand and Vietnam (Govaerts and Frodin 1998). *Q. oblongata* generally occurs at higher elevations ranging from 1200 to 3000 meters. *Q. oblongata* is an important tree species whose products (acorns, bark, timber, and leaves) have been used in ethnomedicine and livestock healthcare by Joshi and Juyal (2017) and Sati *et al.* (2017). Fruits, leaves, barks, and gum of *Q. oblongata* have potential antibacterial and antifungal properties, making them useful in the treatment of several diseases like gonorrhea, digestive problems, diarrhea and asthma (Singh and Bisht 2018).

In India, *Q. oblongata* is widespread in the mountainous regions of western Himalaya, especially in Uttarakhand (Rawat *et al.* 2021). Mountainous regions of the western Himalayas are facing habitat depletion due to deforestation, land fragmentation, construction of roads on hills, and forest fires (Negi *et al.* 2017). Additionally, unsustainable utilization for fuel and fodder resulted in the decline of *Quercus* populations in western Himalayas. These challenges may influence the growth, and distribution of *Q. oblongata* in western Himalayan. Thus, the knowledge of suitable habitat areas can be helpful for the restoration and conservation of *Q. oblongata* in the western Himalayan region of India.

Species distribution modeling (SDM) is an effective tool to map the potential habitat distribution of plant species. The utility of SDM has been exploited in the various research areas of ecology, evolutionary, and conservation studies (Lee-Yaw *et al.* 2022). Applicability of SDM has also been identified in the population discovery, disease prevalence, invasion risk, and species future survival (Srivastava *et al.* 2019). SDM technique utilizes the environmental information and geographical occurrence of species data to provide the species niche information. Various SDM methods has been developed for distribution modeling namely MARS (Multivariate Adaptive Regression Splines), CART (Classification and Regression Trees), GRASP (Generalized Regression Analysis and Spatial Prediction), GARP (Genetic Algorithm for Rule-set Prediction), GAM (Generalized Additive Model) and GLM (Generalized Linear Model), RF (Random Forests) and MaxEnt (Maximum Entropy) (Hao *et al.* 2019). Every model uses a separate set of algorithms and guiding concepts. One such example is requirement of pseudo-occurrence data, which is essentially required by GAM, GLM and RF. Whereas MaxEnt required background information of target species for prediction analysis (Hao *et al.* 2019). Constructing an ensemble model for prediction analysis is generally more reliable rather than a single model as the ensemble model maximizes the prediction analysis (Pecchi *et al.* 2019). Naimi and Araújo (2016), develop an R packages 'sdm', which supports several modeling methods including ensemble function. This R package enables us to compare alternative modeling methodologies in order to achieve the needed multi-model or ensemble model analysis.

Therefore, the present study used ensemble method to identify the potentially suitable habitat for *Q. oblongata* for its management and conservation in western Himalaya with the following objectives: (1) Identify the environmental variables related with the distribution of *Q. oblongata* and (2) determine potentially suitable habitat for *Q. oblongata* within its native habitats related to the current climate scenario (1970-2000).

MATERIALS AND METHODS

Study location

The study area was the western Himalayan region (WHR) of India. The western Himalayan region is the largest section of the Indian Himalayas, encompassing three Indian states: Jammu and Kashmir, Himachal Pradesh, and Uttarakhand. The Himalayas plays crucial role for weather patterns in the Indian subcontinent to south and central Asian highlands to north. On the southern slopes of the Western Himalayas, the average annual rainfall varies from Shimla and Mussoorie (about 1530 mm) to Leh region in the Ladakh of the Indus Valley (75 to 150 mm). The study area covers a geographical area of about 4,55,602 km^2, extends from 28.8°N to 37.0°N latitude to 72.5°E to 80.9°E longitude. The altitude ranges from 186 to 8246 m, increasing northeastward. In addition to its varied height gradients, this region is habitat to a broad range of forest types. According to Haq *et al*. (2023), the main vegetation types include evergreen, deciduous forest, evergreen needle-leaf, mixed, shrubland, and grassland.

Study species

Quercus oblongata is an evergreen tree up to 25 m tall (Figs. 1a–b). Its leaves are narrower, more

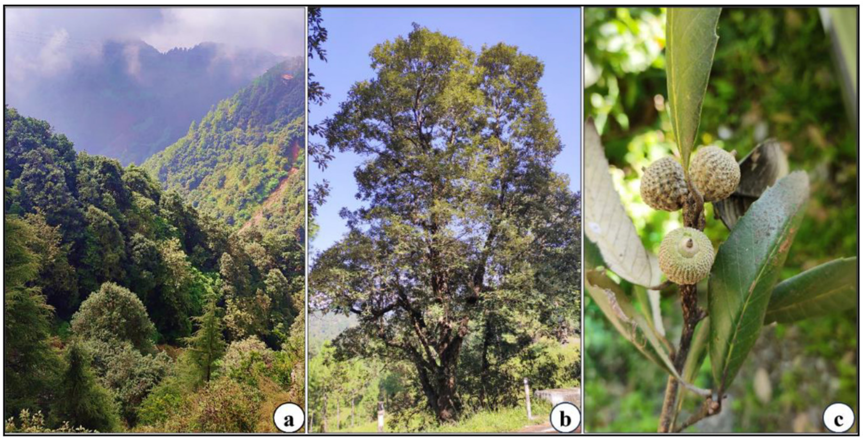

Fig. 1. *Q. oblongata*, habitat in the western Himalayan region of Uttarakhand, India (a), habit (b), acorns (c).

ovate-elliptic or lanceolate, the margin coarsely dentate, and typically, the entire area near the base is densely white, or there is pale tomentose beneath. The leaf base might be acute or cuneate, apex acuminate, 10–20 pairs of nerves; petiole 6–25 mm acorn ellipsoid-ovoid, apex acute; glabrous, singly or paired on a hairy rachis, enclosed 1/3 to 1/2 by cup, cupule sessile with small triangular, appressed scale (Fig. 1c). Male and female flowers are on separate shoots, male flowers are in clusters, pendulous. Male catkin is 3–8 cm long, tomentose; pistillate inflorescences are 1–2 cm long, and 3–8 is flowered. Blooming occurs between April and May, while fruits occur between October to November. Pollination to fruit ripening takes over a year.

Occurrence data

The geographical occurrence information of *Q. oblongata* was obtained by consulting national (CAL,

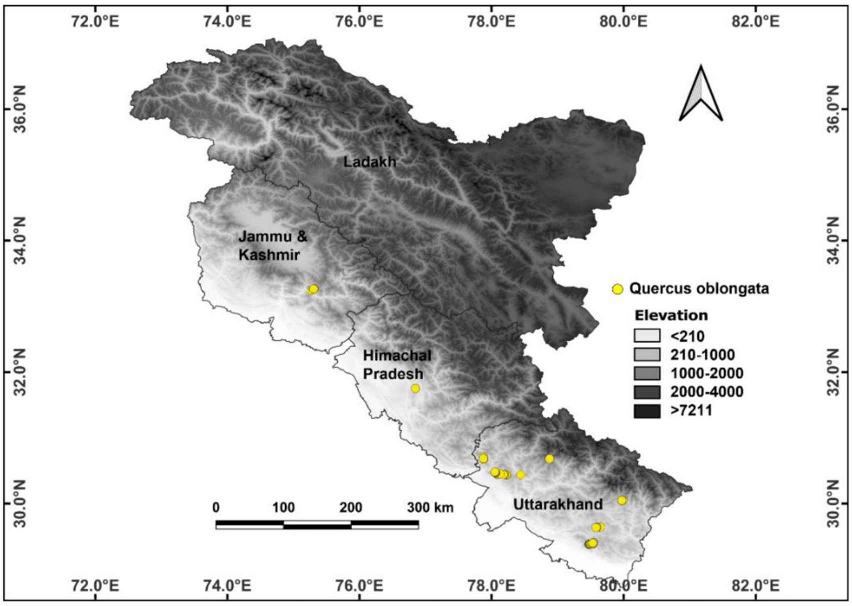

Fig. 2. Map showing the sampling locations of *Q. oblongata* from the western Himalayas in India.

Table 1. Pearson correlation coefficients test of seven unrelated bioclimatic variables for *Q. oblongata*.

Variables	bio 2	bio 3	bio 7	bio 8	bio 9	bio 13	bio 14	bio 15
bio 2	1							
bio 3	0.215	1						
bio 7	0.652	–0.593	1					
bio 8	–0.001	0.754	–0.595	1				
bio 9	–0.199	0.632	–0.655	0.687	1			
bio 13	–0.299	0.712	–0.788	0.774	0.761	1		
bio 14	–0.490	0.360	–0.702	0.292	0.595	0.459	1	
bio 15	0.351	0.507	–0.106	0.481	0.071	0.479	–0.269	1

ASSAM, LWG, BSD and DD), international herbaria (E, BR, GH, G, P and K), and available literature. A total of 46 occurrence records were retrieved. Herbarium specimens lacking geo-coordinate data were analyzed in the Google Earth engine (https://www.google.com/intl/en_in/earth/about/versions/) to determine the exact coordinates based on locality description. Based on the preliminary information obtained from the herbaria and literature, field surveys were conducted in the Himalayan region of Uttarakhand and Himachal Pradesh during 2020–2021. The natural habitat of *Q. oblongata*, such as broad leaves forest, mixed forest and hilly slope (>850 m elevation), was surveyed, and 75 geo-coordinates were documented (Fig. 2). Thus, 121 geo-occurrence records were obtained, including occurrence records from field surveys, herbaria, and literature. To reduce the spatial autocorrelation in occurrence records and improve the model prediction, first, we removed duplicate occurrence records, and therefore ENMTools v1.4.4 (Warren *et al*. 2010) was employed to select the only one occurrence record in a grid size of raster layer of approximately 1 km^2 area. Finally, 87 non-redundant occurrence records were selected for prediction analysis from 121 records.

Environmental data

Nineteen bioclimatic variables (bio1–bio19) and a topographic variable (elevation) were downloaded from World Clim v2.1 (https://www.worldclim.org; Hijmans *et al.* 2005) for the current period (1970–2000). Two topographic variables (slope and aspect) were translated from the elevation (asc file) using QGIS v3.14.1 Pi (QGIS development team 2020). The variables used for niche modeling were at a spatial resolution of 0.5 arcminutes (~1 km^2). Multi-collinearity among the bioclimatic variables may affect the prediction analysis, as they are mainly derived from temperature and precipitation (Wang *et al.* 2022). Therefore, to avoid multi-collinearity among the variables, a Pearson correlation test was performed using ENMTools v1.4.4 (Warren *et al.* 2010). In the correlation analysis, if the two variables with a high cross–correlation coefficient (>0.8 or <–0.8), then only one variable was selected (Yi *et al.* 2016) (Table 1). This analysis led to the exclusion of 11 bioclimatic variables out of 19 bioclimatic variables. Considering the ecological importance of topographic variables, the correlation analysis was not applied for elevation, slope, and aspect. Finally, eight bioclimatic variables and three topographic variables were used in the model prediction: Mean diurnal range (bio2), Isothermality (bio3), temperature annual range (bio7), mean temperature of wettest quarter (bio8), mean temperature of driest quarter (bio9), precipitation of wettest period (bio13), precipitation of driest period (bio14), precipitation seasonality (bio15), aspect, elevation and slope.

Modeling approach

In this study, we employed an ensemble modeling strategy developed in the 'sdm' v1.1-8 package (Naimi and Araújo 2016 https://www.biogeoinfromatics.org) conducted using R 4.1.0 (R Core Team 2021). This platform supports certain recognized distribution models: GAM, GLM, RF and MaxEnt. Model evaluation was carried out using the bootstrap approach with ten replications, with 70% of the occurrence data used for validation and 30% for evaluating the model. In addition, 1000 background points were produced automatically using the 'sdm' v1.1–8 software. Two metrics were used to test the model's accuracy: Area under the ROC Curve (AUC) and True Skill Statistics. An AUC value ranges between 0–1 ;

a value near 1 will be an excellent distinction, and the model will be accurate and descriptive (Carter *et al.* 2016). However, the TSS runs from $^{-1}$ to 1, with values below zero indicating performance comparable to random (Davoudi *et al*. 2020). Suitability maps were created using QGIS v 3.14.1 Pi (QGIS Development Team 2020). The suitability region of the species distribution map ranged from 0 to 1 and was divided into four classes of prospective distribution, namely unsuitable (0–0.25), least suitable (0.25–0.50), moderate suitable (0.50–0.75), and high suitable (0.75–1) (Maurya *et al.* 2023).

RESULTS AND DISCUSSION

Species distribution modeling (SDM) has been widely used to assess the possible distribution of flora and fauna based on the occurrence locations and environmental datasets. SDMs are used to forecast how the distribution of plant species habitats would alter due to increased global temperature (Fourcade *et al.* 2014).

Model performance

The accuracy of GAM, GLM, RF, and MaxEnt predictions is shown in Table 2. The RF model produced the most favorable results (AUC = 0.98, TSS = 0.90), subsequent to MaxEnt (AUC = 0.97, TSS = 0.87) and GAM (AUC = 0.95, TSS = 0.89). Meanwhile, GLM had the lowest performance (AUC = 0.94; TSS = 0.86).

Table 2. Model performance as determined by evaluation criteria in the *Q. oblongata*.

Methods	AUC	COR	TSS	Deviance
GAM	0.95	0.8	0.89	1.65
GLM	0.94	0.76	0.86	0.40
RF	0.98	0.85	0.90	0.19
MaxEnt	0.97	0.79	0.87	0.28

Since the AUC values of all four models in this study were significantly higher than 0.9 and the TSS values were almost equal to 1, all four models performed well of forecasting the potential distribution areas of *Q. oblongata* (Watling *et al.* 2015). Specifically, the MaxEnt model was more precise in determining the distribution limits of the species, followed by GAM, GLM and RF. The high predictive performance of MaxEnt, GAM, GLM and RF suggests that modeling with these models can be applied confidently to mapping the suitable habitats areas for *Q. oblongata* in the WHR (Fig. 3). These models were

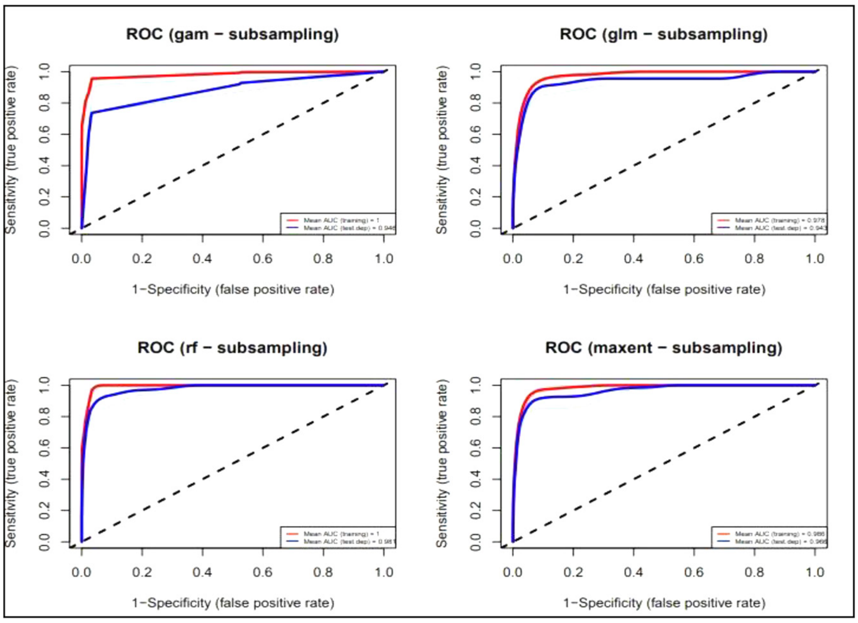

Fig. 3. Results of the bootstrap replication method used for the area under the ROC curve (AUC) of GAM, GLM, RF, and MaxEnt.

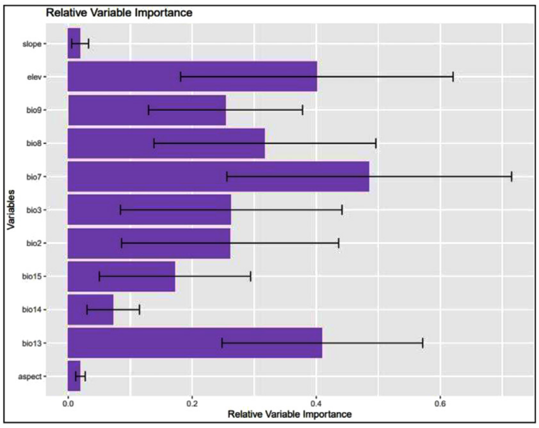

Fig. 4. Relative importance of bioclimatic and topographic variables on the habitat modeling of *Q. oblongata*.

also successfully applied in previous studies of niche modeling in different oak species like *Quercus ilex* (Suicmez and Avci 2023), *Q. brantii* (Mirhashemi *et al.* 2023), and *Q. acerifolia* (Subedi *et al.* 2023).

Contribution of variables to the models

The relative importance of eleven variables influenced to the models and the potential distribution of *Q. oblongata*: Temperature annual range (bio7, 48.5%), precipitation of wettest period (bio13 ; 41%), elevation (elev ; 40%) and mean temperature of wettest quarter (bio 8 ; 37.7%) were the highest contributing variables. Isothermality (bio 3 ; 26.3%), mean diurnal range (bio 2 ; 26.1%), mean temperature of driest quarter (bio 9 ; 25.4%), and precipitation seasonality (bio 15 ; 17.2%) also contributed substantially to the model prediction. Other variables, i.e., precipitation of the driest period (bio 14), aspect, and slope, contribute nominally to model prediction (Fig. 4).

Environmental variables are key components that restrict the distribution of terrestrial plant species. Bioclimatic and topographic variables are recognized as major factors in the distribution of plant species in different parts of the world. In the current study, the temperature variable (temperature annual range ; bio 7), precipitation variable (precipitation of wettest period ; bio 13), and topographic variable (elevation) were the most affecting environmental predictors, which played a crucial role in the distribution of *Q. oblongata* in the WHR.

Temperature is the critical environmental predictor for *Quercus* species, restricting their geographical distribution (Maes *et al.* 2019). Changes in the optimal requirements temperature affect the plant's physiological processes like photosynthesis, and transpiration. It also affects plant growth, leaf water potential, gas exchange, reproduction, and development stages in plants reported by Bahuguna and Jagadish (2015). Therefore, changes in temperature requirements can affect plant distribution as plants cannot migrate or shelter from adverse conditions (Christmas *et al.* 2016). In contrast, lower humidity leads to nearly half of the flowers maturing into acorns, and this cause the decline in the fruits number. However, the low temperature only affects oak flowering once freezing occurs (Körner *et al.* 2016). Saran *et al.* (2010) suggested that the rising of minimal temperature (1 to 2°C) would cause a reduction in the distribution of *Q. semecarpifolia* in the Himalayan region. Similarly, in terms of the importance of precipitation as a climatic driver in *Quercus*, precipitation was the leading predictor of vegetative growth or flowering. Precipitation had an impact on the timing of breaking leaf buds and flowers in *Q. lobata*, while excessive precipitation favored the early development of flowers or flower buds in *Q. alba* (Gerst *et al.* 2017). The elevation is another major factor that contributed greatly to the distribution of *Q. oblongata* as the distribution of *Q. oblongata* only occurs on the montane zone and slope in the western Himalayas. Elevation was also recognized as a major critical predictor of the habitat distribution of different oak species, i.e., Kharsu oak (*Q. semecarpifolia*), Moru oak (*Q. floribunda*), Banj oak (*Q. leuchotrichiphora*), and *Q. suber* (Chakraborty *et al.* 2016, Laala *et al.* 2021). Elevation plays important role in seed germination and physical characteristics, such as length and weight in oak species (Saklani *et al.* 2012). It had hypothesized that topographic factors (such as elevation, slope, and aspect) have a secondary impact on bioclimatic factors (like temperature and precipitation), which directly affect plant growth and development (Maharjan *et al.* 2022). Therefore, temperature, precipitation, and elevation are vital environmental variables affecting the distribution pattern and acorn production of this oak species.

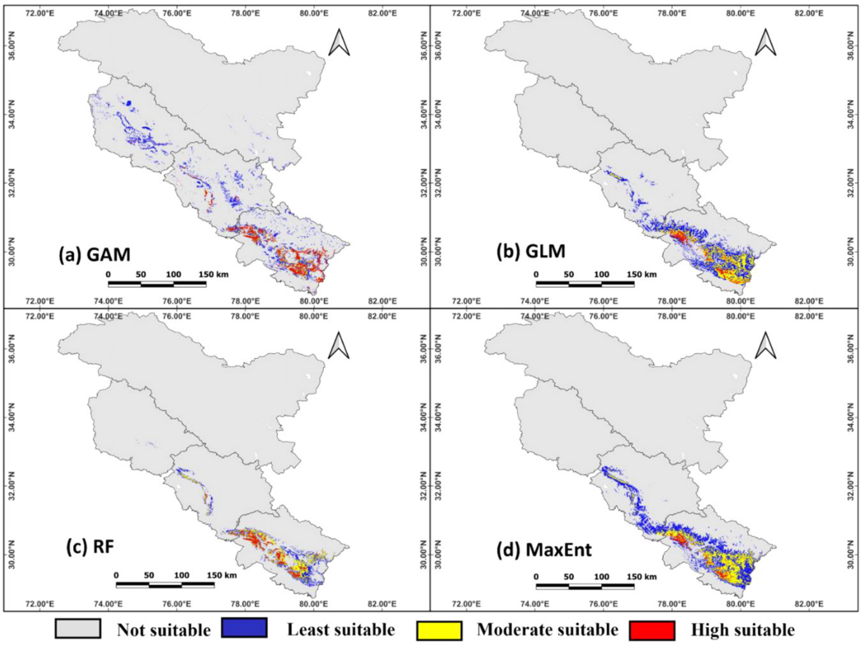

Fig. 5. Current distribution of the suitable habitats for *Q. oblongata* in all four models: (a) GAM, (b) GLM, (c) RF, and (d) MaxEnt.

Current potential distribution

The current potential distribution map of *Q. oblongata* in the western Himalayan region of India is shown in Fig. 5. The MaxEnt predicted more suitable areas (29200 km^2) than the other three algorithms. It cov-

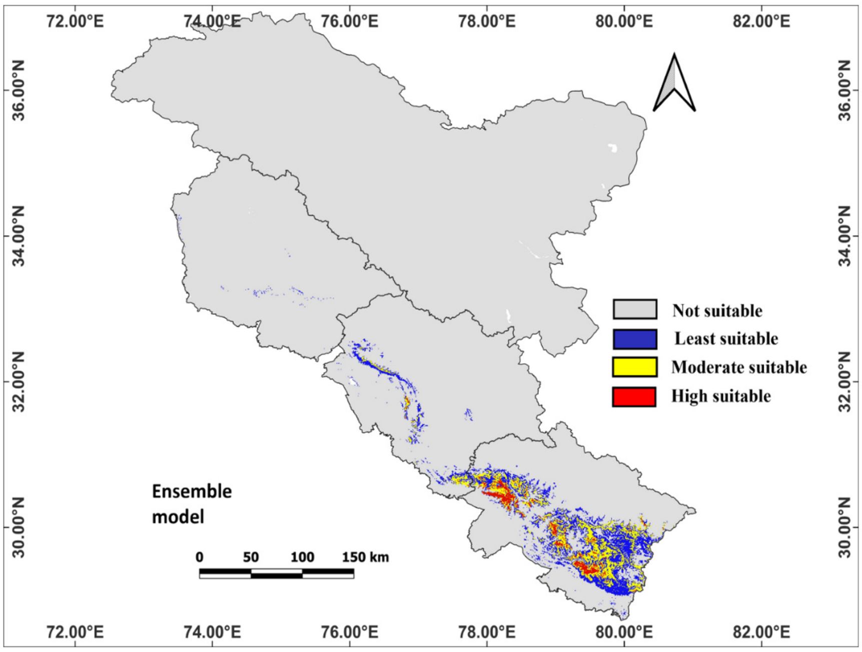

Fig. 6. Current distribution of suitable habitats for *Q. oblongata* using ensemble model in WHR.

Table 3. Potential suitable habitat areas of *Q. oblongata* in GAM, GLM, RF, MaxEnt, and ensemble modeling.

Models	Least suitable areas (km^2)	Moderate suitable areas (km^2)	High suitable areas (km^2)	Total suitable areas (km^2)
GAM	12036	2427	5603	20066
GLM	14097	8440	2423	24960
RF	6140	5246	2837	14223
MaxEnt	17177	10142	1881	29200
Ensemble	10790	6824	1851	19465

ers most of the region of Uttarakhand (Fig. 5d). In contrast, the RF method predicted the least suitable areas (14223 km^2) for *Q. oblongata* (Fig. 5c). The GLM (Fig. 5a) and GAM (Fig. 5b) methods predicted similar suitable habitats accounting for 24960 km^2 and 20066 km^2, respectively (Table 3). In all four algorithms, large parts of suitable areas were observed in the eastern Mussoorie, Raipur, western Dhanaulty, and Chakrata region of Dehradun District, as well as Almora, Ranikhet, and Nainital District of Uttarakhand. GAM is the only model that shows the habitat suitability in northern Shimla, most of the Mandi region, southern Chamba, and central Kangra District of Himachal Pradesh, and sparsely distributed in the bordering area of Raisi and Anantnag region of Jammu and Kashmir.

Based on the ensemble analysis the entire suitable and unsuitable area (~391818 km^2) was classified into four classes. Among the total suitable areas, unsuitable, least, moderate, and highly suitable habitats were 372353 km^2 10790 km^2, 6824 km^2 and 1851 km^2, respectively (Table 3).

An ensemble model analysis predicted that the habitat of *Q. oblongata* was widely distributed across Uttarakhand, central Himachal Pradesh, and some small patches in the Jammu and Kashmir region of Western Himalaya (Fig. 6).

However, the highly suitable areas for *Q. oblongata* were mainly located in Nainital, Almora, some parts of Bageshwar, the maximum region in Tehri Garhwal, and the upper region of Mussoorie and Chakrata region of Dehradun District. In contrast, small patches were sparely distributed in the southern Chamoli district of Uttarakhand. A sizeable wide patch was found in Southern Chamba with northern Kangra District, including the northern region of Mandi District of Himachal Pradesh.

CONCLUSION

In this study, the current suitable habitat for *Q. oblongata* was identified in most of the western Himalayan region of India, although highly suitable habitats were restricted to Uttarakhand, central Himachal Pradesh, and some parts of Jammu and Kashmir. Temperature variables (bio7), precipitation (bio13), and topographic variables (elevation) were the most determining factors for its habitat distribution. The predicted habitat areas in this study will serve as a baseline reference for the development of forest management and conservation planning of this forest tree species. The estimated potential habitat areas could be investigated further for genetic diversity assessment and economic utilization of *Q. oblongata* in India.

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