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Article

Modeling Climate Change Effects on the Distribution of Oak Forests with Machine Learning

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Abstract: The present study models the effect of climate change on the distribution of Persian oak (*Quercus brantii* Lindl.) in the Zagros forests, located in the west of Iran. The modeling is conducted under the current and future climatic conditions by fitting the machine learning method of the Bayesian additive regression tree (BART). For the anticipation of the potential habitats for the Persian oak, two general circulation models (GCMs) of CCSM4 and HADGEM2-ES under the representative concentration pathways (RCPs) of 2.6 and 8.5 for 2050 and 2070 are used. The mean temperature (MT) of the wettest quarter (bio8), solar radiation, slope and precipitation of the wettest month (bio13) are respectively reported as the most important variables in the modeling. The results indicate that the suitable habitat of Persian oak will significantly decrease in the future under both climate change scenarios as much as 75.06% by 2070. The proposed study brings insight into the current condition and further projects the future conditions of the local forests for proper management and protection of endangered ecosystems.

Keywords: species distribution; climate change; Bayesian; machine learning; artificial intelligence; deep learning; mathematics; forest; big data; data science

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1. Introduction

Forest ecosystems have been globally affected by climate change, geomorphic features and human impact [1,2]. Climate change is widely introduced as a main threat to diversity, species survival and ecosystem stability in most biomes [3,4]. In fact, climate change has been introduced as one of the main causes of the emergence of new species, change in a species range, species extinction, destruction of biodiversity, loss of ecosystem resilience and disturbance regimes [4–6]. A species' distribution is an essential spatial feature influenced by the environment and human impact. On a large scale, the climate has been suggested as a fundamental factor determining the distribution of species worldwide [7]. Various plant species in different geographical regions of the world are affected by climate change in different ways [8]. Due to the fact that climate change has a major role in species distribution [9], predicting the distribution of plant species under climate change scenarios is important for ecosystem sustainability and management [10,11]. Recently, several studies have predicted the potential effects of climate change on plant species distribution [12–20], and generally, these studies show that climate change causes changes in the range of plant species.

Species distribution models (SDMs) are widely used to predict species response to climate change [9,21–24]. SDMs were found to be reliable models to anticipate current and future habitats as demonstrated by, e.g., Guisan and Thuiller (2005), Joseph et al. (2009) and Levin et al. (2013) [25–27]. Such models are also used to demonstrate the relationship between species distribution and environmental conditions as investigated by, e.g., Booth et al. (2014) [28]. In addition, the literature includes a diverse range of various statistical and machine learning methods to predict the distribution of species under climate change, conservation planning and predicting the future suitable habitat of a species [9]. The use of machine learning algorithms to predict the geographical distribution of species is a relatively new field of study. Machine learning algorithms can significantly speed up ecological processing and analysis and successfully solve classification problems [29]. Among advanced machine methods, the Bayesian additive regression tree (BART) as a new ensemble-based method has gained significant popularity due to its accuracy in the field [30]. Consequently, in the present study, we aimed at using BART.

Zagros mountain forests, with an area of 5 million hectares in western Iran located in a semi-arid climate, are considered the most important yet sensitive ecosystems of Iran. The Zagros mountain forests are identified as the only ancient and continuous habitat of Persian oak (*Quercus brantii* Lindl.) [31]. The role of these forests is crucial for soil and water conservation and people's livelihood in this region [32]. In addition, the forests are a repository of various plants and animal species. It is believed that the area of these forests in the past was wider than today [33]. These forests have undergone drastic changes in cover and structure in recent decades, which has had many negative consequences for the communities that depend on them [34]. Climate change has negatively affected these forests by increasing temperature and decreasing rainfall [35]. The occurrence of oak decline and secondary pests and diseases in this region in recent decades, according to many researchers, has been associated with the phenomenon of climate change [36–38]. In addition, human activities such as land use change, wood harvesting and livestock grazing have destroyed large parts of these forest ecosystems [34,39,40]. Former studies stated that climate change has already affected the habitat of Persian oak in the Zagros forests. For instance, Safaei et al. (2021) modeled the effect of climate change on the distribution of Persian oak in Zagros forests, and the results revealed that in the future, there will be changes in the spatial distribution of this species [41]. Valavi et al. (2018) investigated the effect of climate change on the habitat of Persian oak in the Zagros forests and anticipated that the potential habitat of this species will decrease and will be further limited to higher altitudes in the future [14]. Malekian and Sadeghi (2019) predicted the effect of climate change on the habitat of Persian oak in western Iran and concluded that the suitable habitat of this species will decrease in some areas and shift to higher altitudes in the future [42]. Malekian and Sadeghi (2019) used statistical projection, and later Safaei et al. (2021) showed the importance and applicability of optimization and evolutionary algorithms. Despite the study by Valavi, et al. (2018) that used an ensemble learning method, there is still a research gap in using various machine learning methods to improve modeling capability. In this study, the applicability of a Bayesian learning method is explored. Our study was limited to one study area and one species. Such limitations must be addressed in future studies by exploring various case studies and different species.

Despite limited studies on the effect of climate change on the habitat of Persian oak in the Zagros forests, the relationship between changes in the distribution of Persian oak in relation to various environmental variables has not been well considered. Therefore, in this study, in order to model the distribution of Persian oak in Ilam province as a specific habitat for this species, the BART method has been used. The BART method is a tree-based machine learning method that has been successfully used to address regression and classification issues. This method was proposed by Chipman et al. (2010) [43] and has become common in recent years due to its high efficiency in regression and classification problems compared to other machine learning methods. Other Bayesian methods have been used for modeling species distribution, but the BART method has not been used for modeling the distribution of plant species, especially not tree species. This research seeks to answer the following questions: Firstly, what are the main environmental attributes that affect the distribution of Persian oak? Secondly, how much of the area of Persian oak habitat will change in the future under different climate change scenarios? Due to the deteriorating situation of

Zagros forests and considering that few studies have been done in the field of modeling the distribution of Persian oak in these forests, the results of the present study can help to understand the current condition and predict the future situation of these forests and provide a guideline for management and protection of these semi-arid ecosystems.

2. Material and Methods

2.1. Study Area

The study area is Ilam province with an area of 20,133 km^2 located in western Iran. This region is located at 32°03′ N to 34°02′ N latitude and 45°40′ E to 48°03′ E longitude [35]. Altitude in this region varies from 34 m to 2632 m. The average annual precipitation in Ilam province is 578 mm. The area of forests in Ilam province is about 641,000 ha, and the predominant species of these forests is Persian oak (*Quercus brantii* Lindl.), which constitutes about 90% of these forests [44] (Figure 1).

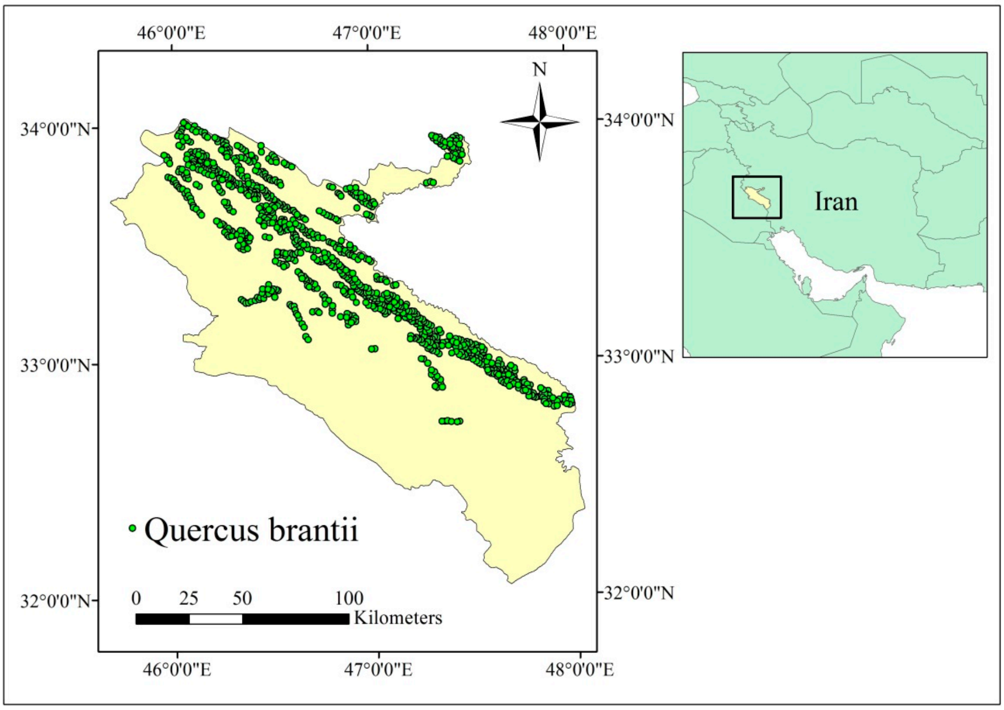

Figure 1. The study area in the west of Iran (www.rsgisc.com accessed on 10 October 2022).

2.2. Species Occurrence Data

The species occurrence locations were collected using field surveys and then thinned with a distance of 1 km using the spThin package in R software [45]. The spThin package randomly thins species occurrence points using the minimum user-defined distance. We thinned the occurrence points with a distance of 1 km because we used climate data with a 1 km spatial resolution [18]. A total of 966 presence records of the species were obtained in the study area. In addition, pseudo-absence points were obtained with the random point method using GIS software.

2.3. Environmental Variables

The environmental variables used in this research include different bioclimatic variables with a resolution of 1 km that were downloaded from the WorldClim database (www.worldclim.org accessed on 10 October 2022) [46]. To detect collinearity among variables, we used the Variance Inflation Factor (VIF) and removed variables with VIF greater than 10 [47,48]. As a result, we used 5 bioclimatic variables to predict the habitat of Persian oak. In addition, slope and solar radiation were selected as predictors for species distribution modeling (Figure 2). A description of the 19 bioclimatic variables is given in

Table 1. To predict the potential habitat of Persian oak in the future, we used two General Circulation Models (GCMs) namely CCSM4 and HADGEM2-ES under the Representative Concentration Pathways (RCPs) 2.6 and 8.5 for 2050 and 2070 [49].

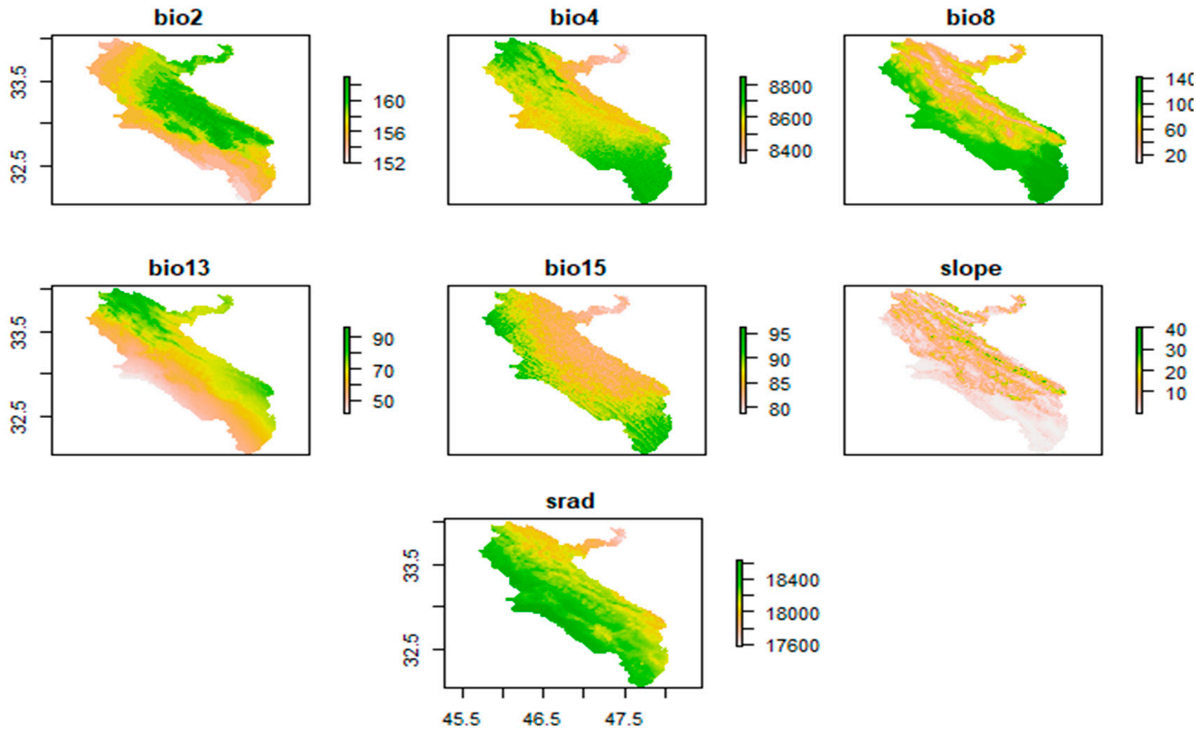

Figure 2. Environmental variables used for modeling the distribution of *Quercus brantii* in the west of Iran.

2.4. Species Distribution Modeling

In order to model the distribution of Persian oak, the BART method has been used. BART proposed by Chipman et al. (2010) [43] is a tree-based data driven method suitable for regression and classification. BART has recently increased popularity due to its high efficiency compared to other machine learning methods. The difference between BART and other tree-based methods is that it controls the structure of each tree using a prior distribution. BART performs modeling using the MCMC process that accepts or rejects trees during iterations. BART is a non-parametric Bayesian algorithm that uses the tree ensembles method [50]. We also used a Generalized Linear Model (GLM) as a benchmark to compare and ensure the performance of BART.

2.5. Model Evaluation

To evaluate the models, the area under the curve (AUC), the true skill statistic (TSS), type I error and type II error were used. AUC is a suitable index to evaluate the accuracy and performance of the model. The closer the AUC value is to 1, the better the accuracy and performance of the model [51]. The threshold values of AUC are as follows: AUC $\geq$ 0.9 = very good, 0.9 > AUC $\geq$ 0.8 = good and AUC < 0.8 = weak [52,53]. The value of TSS is from +1 to -1, in which the value +1 indicates a high performance of the model, and the values 0 and less than 0 indicate a low performance [54].

Table 1. Environmental attributes including mean temperature (MT), maximum temperature, minimum temperature and precipitation considered for modeling the distribution of *Quercus brantii*.

Variables	Description	Unit	Use for Modeling
BIO1	Annual Mean Temperature	°C	✗
BIO2	Mean Diurnal Range	°C	✔
BIO3	Isothermality	%	✗
BIO4	Temperature Seasonality	%	✔
BIO5	Maximum Temperature of Warmest Month	°C	✗
BIO6	Minimum Temperature of Coldest Month	°C	✗
BIO7	Temperature Annual Range (BIO5-BIO6)	°C	✗
BIO8	MT of Wettest Quarter	°C	✔
BIO9	MT of Driest Quarter	°C	✗
BIO10	MT of Warmest Quarter	°C	✗
BIO11	MT of Coldest Quarter	°C	✗
BIO12	Annual Precipitation	mm/m^2	✗
BIO13	Precipitation of Wettest Month	mm/m^2	✔
BIO14	Precipitation of Driest Month	mm/m^2	✗
BIO15	Precipitation Seasonality	%	✔
BIO16	Precipitation of Wettest Quarter	mm/m^2	✗
BIO17	Precipitation of Driest Quarter	mm/m^2	✗
BIO18	Precipitation of Warmest Quarter	mm/m^2	✗
BIO19	Precipitation of Coldest Quarter	mm/m^2	✗
Slope		%	✔
Solar Radiation		kJ m^{-2} day^{-1}	✔

3. Results

3.1. Performance Evaluation of Models

In this study, we used the area under the curve (AUC), the true skill statistic (TSS), type I error and type II error to evaluate model performance. The results of the model evaluation are shown in Table 2. The evaluation using the AUC index shows that BART has a very good performance in predicting the habitat of the Persian oak (AUC = 0.93). In addition, the value of TSS indicates the good accuracy of the model in forecasting (TSS = 0.75). Type I error (0.08) and type II error (0.16) also show that BART is a suitable model for predicting the habitat of Persian oak, and it has a higher accuracy in forecasting compared to the GLM (AUC = 0.86, TSS = 0.68) (Figure 3).

Table 2. Results of the performance evaluation of the models.

Model	AUC	Cutoff	TSS	Type I Error	Type II Error
BART	0.93	0.34	0.75	0.08	0.16
GLM	0.86	-	0.68	-	-

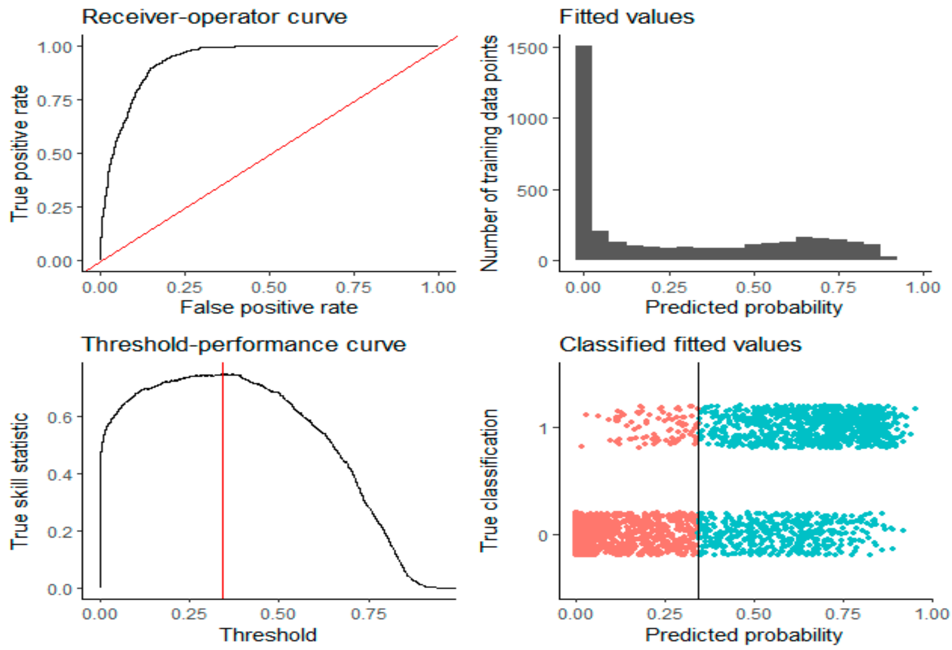

Figure 3. Performance evaluation curves based on the BART model.

3.2. Importance of Environmental Variables

The importance of a variable in BART is usually measured by counting the number of times a given variable is divided by a tree across subsequent trees [55]. In models with more trees, the difference in variable importance is less pronounced. Therefore, variable selection can be performed by implementing models with fewer trees (m = 10 or m = 20) and observing which variables are not included in the trees [43]. Figure 4 shows the importance of environmental variables in modeling the distribution of Persian oak. This diagram indicates that the mean temperature of the wettest quarter (bio8), solar radiation, slope and precipitation of the wettest month (bio13) are the most important variables in modeling the distribution of Persian oak, and precipitation seasonality (bio15) is the least important.

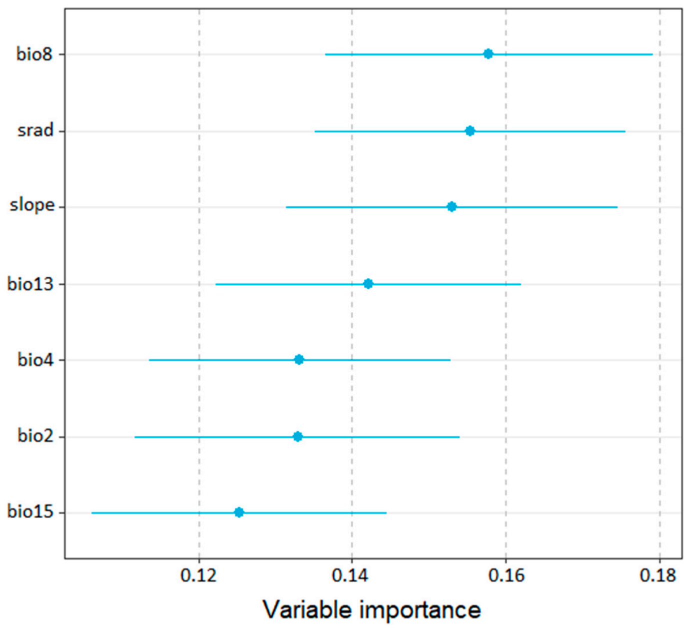

Figure 4. Importance of environmental variables in modeling the distribution of *Quercus brantii* in the west of Iran.

3.3. Response Curves

Examining the response curves of Persian oak to environmental variables showed that with increasing slope and bio13, the occurrence of Persian oak in the study area increases. However, with increasing bio4 and bio8, the probability of species presence decreases. In addition, with increasing bio2, the species presence increases with a gentle slope. Overall, bio15 was the least important variable for the presence of Persian oak in the study area (Figure 5).

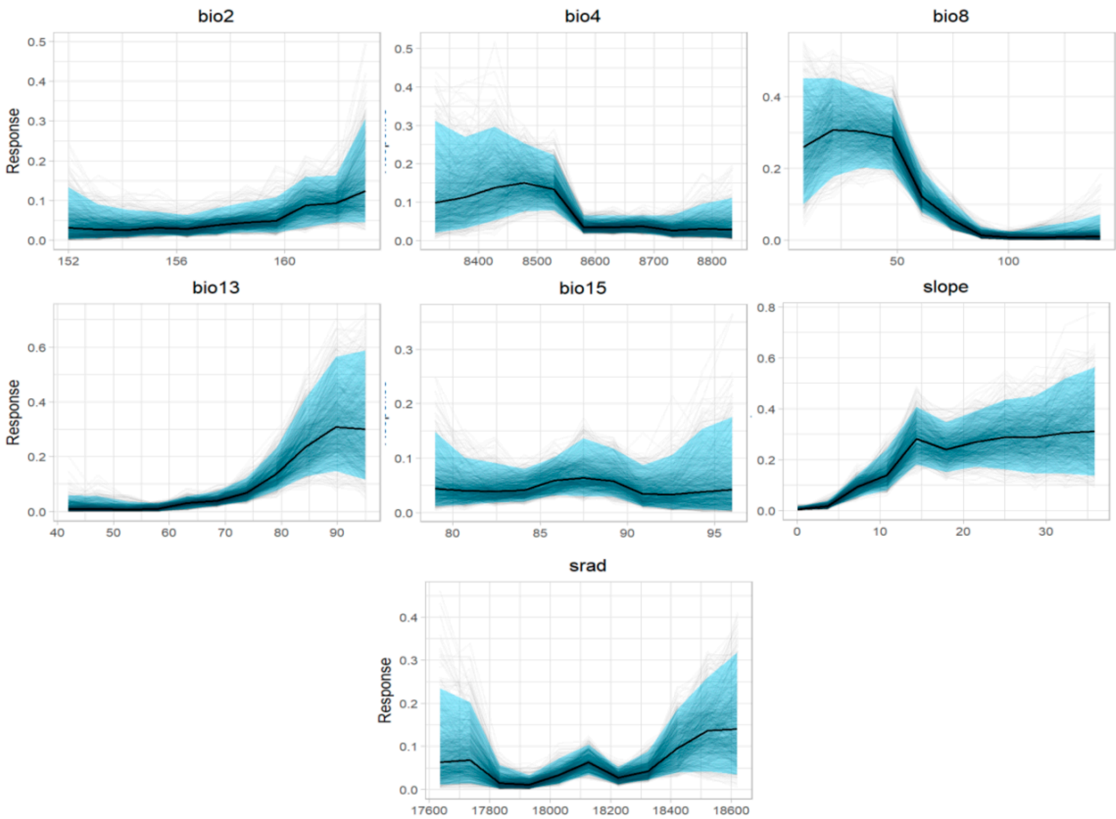

Figure 5. Response curves of *Quercus brantii* to environmental variables.

3.4. Current and Future Potential Distribution of Persian Oak

The habitat suitability map of Persian oak in Ilam province was predicted under current and future climatic conditions (Figures 6 and 7). The results revealed that under current climatic conditions, 2524.36 km^2, which is 12.59% of the study area, has high suitability, and 1603.58 km^2, which is 7.99% of the study area, has moderate suitability for the presence of Persian oak. In addition, 14,211.66 km^2, which is 70.89% of the study area, was categorized as not suitable habitat (Table 3).

Table 3. Areas (km^2) of habitat suitability for Persian oak (*Quercus brantii*) in the west of Iran under current and future climatic circumstances.

	Not Suitable	Low Suitability	Moderate Suitability	High Suitability	Loss	Stable	Gain
Current	14,211.66	1708.57	1603.58	2524.36			
RCP 2.6–2050	15,234.4	1935.68	1319.53	1561.8	1809	4622	115
RCP 2.6–2070	15,108.56	1605.39	1212.76	2123.45	1655	4776	417
RCP 8.5–2050	13,704.13	2553.58	1809.15	1980.43	1267	5164	993
RCP 8.5–2070	18,296.81	811.68	524.19	424.44	4827	1604	2

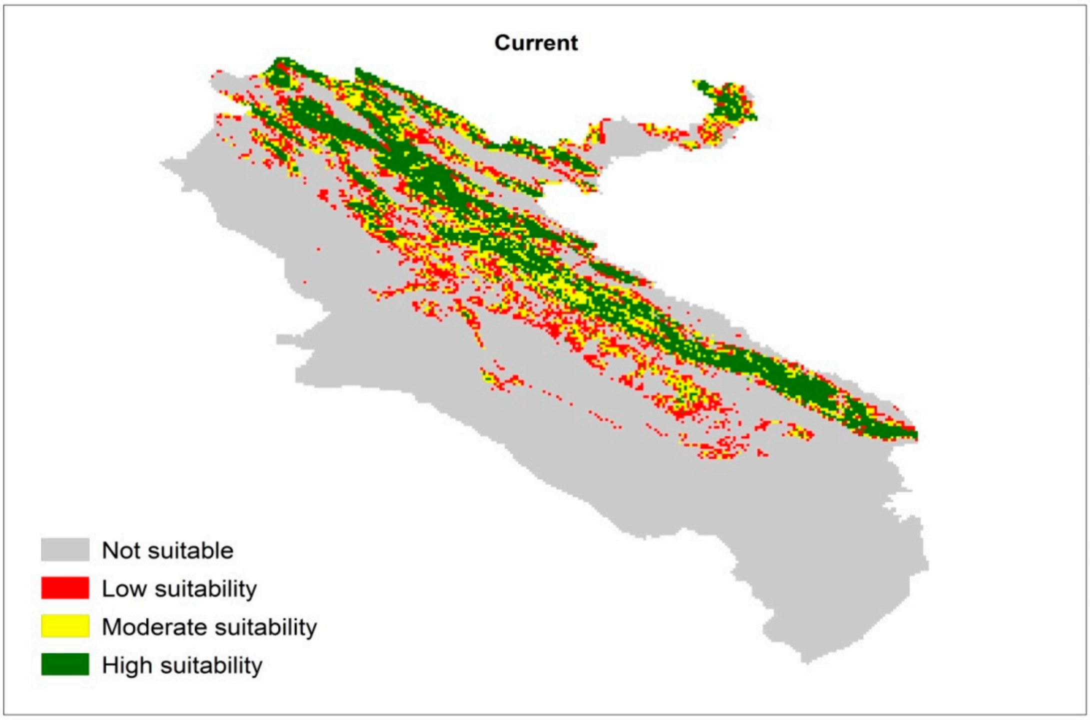

Figure 6. Habitat suitability map for Persian oak (*Quercus brantii*) in the west of Iran based on the BART model under current climatic conditions.

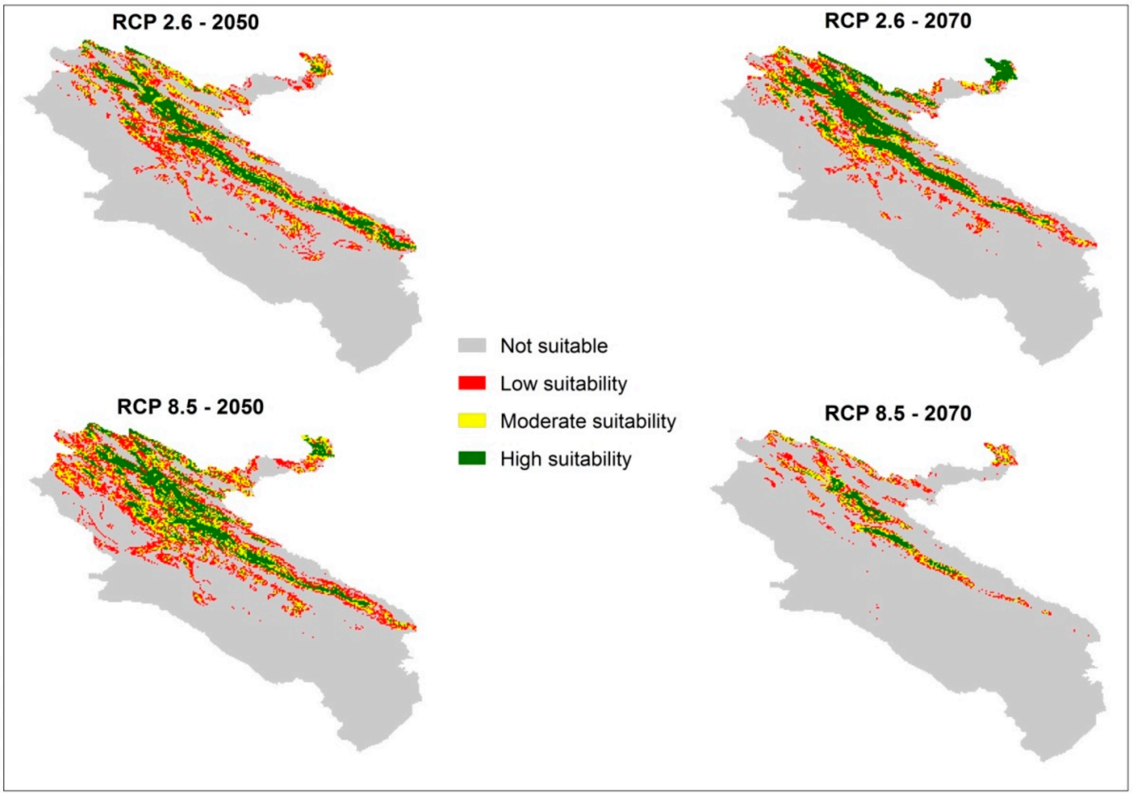

Figure 7. Habitat suitability maps for Persian oak (*Quercus brantii*) in the west of Iran based on the BART model under future climatic conditions.

The results of modeling the distribution of Persian oak under future climatic conditions showed that under RCP2.6 in 2050, 1561.80 km^2, which is 7.79% of the study area, and under RCP8.5 in 2050, 1980.43 km^2, which is 9.88% of the study area, would be suitable for species presence. In addition, under RCP2.6 in 2070, 2123.45 km^2 (10.59%) of the study area, and under RCP8.5 in 2070, 424.44 km^2 (2%) of the area would be suitable for the presence of Persian oak. According to the results, under RCP8.5 in 2070, 4827 km^2 (75.06%) of the species' habitat will be lost (Table 3).

3.5. Elevation and Distribution of Persian Oak

We investigated the relationship between elevation and the distribution of Persian oak under current and future climatic conditions. The findings indicted that the habitat of Persian oak will shift to higher altitudes in the future. Figure 8 shows that Persian oak is currently the most present in altitudes of about 1100 to 1800 m. By 2050, under the RCP 2.6 and RCP 8.5 scenarios, and also by 2070 under the RCP 2.6 scenario, the species' habitat will be slightly shifted to higher altitudes. By 2070, under the RCP 8.5 scenario, the species' habitat will move significantly to higher altitudes and will have the highest density at altitudes of about 1400 to 2300 m.

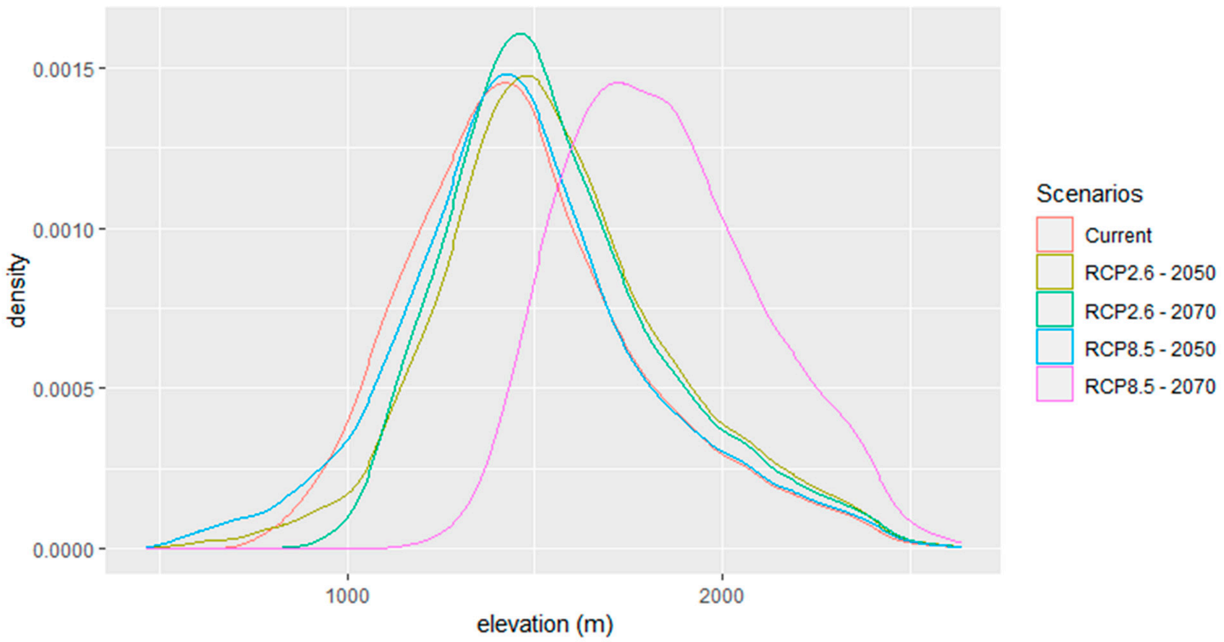

Figure 8. The relationship between elevation and the distribution of Persian oak under current and future climatic conditions.

4. Discussion

This research aimed to investigate the effect of climate change on the distribution of Persian oak (*Quercus brantii* Lindl.) in Ilam province, western Iran, using an advanced machine learning method. So far, the BART has not been used widely in ecology topics. For example, Yen et al. (2011) used BART to select the habitat of birds in Australia [56]. However, it has not been used for modeling the distribution of plant species. In the present study, we used the area under the curve (AUC), the true skill statistic (TSS), type I error and type II error to evaluate the performance of BART. The results showed that BART has a high performance in predicting the habitat of Persian oak. In terms of the importance of environmental variables, the mean temperature of the wettest quarter (bio8) was the main important attribute in the distribution of Persian oak followed by solar radiation, slope and precipitation of the wettest month (bio13). Valavi et al. (2018) showed that the Persian oak was more sensitive to temperature-related factors and in the future, the habitat of this species would shift to higher altitudes with lower temperatures [14]. Safaei et al. (2021) showed that temperature had a significant effect on the spatial distribution of Persian oak, so that the response of this plant species to climate change would shift to higher altitudes with lower temperatures and higher precipitation [41]. Another environmental factor which influenced the distribution of Persian oak was slope. Topography influences the microclimate of plants by affecting the amount of solar radiation received by mountain forests [57]. Generally, topography plays an important role in the distribution of plant species by affecting on the microclimate [58]. Our results confirmed that with increasing slope, the occurrence of Persian oak in the study area increases. One reason for this could be lower grazing and lower destruction in steep slopes. Moradi et al. (2022) reported that livestock grazing reduces tree regeneration in Zagros forests [40].

The findings of the present research showed that the suitable habitat of Persian oak would decrease in the future under both climate change scenarios (RCP 2.6 and RCP 8.5) compared to the current suitable habitat. According to the results, by 2050 under the RCP 2.6 and RCP 8.5 scenarios, 7.79% and 9.88% of the research area, respectively, would be suitable for the presence of Persian oak. In addition, by 2070, under the RCP 2.6 scenario, 10.59%, and under RCP 8.5 scenario, only 2.12% of the study area would be suitable for the presence of Persian oak. The results also showed that under RCP 8.5 in 2070, 75.06% of the species' habitat will be lost. The results of previous studies also show that the habitat of the Persian oak will decrease in the future due to climate change compared to its current habitat [14,41,42]. Other oak species such as *Q. coccifera*, *Q. libani* and *Q. aegilops* were also predicted to reduce their potential habitat in the future [16,59–61]. Examining the relationship between elevation and the distribution of Persian oak showed that the species' habitat will be shifted to higher altitudes in the future. The results showed that by 2070, the species' habitat will move to altitudes above 1400 m. At low altitudes, for various reasons including human activities, degradation and livestock grazing, as well as proximity to residential areas and land use changes, we see more destruction of oak habitats. Furthermore, decreasing temperature and increasing precipitation at higher altitudes are the other factors that will cause the habitat to move to higher altitudes. In response to climate change, many plant species in mountainous areas migrate to higher altitudes [62–64]. Previous studies have shown that different species of oak prefer higher altitudes with lower temperatures and move to higher altitudes under climate change [16,41,61,65], which is consistent with the findings of this study.

In recent years, many trees, especially Persian oak, have been destroyed in large parts of Zagros forests. In Ilam province, climate change, drought and dust stress are among the factors that have caused the decline in oak trees. Among these factors, temperature and precipitation are the most important factors in the decline of oak forests [35]. Shiravand and Hosseini (2020) reported that increasing temperature and decreasing precipitation play a significant role in the decline of the Zagros oak ecosystem [32]. Increasing temperature by affecting evapotranspiration and humidity causes drought stress in Persian oak trees [41]. This species usually occupies higher altitudes with lower temperatures and grows hardly in warmer regions [14]. In addition, human activities such as land use changes and livestock grazing, especially in low altitudes where human activities are more intense, have caused the destruction of large parts of these forests and have increased the vulnerability of this species to climate change. As a result, it is predicted that this species will be shifted to higher altitudes with fewer human activities. Therefore, by controlling human activities, for example, reducing livestock grazing pressure and expanding protected areas, the rate of destruction in these forests can be reduced to some extent.

5. Conclusions

The aim of this study was to predict the effect of climate change on the distribution of Persian oak (*Quercus brantii* Lindl.) in Ilam province, western Iran, using a new machine learning method. The findings of this study revealed that the proposed BART model has a high performance in predicting the habitat of Persian oak. The modeling is conducted under current and future climatic conditions by fitting the machine learning method. For the anticipation of the potential habitats of the Persian oak, two GCMs of CCSM4 and HADGEM2-ES under the RCPs of 2.6 and 8.5 for 2050 and 2070 are used. The mean temperature of the wettest quarter (bio8), solar radiation, slope and precipitation of the wettest month (bio13) are reported as the most important variables in modeling. The results further indicate that the suitable habitat of Persian oak will significantly decrease in the future under both climate change scenarios as much as 75.06% by 2070. The proposed study brings insight into the current condition and further projects the future conditions of the local forests for proper management and protection of endangered ecosystems. The model further anticipated that with an increasing slope, the occurrence of Persian oak in the study area will increase. The reasons for this can be lower grazing practice, human activities and also improving the ability of oak to produce sprouts in these conditions. The results confirmed that the suitable habitat of Persian oak would decrease in the future compared to the current habitat and the habitat destruction will continue. Due to the importance of Persian oak in the Zagros forests, implementation of unified management and conservation actions, particularly at low altitudes, to help seedling regeneration of this species and planting with drought-resistant native tree and shrub species seems essential for this region. The valuation of oak forest proper management is required for these semi-arid ecosystems, especially where climate change impact coupled with increasing anthropogenic pressure have essential negative impacts on forest ecosystem geography. The results of this study can help future researchers carry out research on the protection and management of these forests using previous knowledge about this region and this species. For future studies, it is recommended to apply the proposed method for modeling further species and other regions.

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