Predictive mapping of two endemic oak tree species under climate change scenarios in a semiarid region: Range overlap and implications for conservation

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A B S T R A C T

Quercus infectoria and *Quercus libani* are two important species distributed across most of the Kurdistan Region of Iraq's mountain ranges (KRI). They have significant ecological, medicinal, and socioeconomic values. Recent studies have documented how plant distributions have been impacted by climate change. This study's goal is to establish the existing distributions of both species, measure the consequences of prospective environmental conditions on their distributions, predict possible habitat distributions, map the overlapped habitat ranges for the species in the KRI, and identify the key factors influencing their distributions. For these aims, distribution data points of the species, different environmental factors, including the existing climate, three emission predictions for the 2050s, 2070s, and 2090s of two general circulation models (GCMs), a machine learning approach, and geospatial techniques were used. Modeling revealed that the total magnitude of the habitat increase for the species would be less than the overall magnitude of the habitat contraction. The yearly mean temperature, yearly precipitation, and minimum temperature during the coldest period mostly alter the target species' geographic dispersion. Across the three emission scenarios of the both models, *Q. infectoria* habitat would contract by 2760.9–2856.9 km^2 (5.36–5.55%), 2856.9–3357.2 km^2 (5.55–6.52%) and 2822.1–3400.2 km^2 (5.48–6.60%), whereas it would expand by 1153.3–1638.9 km^2 (2.24–3.18%), 761.0–1556.8 km^2 (1.48–3.02%), and 721.5–1547.1 km^2 (1.40–3.00%) for the 2050s, 2070s, and 2090s, respectively. A similar pattern was also noted for *Q. libani*. The two species' habitat ranges in KRI would be considerably reduced due to climate change. The species' estimated area would extend mostly to the east and southeast of the KRI at high altitudes. The mountain areas, notably those where the species overlap by 1767.2–1807.5 km^2 (3.43–3.51%) for the two GCMs, must be the primary objective of conservation efforts. This research presents new baseline data for future research on mountain forest ecosystems and the techniques of biodiversity conservation to reduce climate change's effects in Iraq.

1. Introduction

Oak trees (*Quercus* spp.) belong to the family Fagaceae, which contains approximately 600 species and covers large parts of the Northern Hemisphere (González-Benito and Martín, 2002). They are known for their great medicinal, ecological and economic characteristics worldwide (Aldrich and Cavender-Bares, 2011; Taib et al., 2020). They are either shrubs or trees with simple deciduous or evergreen leaves and are characterized by their wood, acorns, and ability to survive for centuries (Tantray et al., 2017). Natural forests compose 4% of Iraq's land area (Al-Lami et al., 2014); apart from some riverine forests alongside riverbanks, they are concentrated in the Kurdistan Region of Iraq's mountain ranges (KRI) (Chapman, 1950; Nasser, 1984). A mountain chain that spreads from Iran's eastern border to the north (Turkey) makes up the highlands. In the KRI, *Quercus* species make up approximately 90% of the entire amount of forest cover, and the remaining part of 10% is made up of plantations, pine forests, riverine areas, and other types of forests (e.g., *Crataegus azaro, Pistacia khinjuk*) (Guest and Al-Rawi, 1966; Khwarahm, 2020). Based on previous studies (Khwarahm, 2020; Nasser, 1984; Zohary, 1973), only four distinct species of *Quercus* are found in Iraq and are mainly distributed in the KRI. *Quercus aegilops* is a kind of oak that grows most widely, along with the other types such

as *Q. libani, Q. infectoria*, and *Q. macranthera*. In the KRI, the middle-forest zone (1000–1500 m.a.s.l.) and the upper-forest zone (1200–1500 m altitude) are where *Q. infectoria* and *Q. libani* are most frequently found, respectively (Guest and Al-Rawi, 1966; Townsend et al., 1980).

Forest ecosystems dominated by oak trees are potentially useful for providing ecosystem services, providing biomass for bioenergy generation, high-value timber for industry, a crucial habitat for wildlife, and valuable environs for recreation and other cultural functions (Bosso et al., 2017; Rathore et al., 2019). Furthermore, their fruits, acorn, bark, and roots are all used medicinally by local and native people in the countryside (Ahmad and Askari, 2015; Ghafour et al., 2010). In addition, classical household items and handicrafts are created from twigs. Building houses and supporting roofs both involve wooden beams. For wood fuel, branches and boughs are cut. Charcoal production is a major utilization of oak trees by native people (Mosa, 2016; Townsend et al., 1980). These species are essential to the survival and livelihood of people who live in local and rural societies as well as to the health and productivity of arid and semiarid mountain forests. Habitat degradation by anthropogenic and natural factors, such as overutilization, insect and disease outbreaks, drought, and fire, are threatening factors for *Quercus* ssp. habitats in Iraq (Chapman and Forest, 1948; Khwarahm, 2022; Nasser, 1984; Sefik, 1981). Anthropogenic threats combined with climatic threats could push the small percentage of Iraq's oak forests to the brink of extinction. Therefore, establishing new baseline information based on which effective protection and management efforts can be made is necessary. This is particularly more relevant to a semiarid region such as the KRI, which is under the influence of the arid regions of the southern and southwestern parts of the country (i.e., the rest of Iraq). The novelty of this study is the employment of a combined approach of spatial distribution modeling and geospatial techniques in areas where species data are limited or nonexistent, such as in Iraq. More importantly, this study presents new baseline data for future research on mountain forest ecosystems and the techniques of biodiversity conservation to reduce the effects of climate change in Iraq.

Global climate change profoundly impacts ecosystems worldwide (Scholze et al., 2006). Ecosystems are vulnerable to the alterations of natural disturbance patterns caused by climate change (Seidl et al., 2016; Seidl et al., 2017). The scientific community has become more concerned about climate change in recent decades. Within the current century, more extreme weather is anticipated, including increasing mean global temperature and changing rainfall patterns (Zhou, 2021). The existing regional distribution of plant species could be greatly impacted by changes in rainfall patterns and an increase in the average temperature (López-Tirado et al., 2018). The negative impact of climate change has already been noted in Iraq, as frequent drought episodes (Awchi and Kalyana, 2017) and recurrent fire events (Khwarahm, 2022) in forested areas have become more common than ever. The mountain chains in the northeastern of Iraq (i.e., KRI) are the only refuge for the remaining tree communities in the wake of global climate change (Khwarahm, 2021). To protect oak tree species from reduction and extinction generating new baseline information in an understudied region such Iraq is necessary for the conservation of biodiversity. In addition, exploring how climate change may affect the potential dispersal of species and limiting the severe impacts on forest ecosystems and hence biodiversity is necessary for management decisions (Hulme, 2005).

An effective method for evaluating climate change effects on plant populations of plants is the utilization of Species Distribution Models (SDMs) which are utilized to quantify the expected effects of climate change on species distribution (Sinclair et al., 2010). According to a description by Hutchinson (1957) in regard to environmental niches of species, SDMs associate climatic conditions related to the habitat of the species with the places where each species has been observed (Bellard et al., 2016). Additionally, by using environmental factors and mathematical formulas, ecological niche models attempt to represent and

simulate the geographic distribution of species throughout their climatic nesting areas (McKenney et al., 2007). SDMs are helpful for making significant evaluations of ecological issues since the provided predictions act as the framework for conservation planning decisions (Bosso et al., 2022; Newman et al., 2022).

The maximum entropy model (Maxent) has been established as a dependable and effective tool for improving knowledge of the relationships between environment-related factors and climatic changes, environmental variables and the whereabouts of species (Phillips et al., 2006). Previous studies have successfully employed Maxent in investigating oak and other plant species around the globe (Çoban et al., 2020; Li et al., 2018; López-Martínez et al., 2016). In the KRI and Iraq, studies on oak tree distribution are scant. Thus far, apart from an investigation by Khwarahm (2020) in which a different species (*Quercus aegilops*) was modeled across the Zagros Mountain region, other studies on oaks in the context of this study are not available. Other studies, such as Abdullah et al. (2019), have concentrated on studying pedological features. Shahbaz et al. (2015) studied leaf anatomy, Ghafour et al. (2010) discovered some of the chemical components of oak plants, and Rashid et al. (2014) investigated the effects of common oak sweet acorn flour (*Quercus aegilops* L.). Recently, Tahir et al. (2020) concentrated on using *Q. infectoria* leaves to produce ethanol in the KRI, and Saleem et al. (2021) compared the nutritional value of oak species cultivated in the Mountains of Gara in northeastern of Iraq.

Natural oak forests in Iraq in the mountainous areas of the KRI are under immense pressure from both anthropogenic drivers and climate-related drivers, such as wildfire and drought. Nevertheless, due to political instability and regional conflicts in these areas, they are understudied, and minimal information is available on their current and future status in relation to their environmental and climatic requirements. To reduce knowledge gaps and showcase how climate change conditions influence oak trees in a semiarid mountain ecosystem, *Quercus infectoria* and *Quercus libani* were chosen as our study species for this investigation. Ecological research is required to understand the aspects of the environment in relation to a target species distribution. Particularly in the KRI in the context of current climate change, these investigations can offer a starting point for understanding and projecting the trend of the prospective spread of *Quercus* species.

The study goals are (i) to map the future and current distributions of *Quercus infectoria* and *Quercus libani* linked to climatic conditions in the KRI; (ii) to identify the main environmental factors that affect the distribution of the target species; (iii) to determine the species' future habitats in light of three climate change scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5) according to two general circulation models (GCMs) for the 2050s, 2070s, and 2090s time windows; and (iv) map range changes (i.e., loss and gain) between current and future geographic distributions; (v) visualizing the species' overlapping habitat range which has implications for conservation. The Maxent algorithm combined with Geographic Information System (GIS) techniques, collected localities of *Quercus* species, and environmental variables were all used to achieve our goals.

2. Material and methods

2.1. Study area

The capital of KRI is Erbil city, with the governorates of Sulaimani and Duhok located northeast of Iraq. KRI covers an area of around 51,520.8 km^2, with geographic attributes between (36°52′ N; 42°59′ E). The four geographically different zones that gradually extend from the northeast to the southeast in Iraq are the desert, the uplands (places that are undulating and hilly; a layer that lies between deserts and mountain ranges), the alluvial plain, and the northeastern highlands of KRI (Bor and Guest, 1968; Malinowski, 2002). Synclinal and anticlinal characteristics in the highlands result in valleys, elevated peaks, rocky slopes, gorges, and cliffs. The highlands, which are mostly inaccessible and

remote, are between 800 and 3544 m above sea level (Sissakian et al., 2015). With a yearly precipitation range between (375 to 1200) mm, a summer that is extremely warm and dry, and a winter that is cold and wet, the region has a mean temperature of 35 to 40 °C as well as a 1 °C as a low temperature (Khwarahm et al., 2021).

The species occurrences data was collected in the Sulaimani Governorate (which is mostly mountain) (Fig. 1). The governorates of KRI are very alike in the forest structure, climate, composition, and physiography (Khwarahm et al., 2021). As a result, the modeling is concentrated in the north of the country, which includes the KRI.

2.2. Occurrence data points for *Q. infectoria* and *Q. libani*

The natural occurrence data points along with GPS coordinates (i.e., geographic coordinates), using a GPS device (Garmin e Trex 22×), for *Q. infectoria* and *Q. libani* used in this investigation were sourced from extensive several survey efforts that were implemented in six districts (Sharbazher, Penjwin, Pshdar, Rania, Dukan, and Qadaragh) of Sulaimani Governorate of the KRI in Iraq between 1st September through December 2021, using a stratified random sampling technique (Bhatta et al., 2012). Data points represent geographical locations of fully matured healthy stands in the mountain areas. Furthermore, a comprehensive quality check was performed after combining these datasets. Thus, around 355 occurrence points were initially gathered through these surveys, but only 149 records ($n = 124$ and $n = 25$ for the two species, respectively) were kept and utilized in this research after using some pre-processing techniques like deleting duplicates and spatial filtering.

To reduce the spatial dependence between the locations in the dataset, spatial filtering of at least 1 km was used (Veloz, 2009). By using this method, it may be possible to reduce sample bias and account for the variety of altitudinal changes seen throughout the terrain or study locations (Radosavljevic and Anderson, 2014). The filtering, in turn, possibly improves transferability and produces higher reliable model outputs by decreasing model over-fitting (Boria et al., 2014; Khwarahm, 2020). The ArcGIS 10.4 (ESRI, Redland, CA, USA) and extended

SDMtoolbox 2.4 were employed to perform quality checking and spatial filtering (Brown, 2014).

2.3. Climate and other environmental datasets

The target species, which are mostly found in Sulaimani, Erbil, and Duhok, have their native environment in the KRI mountains, as demonstrated in (Fig. 1). Other regions of Iraq have not been observed to contain natural populations of the species, apart from the highlands. As a result, to limit our study area, the KRI's spatial extent has been used for the purposes of our comprehensive distribution modeling techniques. To extract the environmental components, this spatial extent was used. The importance of training the algorithms depending on how widely a species is found geographically has been emphasized by previous studies (Elith et al., 2010; Soberon and Peterson, 2005).

Three types of datasets related to environmental factors, such as topographic, climatic, and edaphic, have been reported to be important and the primary factors impacting tree species distribution (Huang et al., 2021; Yi et al., 2018). The variables considered for modeling are highlighted in (Table S7). Although we recognize the significance of landscape factors like edge density, the total forest core area, and the human footprint, this information was not included in the model since these datasets were unavailable.

2.4. Climatic data

The first dataset included multiple retrieved bioclimatic factors for the present and future climate situations. The most recent climatic information was obtained using the World Climate database (Hijmans et al., 2005) (www.worldclim.org) (specifically, average climate factors from 1970 to 2000). While the widely used two GCMs of the Beijing Climate Center, China Meteorological Administration (BCC-CSM2-MR) (Wu et al., 2019), and the Meteorological Research Institute Earth System Model version 2.0 (MRI-ESM2. 0) were utilized. These models are built based on several projections of future CO_2 and aerosol emission rates. The new IPCC sixth assessment report's 49 climate models include
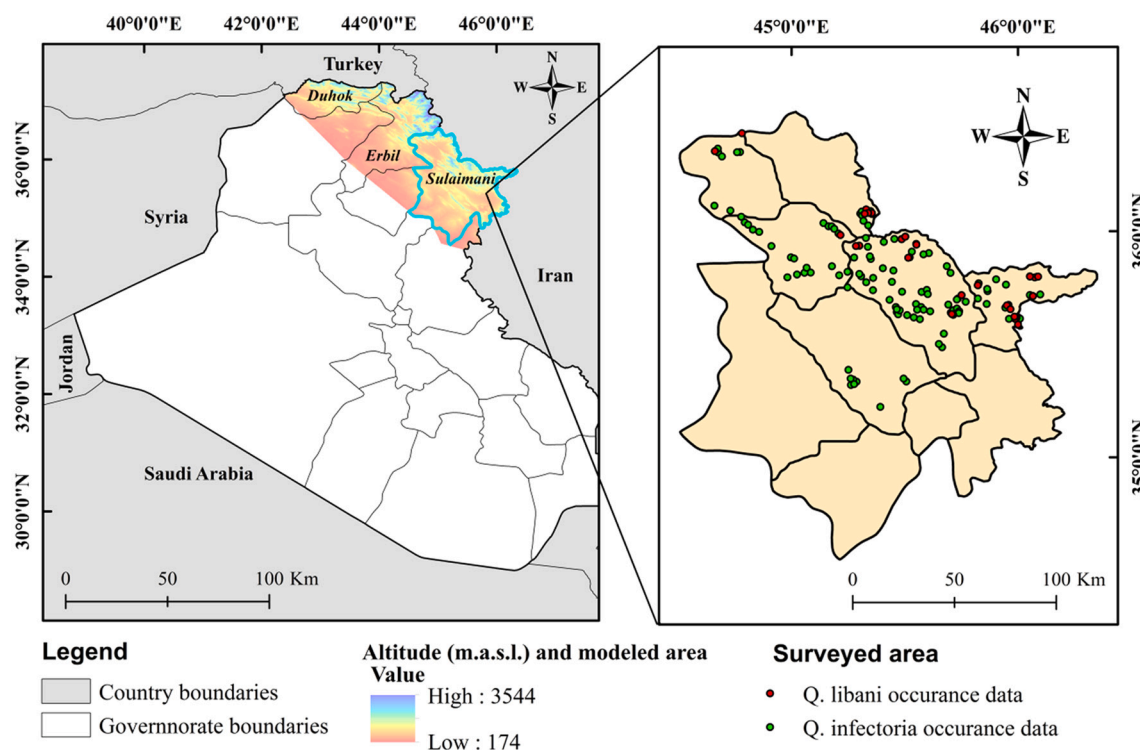

Fig. 1. Administrative boundaries and study area (left) and Sulaimani Governorate (surveyed areas) with the occurrence points of *Q. infectoria* and *Q. libani* (right).

these two. The GCMs Five key emission scenarios, SSP1–1.9, SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5, are part of the shared socioeconomic paths (SSPs) described by Meinshausen et al. (2020). Among these, we utilized three shared SSPs (SSP1–2.6, SSP2–4.5 and SSP5–8.5) for three period times: 2050s (2050s = 2041–2060), 2070s (2070s = 2061–2080) and 2090s (2090s = 2081–2100). Comparing the global radiative force in 2100 to pre-industrial time is described by SSPs). Sustainable development, reduction of inequality, and inclusive development are the cornerstones of SSP1; SSP2 represents a moderate course of action, with minimal reductions in resource and energy consumption and modest progress toward sustainable development goals, and SSP5 is predicated on the rapid advancement of technology, economic expansion, and development supported by fossil fuels (O'neill et al., 2016). This study adopted two global climate models to reduce uncertainties and inaccuracies that might arise when using fewer models. As indicated by Ncube et al. (2020), three SSP scenarios for three-time steps were used. From the Worldclim 2.1 database, bioclimatic information for various climate model scenarios was obtained (www.wordlclim.CMIP6). Coupled Model Intercomparison Project (CMIP6) provides multi-model climate estimates based on potential upcoming emission and land use scenarios made by combined assessment models. The primary distinction between CMIP6 and CMIP5 is the scenario for future. On the foundation of radiative forcing values for four greenhouse gases (GHG) concentration paths, CMIP5 forecasts are available. Contrarily, CMIP6 uses socioeconomic paths (SSPs) with the assumptions of CMIP5 scenarios. The common SSPs are therefore thought of as more likely future situations. Additionally, CMIP6 is concentrating on the biases, procedures, and feeds of climate models (Kamruzzaman et al., 2021). The SSPs are prepared hypotheticals for climate change using a variety of input variables, including the amount of greenhouse gas emissions resulting from economic development and population growth in various states, changes in land use, environmental policies, and the level of technology adoption to be applied in Maxent model.

2.5. Topographic data

Topographic variables were derived using the DEM (Digital Elevation Model) from the Global DEM inventory made by the Shuttle Radar Topography Mission (SRTM), from the Consultative Group for International Agricultural Research (CGIAR) Consortium for Spatial Information) (http://srtm.csi.cgiar.org/srtmdata/). Three features, elevation, slop, and aspect, as the predictor variables were extracted using the DEM within the ArcGIS 10.4 platform.

2.6. Edaphic data

The Center for Sustainability and the Global Environment (SAGE) provided the edaphic variables like soil PH and soil moisture (http://www.sage.wisc.edu/atlas/index.php). These edaphic factors are model-based and derived from indirect measurements of global and/or regional inventories with a 0.5° × 0.5° spatial resolution (Task, 2000; Willmott, 2001). Variable spatial rescaling to 1 km during preprocessing (Hu et al., 2015) was conducted within the ArcGIS 10.4 software.

2.7. Selecting predicting variables

Due to the variables' strong spatial autocorrelation (collinearity), just eight layers from the set of 24 environmental factors (Table S7) were used in the building of the model. Collinearity can affect the estimation of parameters in statistical models by overfitting the variance of the regression parameters and possibly resulting in an inaccurate identification of related predictors (Dormann et al., 2013). Therefore, a conditional threshold method was utilized to keep predictors with Pearson's pairwise correlation $|r| \leq 0.8$ in order to overcome the collinearity issue (Syfert et al., 2013). The predictors were subjected to Pearson's pairwise

correlation analysis using ArcGIS 10.4 platform with SDMtoolbox 2.4 (Brown et al., 2017b).

In the end, five bioclimatic factors (i.e., Bio1, Bio2, Bio6, Bio12, and Bio15) (Table S7) and other environmental factors (aspect, soil pH and soil moisture) were employed to create current and future distribution models for *Q. infectoria* and *Q. libani*.

2.8. Model building

In this study, in order to choose an appropriate model, the predicting ability and presence records were determined as a base. A machine learning-based approach, the Maxent model version 3.4.4 k (Phillips et al., 2006), was selected for this investigation because it is powerful compared to other models, has a high prediction accuracy, is user-friendly, and can give findings that are equivalent to presence-absence model techniques (Yackulic et al., 2013) and its output is even comparable to ensemble modeling approach (Kaky et al., 2020). The KRI, where the species' natural place is in the forested mountains, served as the boundary of the model, as demonstrated in (Fig. 1).

In order to create the model, 70% of the occurrence data points for *Q. infectoria* and *Q. libani* were selected to train the model, and the other 30% were utilized to validate the model. Overall, model parameters are used in "default-mode," as recommended by Phillips et al. (2004), which would result in acceptable results (Ancillotto et al., 2019; Khwarahm et al., 2021). Furthermore, there are many factors, which can affect the output reliability of the model, such as regional knowledge of the modeler in the research area, input data points, and model parameterization. However, the default-mode settings might not always produce accurate models (Morales et al., 2017). Therefore, with 500 iterations and the model replicate choice in this investigation was set to 10. The 10 model-replicate selections yielded sensible average suitability maps showing the occurrence probability for *Q. infectoria* and *Q. libani*. Setting the background points to 850 and 900, respectively, was essential to account for the occurrence records of the species and sample sizes 124 and 25, respectively, for *Q. infectoria* and *Q. libani* (Elith and Leathwick, 2009). Following Phillips et al. (2006) and Merow et al. (2013), when creating the model, the regularization multiplier was set to its default value of 1. The complexity and simplicity of the model can be affected by changing this value within the model. For example, decreasing the value to less than one makes the model more complex, while setting it to more than one makes the model simpler (Merow et al., 2013). The test of Jackknife was used (Phillips, 2005) to evaluate the relative significance of factors and their impact on the distribution probability of species habitat. Additionally, the maximum test sensitivity presence "Logistic threshold" was used as a logistic output format to delineate the continuous map (Liu et al., 2013). To determine the distribution of the two species that are unsuitable and probability of habitat suitability, the average of threshold values from 10 model outputs (10 repetitions) was utilized (Jiménez-Valverde and Lobo, 2007). To determine the distributions area of *Q. infectoria* and *Q. libani*, the pixels with values ≥ 0.3 and 0.32 were declared appropriate regions, whereas pixels ≤ 0.3 were declared unsuitable. Suitability maps were classified based on these thresholds as: A- (i) unsuitable (0–0.3); (ii) low suitable (0.3–0.39); (iii) medium suitable (0.39–0.59); (iv) high suitable (0.59–0.79); and B- (i) unsuitable (0–0.32); (ii) low suitable (0.32–0.39); (iii) medium suitable (0.39–0.59); (iv) high suitable (0.59–0.79) for the two species, respectively. To execute these processes, spatial analyst tools from the ArcGIS 10.4 platform were used.

2.9. Evaluation of the model

Two acceptable evaluation metrics, such as the Area Under Curve (AUC) (Hanley and McNeil, 1982) and the True Skill Statistics (TSS), have been used in this study (Allouche et al., 2006). Using pseudo-absence data and the commonly used AUC, the prediction accuracy of presence-only SDMs was evaluated (Fitzpatrick et al., 2013). AUC values

show the discriminating power, a number between 0 and 1, where by chance; AUC < 0.7 shows that the model's accuracy is low, the outcomes of predictions can be used when AUC is between 0.7 and 0.9, and AUC > 0.9 demonstrates the high degree of accuracy of the prediction findings, which could be utilized for subsequent investigation (Phillips et al., 2017; Raes and ter Steege, 2007). In addition, TSS value where the value ranges from −1 to 1 (Allouche et al., 2006) also indicates better discriminatory power, as the value approaches to 1 the accuracy of the prediction is higher. The Maxent model outputs and Allouche et al. (2006)'s equation (TSS = sensitivity + specificity – 1) were employed to compute the metrics.

2.10. Distribution change analysis between current and future habitat, centroid shift, range overlap

The predictions of the model for distribution changes in the current and future were evaluated using the maps of habitat suitability. The ArcGIS platform's spatial tools were utilized to compare the distributions of current and future habitats. Four classes were used to group the species' distribution changes in the KRI: (i) Expansion range (dispersal range), which refers to places that are anticipated to be appropriate for the species in the future; (ii) Unsuitable, which refers to zones that are currently inappropriate due to environmental variables and will remain so in the future; (iii) No change, which refers to areas that the species has already occupied and will continue to occupy in the future; and (iv) Contraction range, which refer to decline in the future. In addition, the centroid of the species records throughout its geographic range was established over time in order to better comprehend the distributional changes between the present and future conditions. SDMtoolbox, advanced by Brown et al. (2017a), was utilized to define the centroid of the appropriate regions with characteristics of magnitude and direction of the species shift. By condensing the spatial extent of the occurrence data to a single location, the tool also computes the spatial mean of the records. Furthermore, range overlap was calculated using the generated binary map layers for two species, using raster calculator (Spatial Analyst) tool in ArcGIS platform, overlapping areas were calculated for both species for the two (GCMs), BCC-CSM2-MR and MRI-ESM2–0, respectively. Then the pixel numbers of overlap areas were converted to Kilometers.

3. Results

3.1. Performance of the model and variable contributions

In this study, the model performances for *Q. infectoria* and *Q. libani* were AUC = 0.89 ± 0.02 and TSS = 0.81 ± 0.16 and AUC = 0.96 ± 0.01 and TSS = 0.94 ± 0.09, respectively. These findings show that both models have significant discriminatory power. Generally, the models were able to predict the probability of the distributions of habitat suitability for the two species by considering the selected environmental criteria in the KRI. Among the selected predictors, bio1 (annual mean temperature), bio15 (precipitation seasonality), and bio12 (annual mean precipitation) were the most significant factors in determining the habitat of *Q. infectoria*. The yearly mean temperature was demonstrated to be the most influential factor and accounted for 42.8% of the distributions. Precipitation seasonality and annual mean precipitation also accounted for 25.1% and 19.7%, respectively. Together, these three factors considerably increased by 87.6%. In contrast, soil moisture and soil pH demonstrated the lowest contributions (Table S5).

For *Q. libani*, bio1, bio15 and bio 6 (mean temperature of the coldest month) contribute 59.3%, 19.9%, and 18.4% (collectively by 97.6%) to its habitat distribution, respectively. However, yearly precipitation and soil moisture had the lowest proportional effects on the habitat distribution probability (Table S6).

The jackknife test, which is used to regularize training, revealed the contributions gains of the variables, and AUC variable gains showed that

bio1 and bio12 included more gains in the distribution of *Q. infectoria* than other factors. For *Q. libani*, bio1 and bio6 included more gains in their distribution than other factors in the KRI (Fig. S6 and Fig. S7).

3.2. Potential current and future habitat distributions of Q. infectoria and Q. libani

According to the prediction outcomes of the Maxent modeling utilizing two global climate models and three shared socioeconomic pathway scenarios, the habitat unsuitability areas for *Q. infectoria* and *Q. libani* would increase, and the overall suitability habitat distributions would particularly decrease the 'low suitable' category areas. For example, the current unsuitable area of *Q. infectoria* was estimated at 41873.1 km^2 (81.27%), whereas the low, moderate, and high suitability locations were approximately 5375.8 km^2 (10.43%), 3001.6 km^2 (5.83%), and 1270.3 km^2 (2.47%), respectively (Fig. 2; Table 1).

Modeling results predicted that for the mid-century (2050s), the habitat unsuitability areas for *Q. infectoria* would increase to 43,163.5–43,543.4 km^2 (83.78–84.52%), 43,060.6–43,338.8 km^2 (83.58–84.12%), and 43,548.9–43,289.4 km^2 (84.53–84.02%) under the SSP1–2.6, SSP2–4.5 and SSP5–8.5 climate change scenarios of both GCMs, respectively. In turn, the total habitat suitability (sum of low, medium, and high) would decrease from the current 9647.7 km^2 (18.73%) to between 7977.4 and 8357.3 km^2 (15.48–16.22%), 8182.0 and 8460.2 km^2 (15.88–16.42%), and 7971.9 and 8231.4 km^2 (15.47–15.98%), respectively (Fig. 3 & Fig. S1; Table 1& Table S1). In contrast, the moderately suitable area would increase to 7.72% under the SSP2–4.5 scenario of MRI-ESM2–0.

Under the SSP1–2.6, SSP2–4.5, and SSP5–8.5 climate change scenarios (2070s), the unsuitable would expand to between 43,231.7 and 43,539.2 km^2 (83.91–84.51%), 43,232.4 and 44,002.6 km^2 (83.91–85-41%) and, 44,002.4 and 44,216.7 km^2 (85.41–85.82%), respectively. As a result, the sum of habitat suitability categories would contract to between 7981.60 and 8289.1 km^2 (15.49–16.09%), 7518.2 and 8288.4km^2 (14.59–16.09%), and 7304.1 and 7518.4 km^2 (14.18–14.59%), respectively, from the current 9647.7 km^2 (18.3%). Overall, the reduction in suitable locations under the SSP5–8.5 scenario for climate change was slightly larger than that under SSP1–2.6 and SSP2–4.5 scenarios.

By the end of the century (2090s), compared to 2050s and 2070s, unsuitable areas would significantly expand by 43,334.6–44,028.9 km^2 (84.11–85.46%), 43,146.8–43,988.5 km^2 (83.7585.38%), and 44,028.9–44,467.8 km^2 (85.46–86.31%) under the three emission scenarios of both GCMs, respectively. On the other hand, the low suitable habitat would decline from 5375.8 km^2 (10.34%) to between 1785.7 and2018.0 km^2 (3.47–3.92%) under the SSP5–8.5 scenarios (Fig. 3 & Fig. S1; Table 1 & Table S1).

The potential current unsuitable habitats for *Q. libani* were 94.51%; these habitats cover approximately 48,705.6 km^2 of the KRI (Fig. 2; Table 2). Approximately 5.46% (2815.2 km^2) of national territory conservation are suitable habitats for *Q. libani* under current climatic conditions.

The unsuitable habitats would increase to 49,057.6–49,091.7 km^2 (95.22–95.29%), 49,026.3–49,031.1 km^2 (95.16–95.17%), and 49,058.3–49,119.5 km^2 (95.22–95.34% of the total land surface of the KRI) under the SSP1–2.6, SSP-2.45, and SSP5–8.5 scenarios by the 2050s. The total suitable habitats would decline to 2401.3–2494.5 km^2 (4.66–4.84%) from 2815.2 km^2 (5.46%).

Similarly, the Maxent model predicted unsuitable habitats to expand to approximately 49,055.5–49,100.0 km^2 (95.21–95.30%), 49,054.8–49,125.0 km^2 (95.21–95.35%), and 49,123.7–49,205.7 km^2 (95.35–95.51%) under ther three emission scenarios, respectively by the 2070s. However, the suitable category would decline, especially the low suitable class, to approximately 564.8–822.2 km^2 (1.10–1.60%) from the current distribution.

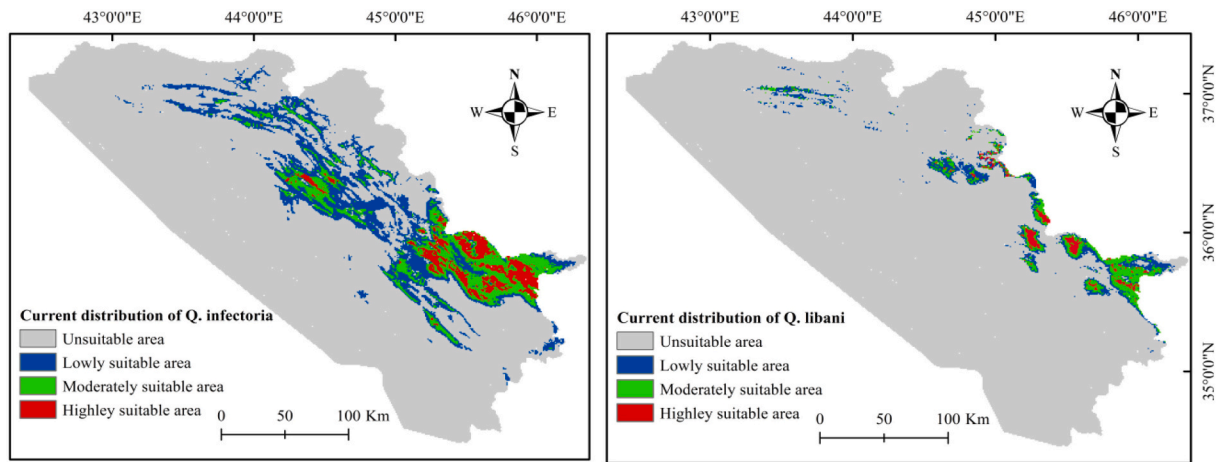In the 2090s, impactful changes would occur, particularly under the

Fig. 2. Current distribution of *Q. infectoria* (left) and *Q. libani* (right).

Table 1

Predicted unsuitable and suitable areas for *Q. infectoria* under current and future climatic conditions (BCC-CSM2-MR model).

SSPs (year)	Unsuitable habitats	Total Suitable habitats	Lowly suitable habitats	Moderately suitable habitats	Highly suitable habitats
	Area /km^2 (%)	Area/km^2 (%)	Area /km^2 (%)	Area /km^2 (%)	Area /km^2 (%)
Current	41,873.1 (81.27)	9647.7 (18.73)	5375.8 (10.43)	3001.6 (5.83)	1270.3 (2.47)
SSP1–2.6 (2050s)	43,543.4 (84.52)	7977.4 (15.48)	2374.9 (4.61)	3871.9 (7.520)	1730.7 (3.36)
SSP2–4.5 (2050s)	43,338.8 (84.12)	8182.0 (15.88)	2654.5 (5.15)	3870.6 (7.51)	1657.0 (3.22)
SSP5–8.5 (2050s)	43,548.9 (84.53)	7971.9 (15.47)	2639.2 (5.12)	3604.0 (7.00)	1728.6 (3.36)
SSP1–2.6 (2070s)	43,539.2 (84.51)	7981.6 (15.49)	2733.8 (5.31)	3755.0 (7.29)	1492.8 (2.90)
SSP2–4.5 (2070s)	44,002.6 (85.41)	7518.2 (14.59)	2492.6 (4.84)	3259.4 (6.33)	1766.2 (3.43)
SSP5–8.5 (2070s)	44,216.7 (85.82)	7304.1 (14.18)	2390.2 (4.64)	3206.1 (6.22)	1707.8 (3.31)
SSP1–2.6 (2090s)	44,028.9 (85.46)	7491.9 (14.54)	2305.3 (4.47)	3388.4 (6.58)	1798.2 (3.49)
SSP2–4.5 (2090s)	43,988.5 (85.38)	7532.3 (14.62)	2092.4 (4.06)	3393.4 (6.59)	2046.5 (3.97)
SSP5–8.5 (2090s)	44,218.8 (85.83)	7302.0 (14.17)	1785.7 (3.47)	3722.3 (7.22)	1794.0 (3.48)

SSP5–8.5 scenario of both GCMs. For example, the unsuitable category would be 49,058.3–49,285.8 km^2 (95.22–95.66%). Overall, by the end of the century, the sum of suitable habitats may decrease from 2815.2 km^2 (5.46%) to approximately 2235.0–2427.7 km^2 (4.34–4.71%). The range of moderately suitable areas would increase to approximately 1115.8–1318.9 km^2 (2.17–2.56%) from 876.5 km^2 (1.70%) (Fig. 4 & Fig. S2; Table 2 &Table S2).

3.3. Analysis of the distribution changes between the current and future habitats of Q. infectoria and Q. libani

The Maxent outcomes revealed a dynamic in the changing habitat distributions of the species; for instance, models created using the MRI-ESM2–0, and BCC-CSM2-MR climate methods demonstrate that there would be a shift in the range of *Q. infectoria* under SSP1–2.6, SSP2–4.5 and SSP5–8.5 from its current distribution. The *Q. infectoria* habitat would contract by 2760.9–2856.9 km^2 (5.36–5.55%), 2856.9–3357.2 km^2 (5.55–6.52%) and 2822.1–3400.2 km^2 (5.48–6.60%), whereas it would expand by 1153.3–1638.9 km^2 (2.24–3.18%), 761.0–1556.8 km^2

(1.48–3.02%), and 721.5–1547.1 km^2 (1.40–3.00%) by the 2050s, 2070s, and 2090s, respectively. The species will gain some ground (expanding in some locations); the greatest expansion range was seen under the SSP2–4.5 scenario for the 2050s by 1638.9 km^2 (3.18%). The greatest contraction range (loss of habitats) was observed under SSP5–8.5 for the 2090s by 3400.2 km^2 (6.60%) (Fig. 5 & Fig. S3; Table 3 & Table S3).

Similarly, *Q. libani* would contract by 700.5–753.4 km^2 (1.36–1.46%), 694.2–843.8 km^2 (1.35–1.64%), and 716.5–846.1 km^2 (1.39–1.64%) while expanding by 339.5–386.8 km^2 (0.66–0.75%), 301.9–387.5 km^2 (0.59–0.75%), and 257.4–329.1 km^2 (0.50–0.64%) by the 2050s, 2070s, and 2090s, respectively. The greatest expansion range (habitat gains) of *Q. libani* was determined by the SSP5–8.5 scenario for the 2070s by 387.5 km^2 (0.75%). However, the contraction range (loss of habitats) would significantly increase under SSP5–8.5 for the 2090s by 846.1 km^2 (1.64%) (Fig. 6 & Fig. S4; Table 4 & Table S4). Overall, under all climate change scenarios of both GCMs, the expansion range will be smaller than the contraction range for both species.

3.4. Direction and magnitude of distributional changes for Q. infectoria and Q. libani

In this study, under the future scenarios for climate change (SSP1–2.6, SSP2–4.5 and SSP5–8.5), the habitat distributional change centroid for *Q. infectoria* and *Q. libani* indicated movement toward the east and southeast, respectively. Overall, the direction and magnitude of habitat distributional changes for *Q. infectoria* from the existing distribution centroid to the new distribution centroid were much stronger under SSP5–8 (2090s). For example, the current geographic coordinates of the centroid of *Q. infectoria* is 44° 59′ 38.693" E; 36°4'25.391" N under SSP5–8.5 (2090s), and this centroid would change to 45° 14′ 7.816" E; 35° 55' 13.046" N (Fig. 7).

On the other hand, the current geographic coordinates of the centroid of *Q. libani* is 45° 24′ 40.995" E; 36° 0' 40.953" N. This current distribution centroid would change to 45° 40′ 48.795" E; 35° 49' 32.358" N (i.e., new significantly stronger distribution centroid in direction) based on SSP1–2.6 (2090s) (Fig. 7).

3.5. Overlapping habitats between **Q. infectoria** and **Q. libani**

This study, under both GCM models, demonstrated that overlapping suitable habitat areas of both species would be 1767.2–1807.5 km^2 (3.43–3.51%), while, unsuitable areas would be 42,706.8–43,085.8 km^2 (82.89–83.63%) of the total area of the KRI. Habitat suitability areas would be 5901.8–6317.9 km^2 (11.49–12.29%) for *Q. infectoria*, whereas it would be 725.8–728.9 km^2 (1.41%) for *Q. libani* (Fig. 8; Table 5).
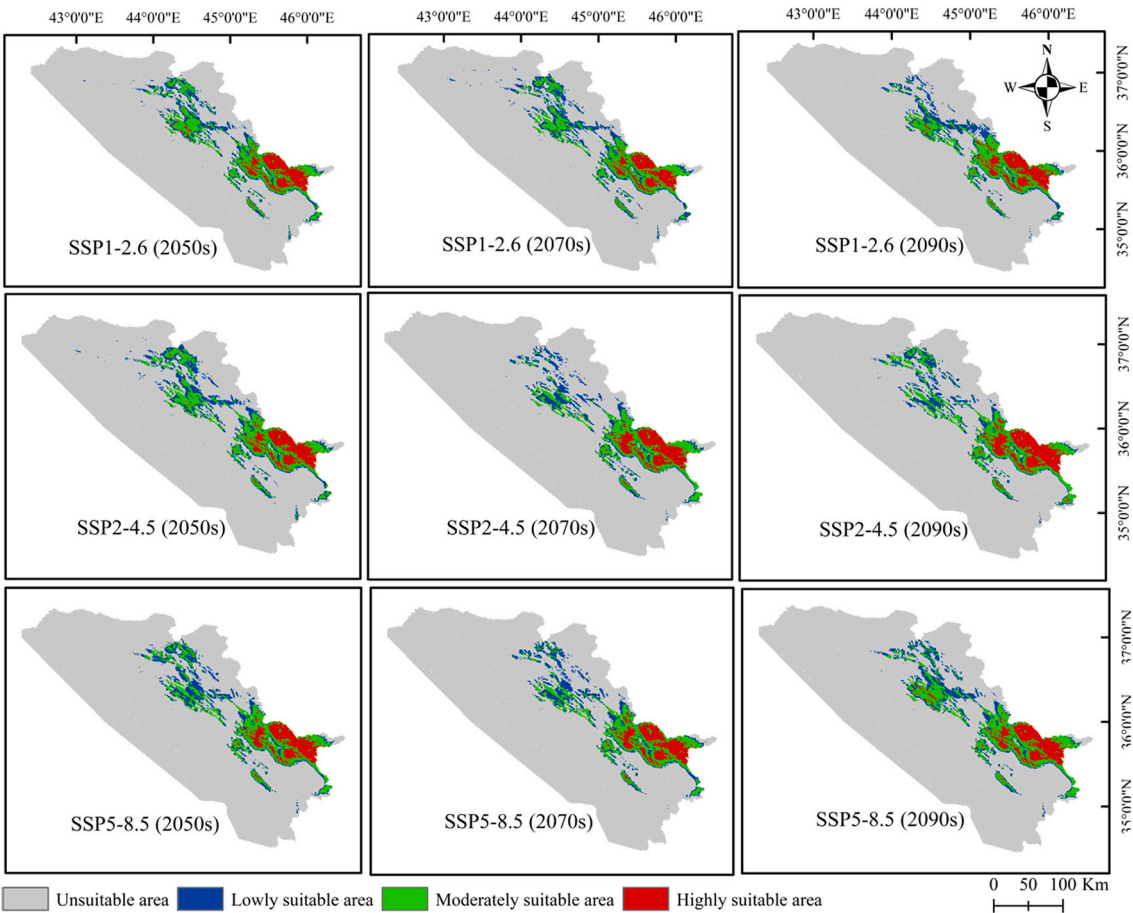
Fig. 3. Future distribution of *Q. infectoria* as a reaction to scenarios for future climate change of the BCC-CSM2-MR model.

Table 2
Predicted unsuitable and suitable areas for *Q. libani* under current and future climatic conditions.

SSPs (year)	Unsuitable habitats	Total Suitable habitats	Lowly suitable habitats	Moderately suitable habitats	Highly suitable habitats
	Area /km^2 (%)	Area/km^2 (%)	Area /km^2 (%)	Area /km^2 (%)	Area /km^2 (%)
Current	48,705.6 (94.54)	2815.2 (5.46)	1481.0 (2.87)	876.5 (1.70)	457.7 (0.89)
SSP1–2.6 (2050s)	49,091.7 (95.29)	2429.1 (4.71)	667.1 (1.29)	1234.7 (2.40)	527.3 (1.02)
SSP2–4.5 (2050s)	49,031.1 (95.17)	2489.7 (4.83)	723.6 (1.40)	1257.0 (2.44)	509.2 (0.99)
SSP5–8.5 (2050s)	49,119.5 (95.34)	2401.3 (4.66)	649.0 (91.26)	1248.7 (2.42)	503.6 (0.98)
SSP1–2.6 (2070s)	49,055.5 (95.21)	2465.3 (4.79)	651.1 (1.26)	1257.7 (2.44)	556.5 (1.08)
SSP2–4.5 (2070s)	49,125.0 (95.35)	2395.8 (4.65)	610.1 (1.18)	1301.6 (2.53)	484.2 (0.94)
SSP5–8.5 (2070s)	49,123.7 (95.35)	2397.1 (4.65)	608.7 (1.18)	1287.6 (2.50)	500.9 (0.97)
SSP1–2.6 (2090s)	49,145.9 (95.39)	2374.9 (4.61)	556.5 (1.08)	1318.9 (2.56)	499.5 (0.97)
SSP2–4.5 (2090s)	49,153.6 (95.41)	2367.2 (4.59)	838.9 (1.63)	1115.8 (2.17)	412.5 (0.80)
SSP5–8.5 (2090s)	49,214.8 (95.52)	2306.0 (4.48)	528.0 (1.02)	1242.4 (2.41)	535.6 (1.04)

4. Discussion

4.1. Distribution of **Q. infectoria** and Q. libani under current and future climatic projections

Quercus ssp. have been observed to be strongly adapted to a variety of climatic situations, for example, temperature (Browne et al., 2019; Sork et al., 2010). Furthermore, this study revealed that the spatial distribution patterns of these species in the KRI will be adversely affected by predicted climate change. Modeling indicated that the ranges of habitat distribution for *Q. infectoria* would decrease from its current range (i.e., from 9647.7 km^2 (18.73%)) to 7971.9–8460.2 km^2 (15.47–16.42%), 7304.1–8289.1 km^2 (14.18–16.0.9%) and 7053.0–8374.0 km^2 (13.69–16.25%) under the BCC-CSM2-MR and MRI-ESM2–0 models for the three time periods (i.e., 2050s, 2070s, and 2090s), respectively. Similarly, for *Q. libani*, the ranges would decrease from its current range (i.e., 2815.2 km^2 (5.46%)) to 2401.3–2494.5 km^2 (4.66–4.83%), 2315.1–2466.0 km^2 (4.49–4.79%), and 2235.0–2427.7 km^2 (4.34–4.71%), respectively. In response, the species habitats would expand geographically in various ways, but amount of the expansion would be less than the magnitude of contraction under climate change scenarios in the future. For *Q. infectoria*, and *Q. libani* the habitat would contract by 2760.9–3400.2 km^2 (5.36–6.60%) and 694.2–846.1 km^2 (1.35–1.64%), respectively, whereas it would expand by only 721.5–1638.9 km^2 (1.40–3.18%) and 257.4–387.5 km^2 (0.50–0.75%), respectively. Climate change affects *Quercus* spp. distributions. Thus, the changes in the habitat distribution of these oak trees will cause a shift in the distribution centroid (Khwarahm, 2020). Our results demonstrated the distributional change of former species toward the southeast and east in the KRI mountains. High altitude areas (mountain areas) are
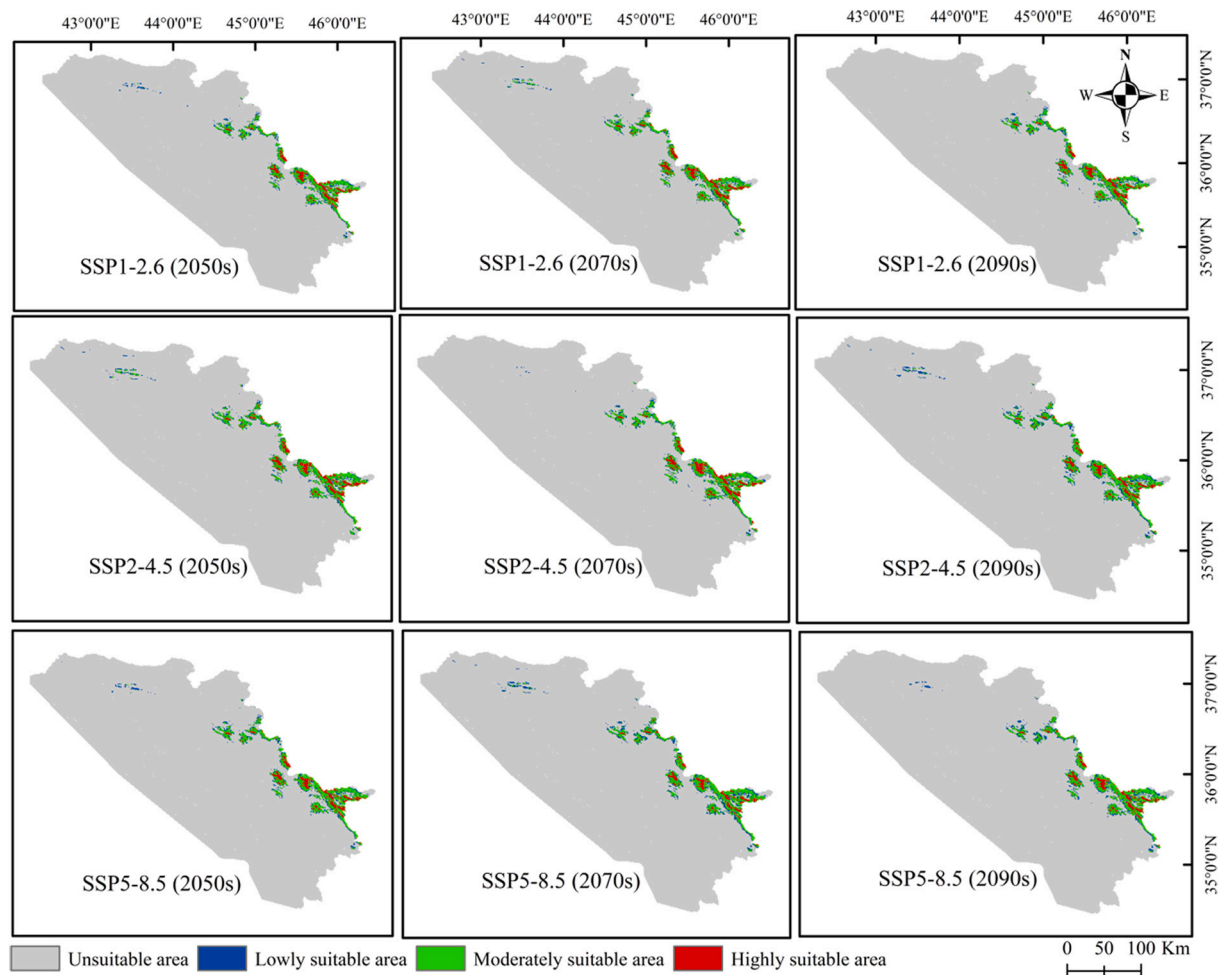
Fig. 4. Future distribution of *Q. libani* as a reaction to future climate change scenarios of BCC-CSM2-MR model.

frequently linked to large amounts of precipitation in the KRI (Nasser, 1984) and hence have a lower temperature compared to that in low lands. Our results corroborate previous studies on species range contraction (habitat loss) and expansions both in the KRI (Khwarahm, 2020) and elsewhere in the world (Çoban et al., 2020; Dimobe et al., 2020; Sommer et al., 2010; Thuiller et al., 2005). For example, in Iran, Naghipour et al. (2021) demonstrated that the suitable habitat of *Crataegus azarolus* L. would decline under future climate change in Iran. Moreover, Taleshi et al. (2019) highlighted that the climatically suitable habitats for most major tree species will tend to shrink and shift in the future. Moreover, Çoban et al. (2020) and Khwarahm (2020) reported that climate change in the future would significantly reduce oak tree habitats (*Q. libani*) and (*Q. aegilops*) in Turkey and Iraq respectively. In addition, Balima et al. (2022) expected that range changes of African oak trees toward the south and a sharp decline in their suitable environments (*Afzelia africana* Sm.) might be accounted for by considerable temperature fluctuations under future climate estimates.

In addition, an expanding body of empirical data supports the idea that shifting climatic conditions will significantly influence the geographic distributions of vascular plant species and lead to range shifts and habitat losses in tree species around the globe (Balima et al., 2022; Dyderski et al., 2018; Larsen et al., 2011). The environmental suitability of plant species and ecosystems will decline due to an increase in temperature in semiarid and arid places in the future (Hassan and Nile, 2021). In addition, suitable areas for plants will increase and shift toward high altitudes with high precipitation and cool temperatures and will be more adapted to plant development. Previous research has also noted an elevational shift in plant group distributions, notably in

mountain habitats (Bazrmanesh et al., 2019; Braunisch et al., 2014; Mahmoodi et al., 2022; Naghipour Borj et al., 2019). These results indicate significant conservation problems for *Q. infectoria* and *Q. libani* and probably other oak species, and reforestation efforts should be taken in the mountainous areas especially in Sulaimani Province to reduce species contraction risks.

4.2. Environmental variables controlling the distribution of *Q. infectoria* and *Q. libani*

Environmental variables partly control species distributions in terrestrial vegetation communities (Guisan and Zimmermann, 2000). They directly impact the physiological and biochemical processes of plants (Meena, 2021). This research used eight environmental factors to predict the geographic distributions of *Q. infectoria* and *Q. libani* in Iraq. Utilizing jackknife tests, the findings showed that among the environmental factors, annual mean temperature (bio1), annual precipitation (bio12) and minimum temperature of the coldest period (bio6) affected the habitat suitability and spatial distribution of *Q. infectoria*. Annual mean temperature (bio1), minimum temperature of the coldest period (bio6), and soil moisture were the significant factors impacting the *Q. libani* distribution in the KRI.

As revealed in this study, temperature is particularly important essential among the environmental factors that affect species dispersion. Due to the effects of temperature on the photosynthetic processes, several parts of photosynthetic metabolism are extremely temperature-sensitive (Zhou et al., 2021). Low temperatures can decrease the transport and hydrolysis of starch that accumulate inside the
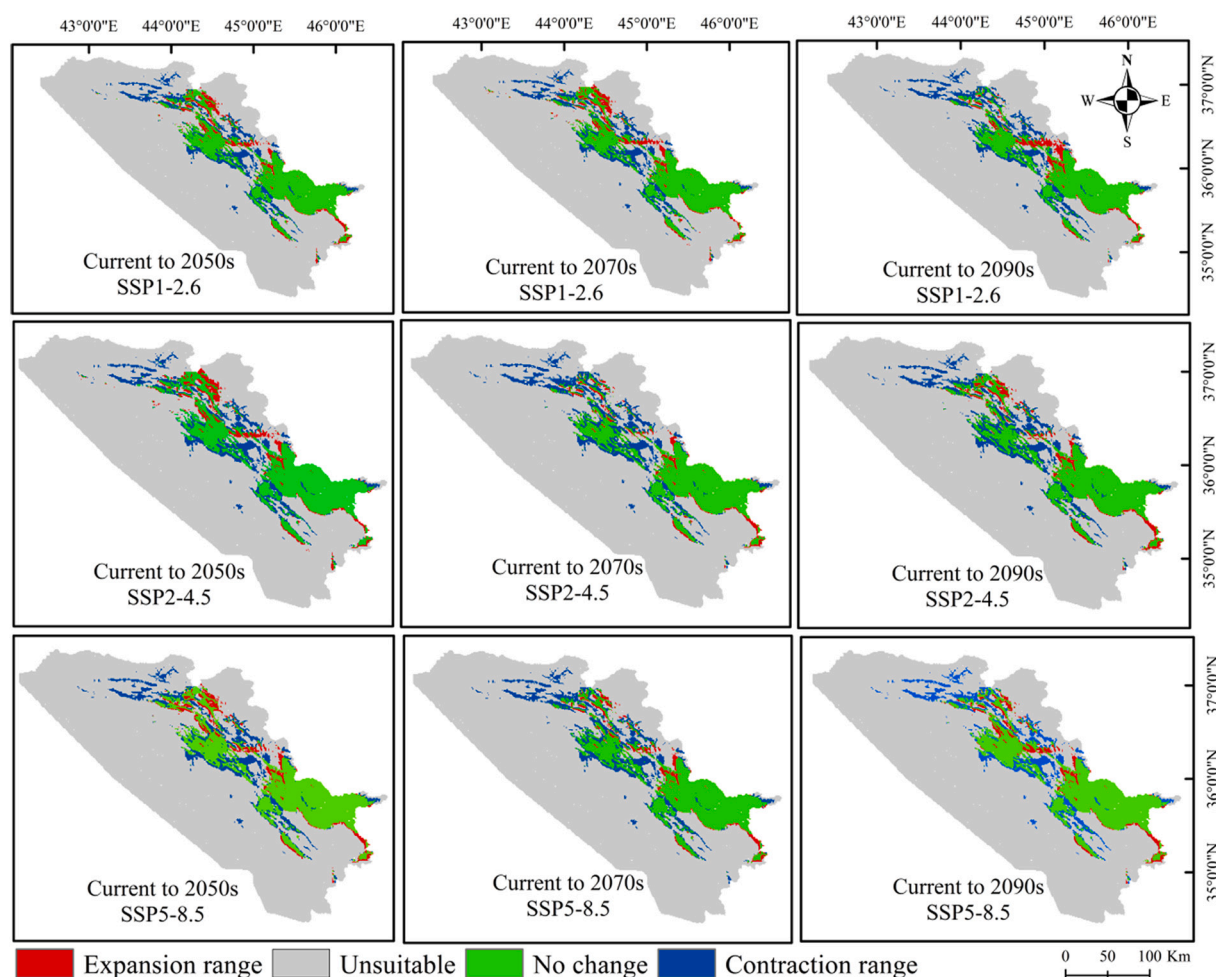
Fig. 5. Changing distribution in habitat areas between the current and future scenarios for climate change of model BCC-CSM2-MR for *Q. infectoria* in the KRI.

Table 3
Changing distribution in habitat areas between the current and future scenarios for climate change of the BCC-CSM2-MR model for *Q. infectoria*.

Current to SSPs (year)	Expansion range		Unsuitable		No change		Contraction range	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
SSP1–2.6 (2050s)	1153.3	2.24	40,718.4	79.03	6826.2	13.25	2822.9	5.48
SSP2–4.5 (2050s)	1336.3	2.59	40,535.5	78.68	6845.6	13.29	2803.4	5.44
SSP5–8.5 (2050s)	1180.5	2.29	40,691.3	78.98	6791.4	13.18	2857.6	5.55
SSP1–2.6 (2070s)	1218.0	2.36	40,653.7	78.91	6765.6	13.13	2883.4	5.60
SSP2–4.5 (2070s)	761.0	1.48	41,110.7	79.79	6291.9	12.21	3357.2	6.52
SSP5–8.5 (2070s)	851.4	1.65	41,020.3	79.62	6452.6	12.52	3196.4	6.20
SSP1–2.6 (2090s)	1021.9	1.98	40,849.9	79.29	6471.4	12.56	3177.6	6.17
SSP2–4.5 (2090s)	1015.6	1.97	40,856.2	79.30	6519.4	12.65	3129.6	6.07
SSP5–8.5 (2090s)	721.5	1.40	40,805.4	79.20	6763.6	13.13	3230.3	6.27

chloroplast, which in turn decreases the rate of photosynthetic activity. In contrast, the rate of photosynthetic reactions rises in response to temperature changes until it reaches a thermal optimum, at which point rates fall as enzymes become inactive at increasingly higher temperatures. High-temperature enzyme decomposition can reduce electron transport rates and chlorophyll concentrations (Zhou et al., 2021). In addition, temperature affects plant ecology and metabolism activities such as plant growth, leaf water potential, gas exchange, reproduction and development stages (Bykova et al., 2012; Xu and Zhou, 2006) and therefore, it can affect plant distributions, as they cannot avoid adverse bioclimatic conditions by sheltering or migrating (Hirzel and Le Lay, 2008). In other words, each plant species' spatial distribution is influenced by its range of climatic tolerance, ecological niche, and biological

interactions (Pearman et al., 2008). One factor that can impact species survival in an ecosystem is a reduction in the region of species habitat because of climate change (Becerra-López et al., 2017). Indeed, climate change may impact the geographic range of species distribution since species need a certain temperature and amount of moisture. A higher value of the annual mean temperature and lower value of (annual and seasonal precipitation) decreased the habitat suitability of both species. This species' predilection is shown by the fact that temperature contributes more than precipitation to moderate and cool areas, particularly for *Q. libani*. The findings highlight the ecology of *Q. infectoria* and *Q. libani*, which occur in semidry and humid forests in the KRI (Chapman, 1950; Sefik, 1981), demarcating the transition zone between intermediate zone forests and upper zone forests. The model indicated a
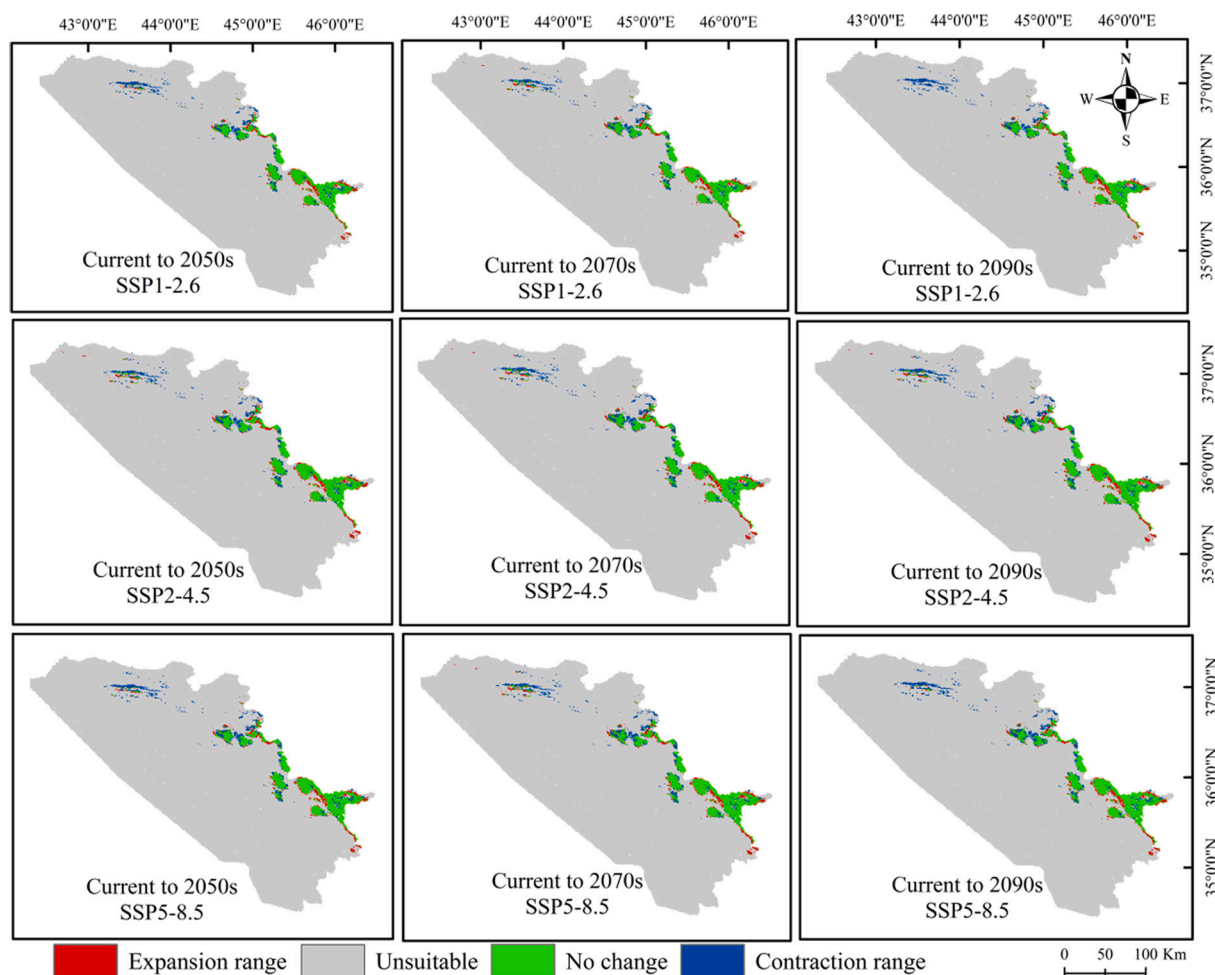
Fig. 6. Changing distribution in habitat areas between the current and future scenarios for climate change of BCC-CSM2-MR for *Q. libani* in the KRI.

Table 4
Changing distribution in habitat areas between the current and future scenarios for climate change for *Q. libani*.

Current to SSPs (year)	Expansion range		Unsuitable		No change		Contraction range	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
SSP1–2.6 (2050s)	345.8	0.67	48,359.8	93.86	2083.4	4.04	731.8	1.42
SSP2–4.5 (2050s)	386.8	0.75	48,318.8	93.79	2102.9	4.08	712.3	1.38
SSP5–8.5 (2050s)	339.5	0.66	48,366.1	93.88	2061.8	4.00	753.4	1.46
SSP1–2.6 (2070s)	381.9	0.74	48,323.7	93.79	2087.6	4.05	727.6	1.41
SSP2–4.5 (2070s)	324.9	0.63	48,380.7	93.91	2070.9	4.02	744.3	1.44
SSP5–8.5 (2070s)	387.5	0.75	48,318.1	93.78	2009.7	3.90	805.5	1.56
SSP1–2.6 (2090s)	297.8	0.58	48,407.8	93.96	2080.6	4.04	734.6	1.43
SSP2–4.5 (2090s)	301.9	0.59	48,403.7	93.95	2065.3	4.01	749.9	1.46
SSP5–8.5 (2090s)	320.7	0.62	48,384.9	93.91	1985.3	3.85	829.9	1.61

tolerance range of yearly mean temperature between 5 and 20 °C, and 5–16 °C, which is the favored area for both species' distribution in the KRI. Temperature was identified as the primary factor affecting vegetation habits and the distribution of woody plants in previous research on species distribution modeling worldwide (Çoban et al., 2020; Huang et al., 2021). In addition, the function of corresponding bioclimatic factors and precipitation cannot be ignored as they are interconnected.

Water availability has a great impact on plant metabolism processes (Wang et al., 1998). Therefore, water availability may be the main issue restricting plant growth and development in arid and semiarid environments (Khwarahm, 2020). The KRI's highlands have a dramatic decrease in precipitation from June onward (for example, until early October), yet the mean temperature in these regions continues to be much lower than that in the lowlands. These findings support earlier research that found climate, notably precipitation and temperature, had a significant effect in detecting the spatial distribution (latitudinal and elevational) of terrestrial ecosystems, particularly in mountain regions, on a global scale (Bradie and Leung, 2017; Hamid et al., 2019; Yuan et al., 2020). The KRI's present habitat suitability for these species depends on the yearly rainfall, which must be between 650 and 1050 mm. High altitude and this amount of rainfall are frequently related in the KRI (mountainous areas) (Nasser, 1984). These findings are consistent with earlier research that points to rain as the primary ecological factor restricting the range of oak forests in northeastern Iraq (including KRI) (Guest and Al-Rawi, 1966; Khwarahm, 2020; Zohary, 1973). Similarly, Laaribya et al. (2021) also demonstrated that seasonal precipitation and
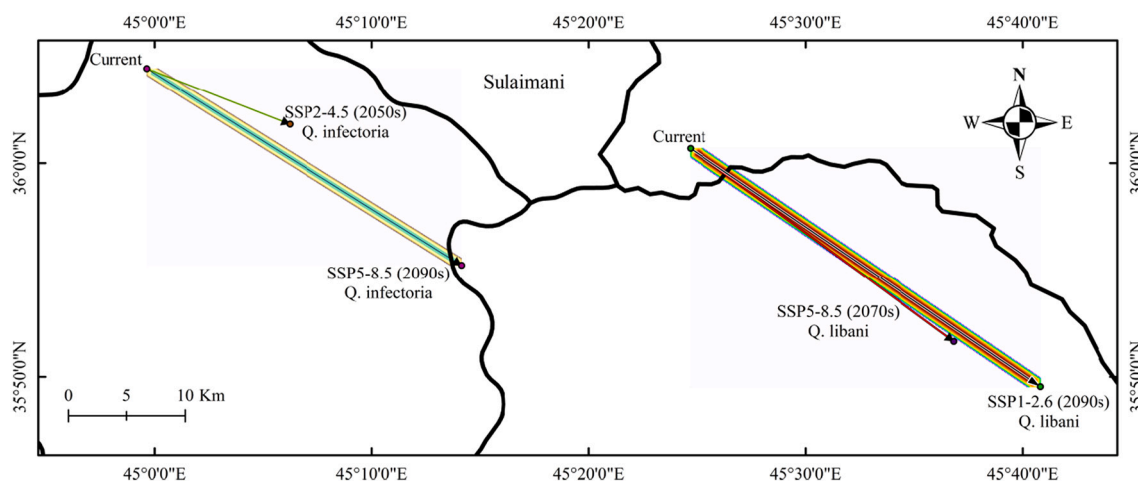
Fig. 7. Distribution of current centroid of *Quercus* ssp. and changes of distributional centroid under future climate scenario of BCC-CSM2-MR model.
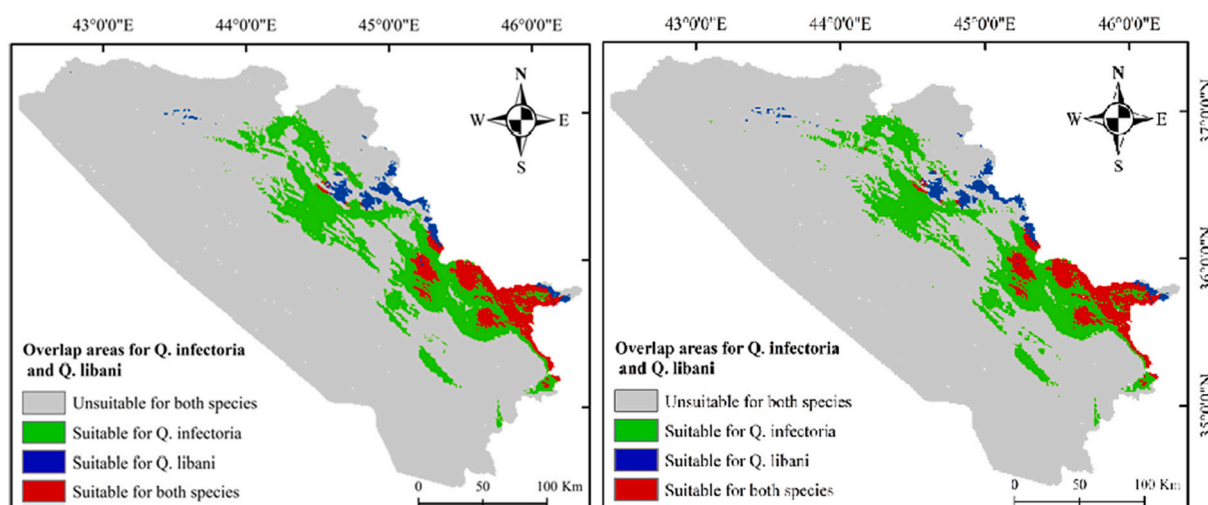

Fig. 8. The geographic depiction of the overlapping habitat for *Q. infectoria* and *Q. libani* in the KRI using the MRI-ESM2. 0 models (right) and BCC-CSM2-MR model (left).

Table 5
Average overlapping habitat areas for *Q. infectoria* and *Q. libani* under future climate change scenarios in the KRI.

Class	BCC-CSM2-MR model		MRI-ESM2. 0 model	
	Area (km2)	%	Area (km2)	%
Suitable for both species	1807.5	3.51	1767.2	3.43
Suitable for *Q. infectoria*	5901.8	11.46	6317.9	12.26
Suitable for *Q. libani*	725.8	1.41	728.9	1.41
Unsuitable for both species	43,085.8	83.63	42,706.8	82.89
Total	51,520.8	100.00	51,520.8	100.00

seasonal variations in temperature play significant roles in the habitat distribution of cork oak (*Quercus suber L.*) in Maamora Forest, Morocco. Furthermore, this study supports earlier work of (Yilmaz et al., 2016), which demonstrated that (Bio1), (Bio6), and (Bio12) are highly correlated bioclimatic factors that affect the distribution of *Q. robur* L. in Turkey. Similarly, Çoban et al. (2020) revealed that temperature was the more significant predictor in defining the distribution of *Q. libani* in Turkey. In addition, Li et al. (2018) highlighted that annual mean temperature was a key factor for *Quercus fabri* distribution in China. For other vascular plants, for example, common hornbeam (*Carpinus betulus L.*) and *Pinus densiflora,* the important role of (Bio1) in their spatial

distributions was reported by Gülçin et al. (2021) and Duan et al. (2022), respectively.

4.3. Modeling of species distribution is affected by certain factors

According to this study, the regional distribution of *Q. libani and Q. infectoria* under future climate change differed within and among the two GCMs across the three climate change scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5) that have less bias in predicting future conditions (i.e., during the 2050s, 2070s, and 2090s) for the study region. Previous studies (Hosseini et al., 2022; Zhang et al., 2022) demonstrated how the results of distribution modeling vary depending on some variables. In fact, the model's outputs are initially affected by the environmental factors chosen as predictors (Guisan and Zimmermann, 2000). Future prospective ranges of the species are altered by significant differences in these variables. For example, the predicted range extension of various plants worldwide is due to the climate (Hounkpèvi et al., 2016; Kirchmair, 2017). Although the two models indicated a broad pattern in the species' global distribution, there were some variances in the extent of habitat loss. The two climate models anticipated different levels of habitat loss within each horizon and each emission scenario. These results confirm that the selection of climate approaches in species distribution modeling affects the anticipated models (Fandohan et al.,

2013; Heubes et al., 2013). As a result of the three emission strategies at all horizons, the MRI-ESM2–0 model anticipated the lowest impact of climate change on appropriate habitats among the two global climate models. The BCC-CSM2-MR model, however, foresaw the greatest effects of climate change on appropriate ecosystems. Such disparities in climate models highlight how they differ from one another, which raises questions about model uncertainty (Harris et al., 2014). As a result, a particular species can be predicted to be extinct by a set of global climate models, but under habitat loss or range expansion by other global climate models. Therefore, selecting climate models for species distribution modeling provides a significant difficulty (Heubes et al., 2013). The majority of research on species distribution modeling in the KRI and throughout the globe has utilized global climate models (Çoban et al., 2020; Guidigan et al., 2018; Khwarahm, 2020). Our research shows that the regional distribution of *Q. infectoria and Q. libani* is affected differently by future climate change depending on the emission scenario. This result concurs with Harris et al. (2014) who found that the main source of model uncertainty comes from emission scenarios. By comparing the highest emission scenario (SSP5–8.5) to the scenario with the fewest emissions, it was discovered that the possible unsuitable locations had a higher geographic extent (SSP1–2.6). This implies that, as projected by SSP5–8.5, climate change will have a significant impact on species distribution range in the absence of mitigating measures. In the event of a mitigation assumption under SSP1–2.6, however, the impact of climate change may be lessened. The research also revealed that modeling results changed with time, with more significant changes anticipated by the 2090s. Loss of habitat anticipated (Çoban et al., 2020; Khwarahm, 2020) and range expansion (Hounkpèvi et al. O'neill et al., 2016; Kirchmair, 2017) in reaction to future climate change, as expected for woody plants, show the uncertainty of the global climate.

4.4. Implications for conservation

An integrated approach should be used with the currently available species data and potent statistical approaches to determine the optimum conservation strategy for plant species. In the investigation of vegetation and modeling, machine learning algorithms (e.g., Maxent) and GIS platforms are usually employed as means for creating areas of interest for conservation purposes. Often the model outputs are altered to binary maps and in some cases, the maps are further classified into priority classes based on the probability of the habitat distribution (Gong et al., 2022; Khwarahm et al., 2021; Radha and Khwarahm, 2022). Therefore, the delineated area of interest is often adequate for conservationists. Alongside the modeling approach, extra GIS techniques should be used to assess the environmental elements that govern the spatial distribution of plants by creating map layers and databases, particularly when more than one species is considered in modeling. In the wake of global climate change identifying high-priority areas for tree conservation and restoration across mountain ecosystems is crucial. Therefore, considering evolving spatial techniques such as detecting *range overlap* or habitat overlap, presumably overlapping ecosystems, implies significant species diversity and appears more sensible and useful for delineating sites targeted or proposed for conservation actions. This procedure is more useful for detecting overlapping areas when more than one species is considered for conservation planning.

Our results reveal that *Quercus* species are under threat of contraction and depletion, often due to the impacts of climate changes in addition to human activity. To protect plant species from the threat of contraction and extinction and maintain biodiversity, it is important to have a thorough understanding of the needs of plant habitats. It is also important to identify the locations most at risk for extinction and to plan potential measures for plant conservation. In addition, the current study created an overlapping map (Fig. 8; Table 5) for both species, which coexist in the same geographic area. This model map can establish priorities that will make saving *Quercus* trees and restoration easier. The results showed that the most favorable habitats for *Q. infectoria* and

Q. libani were predicted in the Penjwen and Sharbazher in the Sulaimani governorate.

Quercus infectoria and *Q. libani* are valuable and significant trees in KRI forests; despite ongoing degradation, they are widely distributed in the semiaired and humid eco-regions of the KRI. However, climate change is also serious in addition to continued human-caused hazards (e. g., cutting, clearing, and war). Therefore, we suggest planting oak seeds in high altitude areas (high elevations) where *Quercus* species habitats are crucial (both now and in the future) and where conservation efforts should be prioritized. The initial implementation of a management and monitoring policy should also be used to restrict human actions, such as cutting and clearing forests. A present emphasis should be placed on safeguarding these places since the overlapping ecosystems imply significant biodiversity.

5. Conclusion

In this work, the consequences of climate change on the geographic distribution of *Q. infectoria* and *Q. libani* were examined via two groups of global climate models. To do this, a machine-learning algorithm combined with geospatial techniques was employed. We found that the geographic distribution of the species will be significantly impacted by climate change, leading (migrating) to eastward and southeastward ranges, suggesting species preference for high altitudes. In Sulaimani city, in particular, the two pecies overlap in an area of 1767.2–1807.5 km^2, which is only 3.43–3.51% of the total study area of 51,520.8 km^2 (Fig. 8; Table 5). Therefore, the overlapping regions should be the primary focus for conservation and management efforts where the species coexist. Under the climate models, emissions scenarios, and horizons, the expansion magnitude of the habitat for the species would be inferior to the contraction magnitude, and there would be a drastic loss in the overall appropriate habitats. Habitat loss would be greater for *Q. infectoria* than *Q. libani.* We also found that the annual mean temperature, annual precipitation, and minimum temperature of the coldest period mostly influenced the geographic distribution of the target species.

To enhance and launch conservation plans, classified habitat suitability maps (for the present and future) and overlapping habitat regions for *Q. infectoria and Q. libani* are helpful. GIS approaches combined maximum entropy modeling are helpful tools for creating these means for conservation actions. The results (i.e., category maps of existing and future geographic distributions) provide a starting point for additional research on mountain forest ecosystems and biodiversity conservation methods to reduce the impacts of climate in Iraq and comparable ecoregions. This study, for the first time, provides new baseline information on the current and future distributions of two endemic oak tree species in Iraq. This highlights the importance of distribution modeling combined with geospatial techniques in regions with scant or nonexistent species data, such as in Iraq.

More research on ecological niche modeling must be conducted to include the other important KRI tree species to stop the loss of species habitat. The development of better distribution models could be aided by using several sets of global climate models, including additional environmental factors.

Author's contributions

NRK conceived, designed the study; AH performed field surveys and data collections,data analysis and writing; NRK also participated in writing and compiling the final version of the manuscript. All authors read and approved the final manuscript.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi. org/10.1016/j.ecoinf.2022.101930.

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