



Climate-change habitat shifts for the vulnerable endemic oak species (*Quercus arkansana* Sarg.)

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Abstract *Quercus arkansana* (Arkansas oak) is at risk of becoming endangered, as the total known population size is represented by a few isolated populations. The potential impact of climate change on this species in the near future is high, yet knowledge of its predicted effects is limited. Our study utilized the biomod2 R package to develop habitat suitability ensemble models based on bioclimatic and topographic environmental variables and the known locations of current distribution of *Q. arkansana*. We predicted suitable habitats across three climate change scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) for 2050, 2070, and 2090. Our findings reveal that the current suitable habitat for *Q. arkansana* is approximately 127,881 km² across seven states (Texas, Arkansas, Alabama, Louisiana, Mississippi, Georgia, and Florida); approximately 9.5% is encompassed within state and federally managed protected areas. Our

models predict that all current suitable habitats will disappear by 2050 due to climate change, resulting in a northward shift into new regions such as Tennessee and Kentucky. The large extent of suitable habitat outside protected areas suggests that a species-specific action plan incorporating protected areas and other areas may be crucial for its conservation. Moreover, protection of *Q. arkansana* habitat against climate change may require locally and regionally focused conservation policies, adaptive management strategies, and educational outreach among local people.

Keywords Biomod2 · Climate change · Conservation · Habitat loss · Habitat shift · Species distribution modeling · Oak species

Introduction

Oaks (*Quercus* L.) have significant ecological, economic, and aesthetic importance in North America (see Bocsí et al. 2021). They play a critical role in maintaining the health and function of forest ecosystems by providing essential habitat and food for multiple species. However, many oak species are threatened with extinction in the wild (Gómez-Mendoza and Arriaga 2007; Beckman et al. 2019) due to habitat loss, climate change, diseases, and other anthropogenic stresses. Among them, climate change is the major threat for most of the oak species of concern (Beckman et al. 2019). Out of 28 species of conservation concern in the IUCN Red List, Arkansas Oak (*Quercus arkansana* Sarg.) is listed as a vulnerable species at high risk of extinction due to its population being subject to widespread declines (NatureServe 2022). Historically, *Q. arkansana* had a wide distribution across the southeastern U.S. but is now restricted to isolated populations (Beckman et al. 2019). As most of its remaining

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habitats with large populations are unlikely to contribute to the long-term sustainability of the species, *Q. arkansana* is at risk of becoming endangered.

One high impact threat to the species in the near future will be climate change. The red oak group (*Quercus* section *Labiatae*), including *Q. arkansana* requires low temperatures (chilling effect) and high moisture for seed germination (Bonner 1987). In the southeastern United States, nighttime minimum temperatures have increased in past decades, resulting in higher average temperatures (Powell and Kiem 2015). In addition, increased variability in summer precipitation has been documented in the Southeastern United States (Wang et al. 2010). Precipitation has decreased in dry summer months recently and increased in wet summer months creating periods of extreme drought (Wang et al. 2010). Subsequently, dry seasons in the Southeastern United States have lengthened by 12 to 156 days (Fill et al. 2019). It has been reported that, in some populations of *Q. arkansana* in Alabama, extensive dieback has been attributed to localized drought patterns (Jerome et al. 2017a). Moreover, *Q. arkansana* was the top-ranked among the North American tree species vulnerable to climate change (Potter et al. 2017). Therefore, assessment of current habitats and information on potential changes in the range of this endemic species is vital for their conservation.

Despite the potential risks posed by climate change for *Q. arkansana* populations (e.g., drought), which will likely intensify in the future (McDowell et al. 2020; Subedi et al. 2015), no specific research exists on projecting how climate change will impact this species. With its limited and isolated populations, and habitat specificity, *Q. arkansana* could face significant challenges to future recruitment and population stability within a changing climate (Beckman et al. 2019). Moreover, current habitats that support wild populations may not be suitable in the future due to rapidly changing climate conditions (Hawkins et al. 2008). In this regard, species distribution modeling (SDM) can be used in the identification of sites appropriate for conservation (Vincent et al. 2019; Gaisberger et al. 2020). Predicting existing and future suitable habitats in different projected scenarios using SDM can provide valuable insights into the potential impacts of climate change on species and groups of species (Coetzee et al. 2009; Bladon et al. 2021; Sierra-Morales et al. 2021). According to the Conservation Gap Analysis of North American Oaks (Beckman et al. 2019), research related to SDM under variable climate change scenarios should be prioritized for the conservation of *Q. arkansana*. As the distribution of plant species is mostly linked to topographic factors and climatic fluctuations (e.g., Williams et al. 2009; Adhikari et al. 2012; Sousa-Silva et al. 2014; Syfert et al. 2014), it is crucial to evaluate the influence of these variables on *Q. arkansana* distribution and to identify the extent of range change under future climate scenarios. Utilizing

SDM by incorporating the effects of topographic and global climatic variables could effectively address the information gap regarding the extent of *Q. arkansana* distribution and conservation practices. In this study, there were two objectives: (1) evaluate the current *Q. arkansana* distribution and variables influencing it; and, (2) investigate how the range of this vulnerable species would vary under future climate change. The distribution of *Q. arkansana* is largely concentrated in the southeastern United States and we hypothesized that its distribution would decline with climate change.

Materials and methods

Occurrence data

Q. arkansana occurs from southwestern Georgia to eastern Texas and from southwestern Arkansas to the Florida Panhandle (Fig. 1). Occurrence records of *Q. arkansana* were acquired from current populations and historical collections, representing 741 records. Current populations were sampled in 89 locations (Fig. S1). Historical data were collected from multiple herbaria through the Southeast Regional Network of Collections (<https://sernecportal.org/portal/>), encompassing 130 herbarium records from 22 herbaria, and the Global Biodiversity Information Facility (GBIF.org 2022). Any duplicate, cultivated, and questionable records (hybrids or recordings outside their natural habitats) were removed from the historical data and geolocated using the geolocation tool (<https://www.geo-locate.org/web/default.html>).

Environmental data

A combination of bioclimatic and topographic variables was used to predict the current and future habitats for *Q. arkansana* of 16 states in the southeast United States (Arkansas, Oklahoma, Alabama, Florida, Georgia, Kentucky, Kansas, Louisiana, Missouri, Mississippi, North Carolina, Tennessee, Texas, South Carolina, Virginia, and West Virginia) (Fig. 1). Twenty-two environmental variables (19 bioclimatic and three topographic) variables were initially considered (Table S1; <https://www.worldclim.org/data/bioclim.html>). Three scenarios, SSP1-2.6, SSP2-4.5, and SSP5-8.5, were used to model suitable habitats for *Q. arkansana* considering low, medium, and high climate change scenarios. EC-Earth3 (Earth System Model)-Veg data for present-day (historical) and future emission scenarios were used, which are relevant for evaluating the impact of model resolution on future low to high projections.

Environmental variables were checked for multi-collinearity, and those with correlation coefficients > 0.7 and variance inflation factors (VIF) > 5 were excluded (Dormann et al. 2013; Table S2; Fig. S2). After removal, eleven

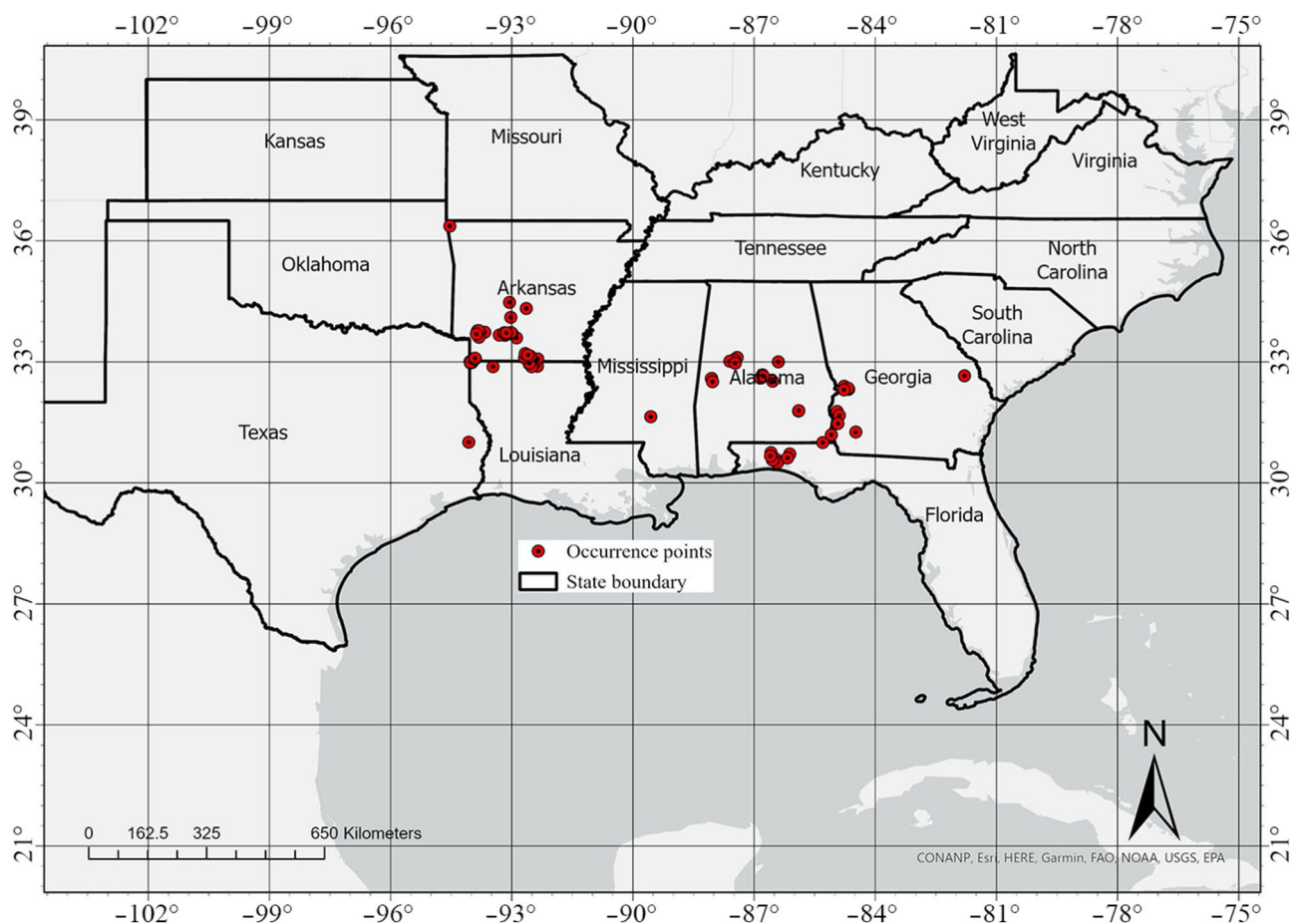


Fig. 1 *Quercus arkansana* (Arkansas oak) occurrence and modelling extent (southeastern United States)

Table 1 Percentage contribution by environmental variables in model prediction of suitable habitat

Variable code	Variable	Unit	Percentage contribution (%)
Bio10	Mean temperature of warmest quarter	°C	30.3
Bio9	Mean temperature of driest quarter	°C	23.3
Bio15	Precipitation seasonality	Unitless?	15.0
Bio18	Precipitation of warmest quarter	mm	13.0
Bio13	Precipitation of wettest month	mm	3.7
Bio3	Isothermality	unitless	3.5
Elevation	Elevation	meters	3.3
Bio2	Mean diurnal temperature range (mean of monthly (max temp—min temp)	°C	3.0
Slope	Slope	%	2.7
Bio8	Mean temperature of wettest quarter	°C	1.8
Aspect	Aspect	degree	1.0

variables remained for further analysis (Table 1). All variables were projected to WGS84 at a spatial resolution of 1 km². Bioclimatic data for the current (1970–2000) and future (2040–2060, 2060–2080, and 2080–2100) were downloaded from Worldclim Global Climate Data (<https://www.world>

[clim.org/](https://www.worldclim.org/)). For topographic data, elevation data were downloaded from the United States Geological Survey Digital Elevation Model (DEM) database, ~3 m resolution (<https://earthexplorer.usgs.gov/>). Slope and aspect data were then

calculated from the DEM in ArcGIS Pro software (esri.com).

Species distribution modelling

To perform SDM, a standard protocol was followed, ODMAP (overview, data, model, assessment, and prediction), which reflects the steps in building SDMs (Zurell et al. 2020). Among the various SDMs, Random Forest (RF) and (Maximum Entropy) MAXENT have been shown to be most effective for new population discovery of rare plant species based on only presence data (Williams et al. 2009). As recent SDM studies have successfully improved predictive accuracy by combining models generated from several algorithms (Hao et al. 2020; Adhikari et al. 2022, 2023; Subedi et al. 2023), rather than a single algorithm in SDM, an ensemble modeling approach was used to develop habitat suitability models, combining multiple SDM algorithms.

First, sampling bias and spatially autocorrelated occurrence data were addressed through spatial rarefaction or filtering (Kramer-Schadt et al. 2013; Boria et al. 2014; Aiello-Lammens et al. 2015). Because current only data in collections are typically biased as most records are samples of convenience and occur near roads with a lack of full representation of any systematic sampling (Graham et al. 2004). Thinning artificially reduces the number of occurrence points within a set distance to reduce the effects of spatial autocorrelations (i.e., one record retained for 1 km radial distance). Since thinning is a random process, 100 iterations will allow the creation of multiple datasets to find the maximum number of records that can be retained. After occurrence thinning, one dataset with the highest number of retained occurrences for modelling was randomly selected. As a result, 328 *Q. arkansana* present locations were retained with only one data point at each grid cell (1 km²), thereby reducing spatial autocorrelation, sample bias, and improving predictive performance of the SDMs.

The prediction accuracy of nine algorithms were checked: artificial neural network (ANN), classification tree analysis (CTA), flexible discriminant analysis (FDA), generalized additive model (GAM), generalized boosting model (GBM), generalized linear model (GLM), maximum entropy (MAXENT), random forest (RF), and surface range envelope (SRE). Only three SDMs were used to predict *Q. arkansana* distribution, including maximum entropy (MAXENT) and random forest (RF) suggested by Williams et al. (2009) for rare species, plus gradient boosting model (GBM) based on their predictive accuracy, true skill statistics (TSS) and area under curve (AUC) values of > 0.90.

Because absence data for the species was not recorded in original field surveys, randomly selected pseudo-absences were used in lieu of actual data. Pseudo-absences were generated by randomly assigning unoccupied grid cells within

a polygon containing the collective known distribution of *Q. arkansana* within the region based on field sampling, which used presence data and information about the background matrix where the species was absent. We randomly generated 10,000 background samples for model training.

Once SDMs were fitted with optimized parameters (TSS > 0.9), all were run three times using a randomly chosen 80% of the presence data, with the remaining 20% used to cross-validate model results. Altogether, 27 models were run, using three model algorithms (GBM, MAXENT, RF), three pseudo-absence selections, and three evaluation runs. Models were calibrated to generate habitat suitability maps. True Skill Statistics (TSS) were used (from −1 to +1) as a model evaluation criterion with models having a TSS value > 0.90 to build an ensemble model through a weighted mean approach (Marmion et al. 2009). The built-in BIOMOD2 function was used to compute the relative variable importance and response curve, which determines the role of predictor variables in explaining species distribution. BIOMOD2 uses a randomization procedure that measures the correlation between the predicted values and predictions where the variable under investigation is randomly permuted. If the contribution of a variable to the model is high, then the prediction is more affected by a permutation and therefore the correlation is lower (Thuiller et al. 2009; Kunwar et al. 2023). A low correlation score, i.e., randomized variable, has more influence on the prediction making and is considered important for the model in its prediction. In the variable importance output, the values given correspond to 0–1, the correlation score. High values will therefore reveal a high importance of the variable, whereas a value close to 0 will indicate little or no importance. To calculate the percentage contribution of each environmental variable in the model, the variable importance value was converted into a percentage (divided by a total, i.e., a sum of all the variable values in the model). All analyses were run in R v4.0.0 (R Development Core Team 2020) using the ‘biomod2’ package (Thuiller et al. 2020). Biomod2 is a species distribution modeling platform developed for multi-model ensemble modeling. By combining predictions from multiple models, ensemble SDMs account for the strengths and weaknesses of each modeling technique and produce more accurate and robust predictions. To calculate range shifts under different climate scenarios, the ‘range size’ function within the BIOMOD2 package was used.

Protected area calculations

A shapefile was downloaded for protected areas of the United States (PAD-US database), managed in part by the US Geological Survey and Gap Analysis Project (USGS 2022). Attribute information contained in the database for each protected area boundary include, but are not limited to,

agency names, protected area names, size of the protected area, and area manager type (USGS 2022). Prior to calculating the area of suitable habitat within protected boundaries, predicted habitat suitability raster images were reclassified to suitable habitat (> 80% suitability), as present (value = 1), and as not suitable (< 80% suitability) as “NODATA”. Using the zonal statistics as table tool in ArcGIS Pro v3.0.2, the area of predicted suitable habitat within protected areas was calculated for all states under the three climatic scenarios for 2050, 2070, and 2090. Zone type setting was set to manager type of the protected area. When calculating total area of suitable habitat that is protected, only state and federally managed lands were considered due to uncertainty of management practices by other organizations.

Results

Contribution of environmental variables in the model.

Mean temperature of the warmest quarter (bio10, 30.3%), mean temperature of the driest quarter (bio9, 23.3%), seasonal precipitation (bio15, 15%), and precipitation of the warmest quarter (bio18, 13%) contributed the most to the

model (Table 1). Topographic factors (elevation, aspect, and slope) contributed < 7% to the model, relatively low (Fig. 2, Table 1). Temperature-related variables contributed ~ 60% (Table 1). The mean temperature of warmest quarter (bio10) contributed the highest, with habitat suitability peaking at 25–27 °C (Fig. 2). Similarly, increasing the mean temperature of the driest quarter increased habitat suitability. Precipitation-related variables (bio13, 15, 18) contributed ~ 30% to the model (Table 1). Both precipitation of the warmest quarter (bio 15, 13%) and seasonal precipitation (bio 15, 15%) were important for the distribution of *Q. arkansana*. Areas with high precipitation (~ 250 mm) during the warmest quarter and low seasonal precipitation were highly suitable for *Q. arkansana* (Fig. 2).

Current suitable habitat

The predicted habitat for *Q. arkansana* is over 127,000 km² (Fig. 3). Currently, 12,147 km² or approximately 9.5% is within state and federally managed protected areas (Table 2). Among the 16 states included in this study, the model predicted that only seven states (Texas, Arkansas, Alabama, Louisiana, Mississippi, and Florida) currently have suitable

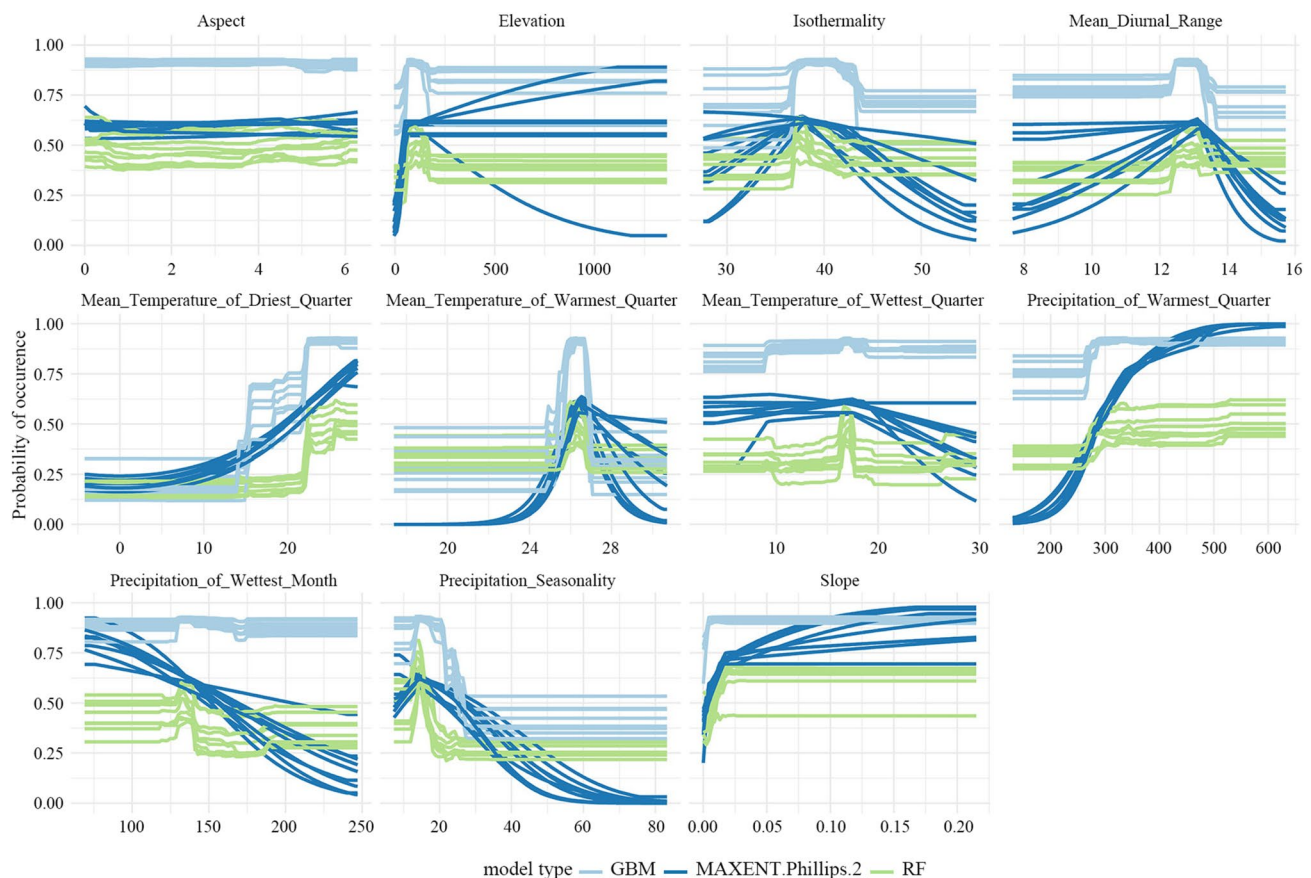


Fig. 2 Response curves for environmental variables for the three models, GBM (light blue), MAXENT (dark blue), and RF (green)

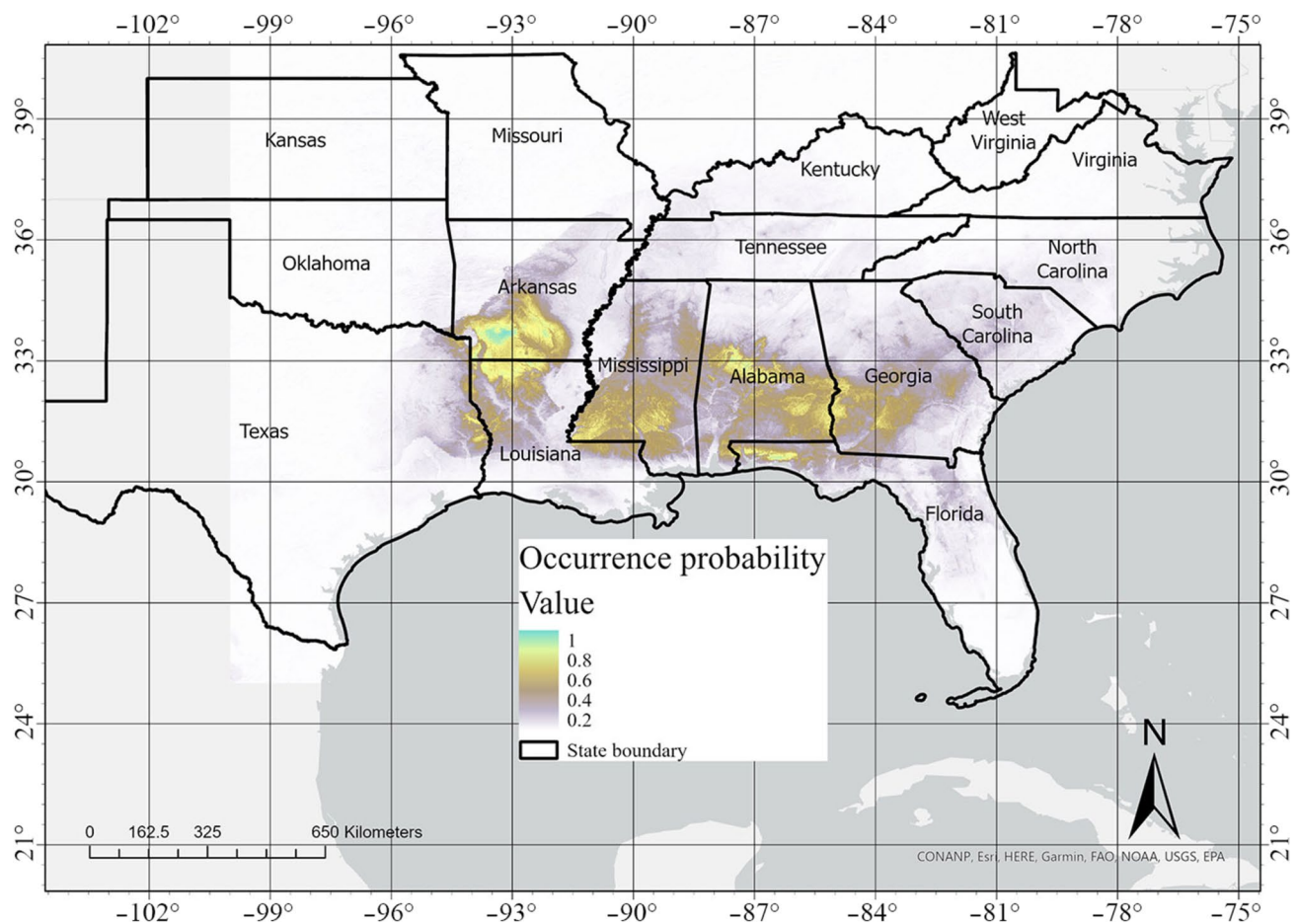


Fig. 3 Predicted current occurrence probability distribution of *Q. arkansana* across 16 states with blue-green areas representing a high occurrence probability and white representing low probability

Table 2 Projected suitable habitat for *Q. arkansana* under future climate change scenarios; protected habitat only includes state and federally managed land

Year	Scenario	Suitable Habitat (km ²)	Protected Habitat (km ²)	% of suitable habitat inside protected habitat
2050	SSP1-2.6	82,222	16,330	20
	SSP2-4.5	53,170	5,869	11
	SSP5-8.5	45,700	8,649	19
2070	SSP1-2.6	70,890	15,544	22
	SSP2-4.5	74,850	17,077	23
	SSP5-8.5	15,790	10,087	64
2090	SSP1-2.6	87,148	17,762	20
	SSP2-4.5	21,982	9,226	42
	SSP5-8.5	299	139	46

habitats for *Q. arkansana*. Among these states, the largest suitable habitats was predicted in Arkansas (34,490 km²) followed by Alabama (31,571 km²), Mississippi (22,768 km²), Louisiana (17,194 km²), Georgia (13,828 km²), Florida

(4,663 km²), and Texas (3,367 km²) (Fig. 3). States with the highest suitable areas within the current protected areas are Mississippi (3,040 km²), Alabama (2,209 km²), Florida (2,171 km²), Arkansas (1,248 km²), Texas (1,256 km²), Georgia (1,016 km²), Louisiana (914 km²), and Oklahoma (293 km²) (Table S1).

Future suitable habitat

By 2050, the model predicts a reduction of suitable habitat from 82,222 km² to 45,700 km² (Table 2), a loss of 35.7% to 64.3% under low to high climate scenarios (Figs. 4 and 6). By 2050, it is predicted that 20%, 11% and 19% of suitable habitat will be within protected areas under SSP 1–2.6, 2–4.5 and 5–8.5 respectively (Table 2). Similarly, the model predicted a suitable habitat area of 70,890 to 15,790 km², a loss of 41.5% to 87.7% in current habitat under low to high climate scenarios by 2070 (Table 2; Fig. 4, 5 and 6). By 2070, 22%, 23% and 64% of suitable habitat will be 0 in protected zones under SSP 1–2.6, 2–4.5 and 5–8.5, respectively (Table 2, S2). By 2090, a suitable

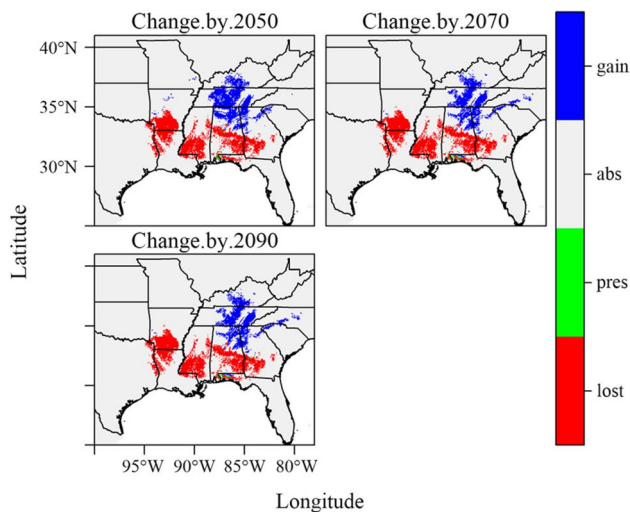


Fig. 4 Projected habitat changes for *Q. arkansana* by 2050, 2070, and 2090 under the SSP1-2.6 climate scenario

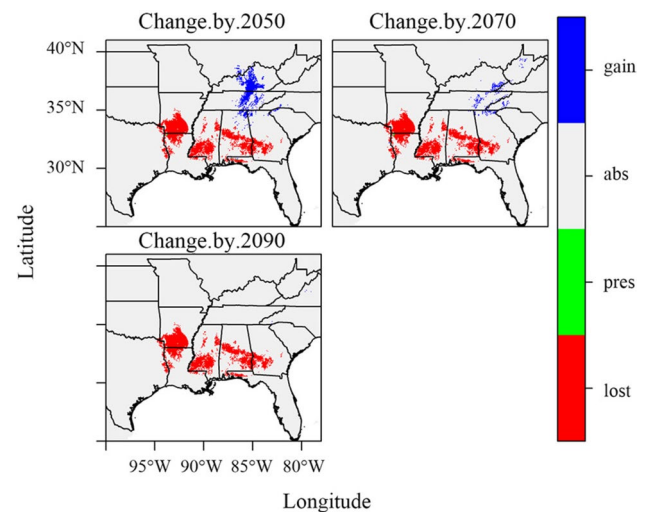


Fig. 6 Projected habitat changes for *Q. arkansana* by 2050, 2070, and 2090 under the SSP5-8.5 climate scenario

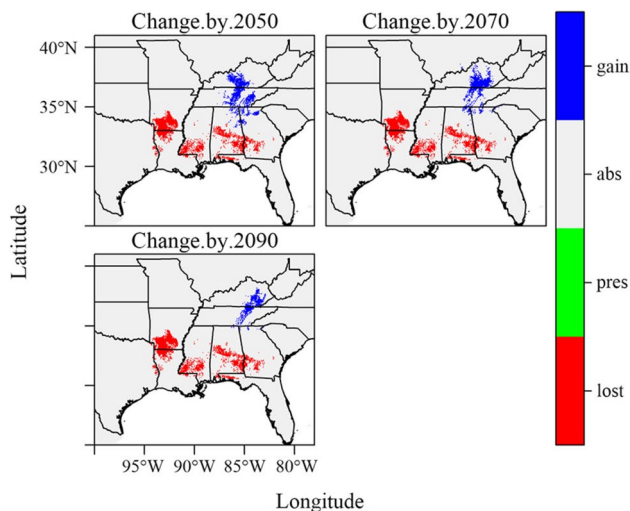


Fig. 5 Projected habitat changes for *Q. arkansana* by 2050, 2070, and 2090 under the SSP2-4.5 climate scenario

habitat area of 87,148 to 299,000 km² is predicted with 31.9 to 99.8% loss of current suitable habitat under the SSP 1–2.6–5–8.5 climate scenarios (Table 2; Figs. 4, 5 and 6). These habitats are mainly in Tennessee, Kentucky, and northern Georgia (Figs. 4, 5 and 6). By 2090, 20%, 42% and 46% of suitable habitat will be in protected zones under SSP 1–2.6, 2–4.5 and 5–8.5, respectively (Tables 2, S2). Under the SSP1-2.6 scenario for 2050, the lowest net loss of 35.7% in suitable habitat is predicted, whereas the highest net loss is under the SSP5-8.5 scenario for 2090, with a net loss of 100% (Table 2; Figs. 4, 5, 6 and 7). More importantly, we predict that current suitable habitats of *Q. arkansana* will be substantially lost under future climate

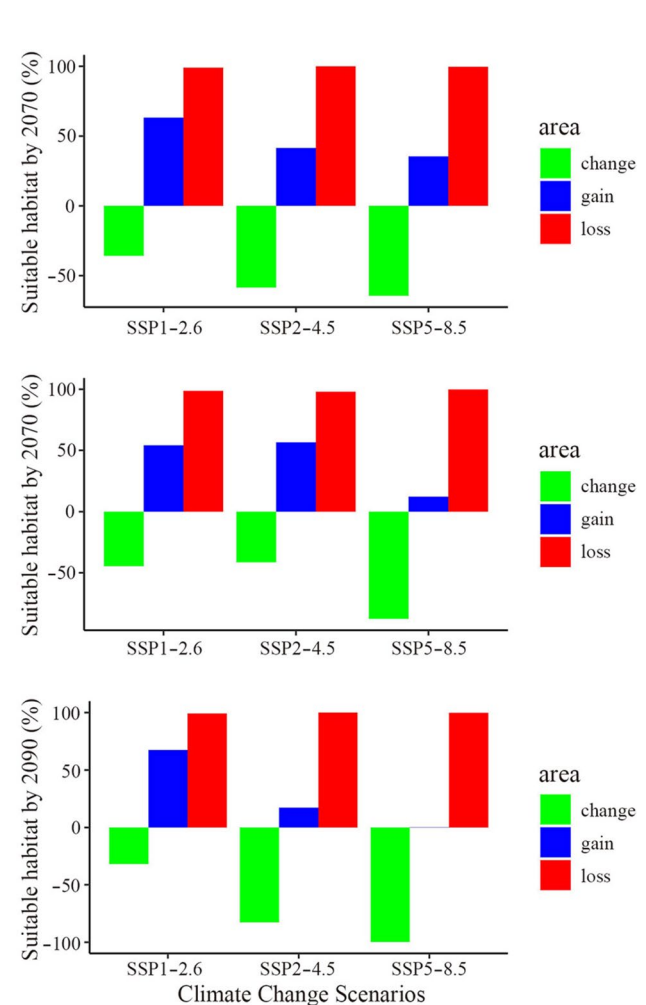


Fig. 7 Projected habitat changes for *Q. arkansana* under three climate change scenarios by 2050, 2070, and 2090

scenarios (very low to very high) by 2050, 2070, and 2090 (Fig. 7).

Discussion

The SDM approach provides a realistic picture of the potential distribution of *Q. arkansana* within its native range in the southeastern U.S. that can be used to guide conservation strategies for this endemic and vulnerable species. Our results highlight suitable habitat across seven states, including both current known observations as well as additional areas where the species potentially exists. Among the bioclimatic and topographic factors used in the model, distribution of *Q. arkansana* was influenced primarily by four temperature and precipitation related variables with approximately 90% contribution to habitat prediction. The inclusion of these four variables in combination effectively described the most favorable climatic and topographic environment for this species. Under climate change scenarios, by 2050, 2070, and 2090, all current suitable habitats for *Q. arkansana* are predicted to shift northward into new areas, mainly in Tennessee and Kentucky.

Mean temperature of the growing season (typically June to August), was the most influential variable describing the distribution of *Q. arkansana*, which may limit its local survival and long-term population persistence. The response curves generated from our model suggested that *Q. arkansana* may require a mean temperature between 24–28 °C (Fig. 2) during the growing season. This requirement might be related to the long-term sustainability of populations, as it is restricted to the southern edges of southeastern states and extending along the coastal plain of the Gulf of Mexico. On the other hand, during this quarter, it may need large amounts of rainfall (> 300 mm). Precipitation deficit during the wettest month might prevent fruit from maturing over the 18 months required for the species (Löf et al. 2019). In addition, a certain minimum amount of precipitation and warm temperatures during early spring are also required to satisfy multiple regeneration-centric phases, including the completion of winter seed dormancy requirements, initiation of both vegetative bud development and flower bud differentiation (Johnson et al. 2019). The topography of some of the habitats of *Q. arkansana* from southwestern Arkansas is diverse, consisting of low hills and sharp ridges dissected by deep ravines on the slopes to sandy barrens, and dry to mesic woodlands (Palmer 1925; Ogle et al. 2020). The ability of *Q. arkansana* to maintain colonies on such diverse sites might represent evidence of present relics of a former wider distribution that have managed to persist in these more favorable diverse areas.

Our estimation of suitable areas mainly occurs on the Gulf Coastal Plain in southern Arkansas, as well as in scattered

locations in South Georgia, northwest Florida, northwest Louisiana, and eastern Texas. The model also predicted the existence of suitable habitat in Mississippi, which was expected, although it has yet to be documented in the state (NatureServe 2022). However, there are numerous historic occurrences from the 1900s along the Gulf Coastal Plain which very well may be still in existence, but unconfirmed without surveys. Although it was predicted for the species to occupy a larger ecological niche, they are mostly fragmented and isolated. More commonly, they are often distributed in local, discontinuous patches in Alabama, Arkansas, Georgia, Florida, and Texas. Due to the patchiness of this species, *Q. arkansana* has been poorly recorded and may be more widespread than is currently understood. It may be present in unknown habitats within its native range, and may be overlooked or mistaken for the common blackjack oak (e.g., *Q. marilandica* Muenchh.) due to its cryptic nature (see Beckman et al. 2019). Surveys in the species western range have located populations in Texas (Hunt et al. 1995) and it may be present in other locations based on our predictions in this study that have not been surveyed. It is recognized that SDM only predicts the species climatic niche (climatically suitable habitats) (Pearman et al. 2008), rather than its actual niche; other biotic factors (e.g., competition among species), geographical barriers, and natural and anthropogenic disturbances may influence the species distribution in predicted suitable habitats.

According to our predictions of suitable habitat, only 9.5% is currently incorporated within protected areas. The southeast is one of the most rapidly urbanizing areas of the United States (Alig et al. 2004), and the U.S. Census Bureau (2020) reports that the number of people there has grown quickly over the past few decades. Currently, the southeast experiences high levels of landcover disturbance and change, primarily due to timber harvest, agriculture, disease, and urbanization (Homer et al. 2015). Urbanization in this region is predicted to increase by 63% to 71% from 2001 to 2051 (Lawler et al. 2014). As such, with urbanization comes the loss of forest habitat due to deforestation (Drummond and Loveland 2010), and the increasing use of forestry practices (Lawler et al. 2014). Increased urbanization will result in the loss of suitable habitat for *Q. arkansana*. Further, urbanization is expected to increase by 2051 in close proximity to protected areas such as national parks and forests, resulting in an estimated 30% decline in plant cover, thus most likely increasing the fragmentation of suitable habitats under future climate scenarios (Martinuzzi et al. 2015; Subedi et al. 2022).

The predicted estimates of suitable habitat support the hypothesis that climate change will shift *Q. arkansana* distribution to the more northerly states of Tennessee and Kentucky. This indicates a positive response of *Q. arkansana* to the projection of increased temperatures and rainfall in

North America. Current *Q. arkansana* distribution occurs in warmer and moist areas in southeastern states as well as in coastal areas (Jerome et al. 2017b; Beckman et al. 2019; NatureServe 2022). Models projected that the effects of climate change would effectively shift the species by increased temperature and rainfall in places where *Q. arkansana* currently does not occur. Because it currently is found in warm, moist areas, suitable habitat for *Q. arkansana* is expected to expand into more northern and north-eastern parts of the country with increases in temperature and moisture. Our model predicted a significant contraction in habitat suitability for this oak species under medium and high climate scenarios for 2050, 2070, and 2090. Current habitats will become unsuitable and current unsuitable areas will show higher climatic suitability. Overall, all future climatic scenarios showed a significant contraction of suitable habitats across all scenarios and time periods. Under an extreme future climate change scenario (SSP5-8.5), the climatically suitable habitat for *Q. arkansana* was predicted to be zero by 2090.

Plant species may respond to climate change by expanding their habitats, being restricted to refugia, or disappearing (Iverson and McKenzie 2013). Species with a wide ecological niche can benefit from future climatic conditions and may likely expand their range. However, species with limited geographical distribution, sensitivity to exposure to new environments such as drought, and low adaptive capacity will become more threatened (Westoby and Burgman 2006). Our model projected that *Q. arkansana* populations would shift significantly northward. At present, *Q. arkansana* is represented by a number of restricted populations, vulnerable to extinction by extreme environments due to climate change (Kluza et al. 2007; Kliejunas 2010). Moreover, considering the need for several weeks of a moist and cold environment for seed germination in red oak group species, prevailing conditions may not support such broad migration of all localized populations (Bonner 1987; Löf et al. 2019).

Conclusions

Our results indicate that *Q. arkansana* will face a considerable decrease in habitat suitability over the next 30 years. With a predicted loss of nearly 100% of current habitat by 2050, even under a low climate change scenario, a complete loss of suitable habitat is predicted by 2090 under the highest greenhouse gas emission scenario. *Q. arkansana* will experience extreme vulnerability due to climate change. The large geographic shifts projected under very low to extreme climate change scenarios constitute a major threat for *Q. arkansana* survival. Our analysis contributes to the prediction of future distribution of *Q. arkansana*, a species of conservation concern, and can be utilized as a valuable

management and conservation planning tool for this threatened species.

Q. arkansana is already critically imperiled in Arkansas, imperiled in Georgia, and Louisiana, and vulnerable in Arkansas, Alabama, and Florida (NatureServe 2022). The large extent of suitable habitat outside of protected areas suggests that a species-specific action plan incorporating protected areas and other areas is crucial for its sustainable conservation. To reduce *Q. arkansana* extinction risk due to climate change, one option would be to identify current and future suitable habitats, and to establish new, viable populations. Similarly, this species may be present in numerous unknown habitats; more surveys in suitable areas are warranted. Moreover, protection of *Q. arkansana* habitat against climate change requires locally and regionally focused sustainable conservation policies, adaptive management strategies, and educational outreach among local populations. One important aspect of the conservation of rare species is to enhance the genetic diversity of the remaining populations, and conserve plants in situ and ex situ. Similarly, public education is urgently needed because most suitable habitats, including current populations, are within non-protected areas.

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