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RESEARCH ARTICLE

Ensemble modelling of dominant tree communities for smart afforestation planning in China

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Abstract
Context Southern and central China harbor some of the most diverse and ecologically significant forest ecosystems in China, making them priority regions for biodiversity conservation and afforestation planning. Within this broader context, the Qinling Mountains serve as a representative case study, as they are recognized as a global biodiversity hotspot and one of China's most important temperate broad-leaved forest regions. Understanding the spatial distribution of dominant tree communities in this area is essential for biodiversity conservation and ecosystem management in the face of increasing anthropogenic pressures and climate change.
Objectives This study aimed to (1) identify the potential distribution and richness patterns of dominant tree communities in the Qinling Mountains and adjacent regions, and (2) assess their vegetation associations and key environmental drivers to inform afforestation and conservation planning; and (3) Explore the potential species richness and endemicity to identify the most suitable areas for afforestation of target communities or group of the dominant tree communities.
Methods We applied ensemble stacked species distribution models (S-SDMs) using ecological niche modeling to predict the potential distribution of target dominant tree communities across China, capturing diverse ecological regions including the Qinling region. Key environmental variables included climatic, edaphic, and anthropogenic factors. Vegetation associations were explored using non-metric multidimensional scaling (NMDS) analysis based on environmental gradients and field data collected from the Qinling Mountains and surrounding areas.
Results The S-SDMs showed high predictive performance (AUC > 0.8, TSS > 0.5). Key predictors of species distribution included mean diurnal temperature range (Bio2), human influence, precipitation

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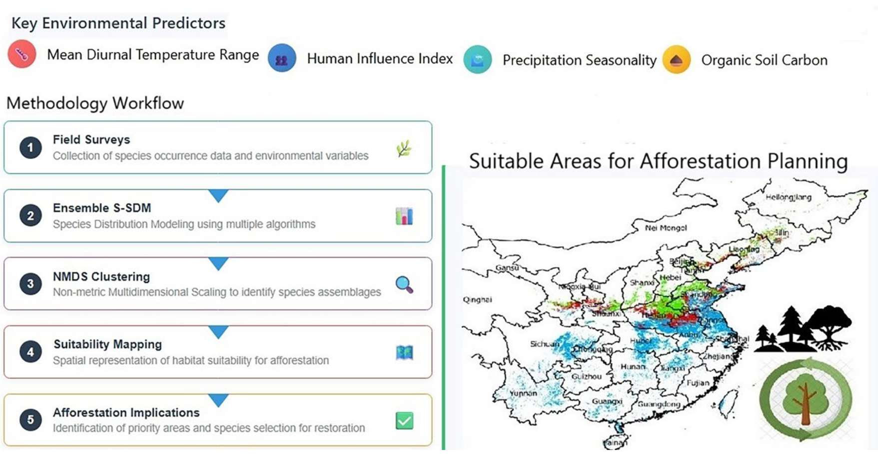
seasonality (Bio15), and organic soil carbon. Richness and endemicity hotspots were concentrated in southeast and south-central China, particularly in Hainan and Taiwan Islands. NMDS analysis revealed three distinct tree associations structured along environmental gradients, notably human disturbance, precipitation, and soil characteristics. Spatial prioritization highlighted provinces such as Henan, Anhui, Shandong, and Jiangsu as key areas for afforestation by dominant tree communities.

Conclusions The findings along with the developed interactive map offer valuable insights for landscape-scale biodiversity conservation, afforestation efforts, and ecosystem restoration, supporting the achievement of global Sustainable Development Goals (SDGs). Incorporating climate change modeling into future analyses will be critical to ensuring the long-term resilience and success of restoration initiatives.

Graphical abstract



Keywords Qinling Mountains · S-SDMs · Machine learning · Restoration planning · Agricultural landscape

Introduction

Forests cover about 31% of the Earth's surface and play a vital role in carbon sequestration, climate regulation, water cycle stability, and biodiversity conservation (MEA 2005; Ellison et al. 2017; FAO 2020). They also support rural livelihoods through timber, non-timber products, and essential ecosystem services. Afforestation efforts i.e., establishing forests in historically non-forested lands such as croplands or degraded shrublands (FAO 2020) can help expand carbon sinks beyond existing forested regions. Global assessments suggest up to 0.9 billion hectares are suitable for such carbon-focused afforestation (Bastin et al. 2019). In China, afforestation is a key national strategy to expand forest cover, enhance carbon sinks and restore degraded or marginal lands, especially in southern and eastern regions (Liu et al. 2008). Therefore, China has implemented several large-scale afforestation initiatives, such as the Three-North Shelterbelt Forest Program, *a.k.a.* the 'Great Green Wall', the Natural Forest Conservation Program, and the 'Grain for Green Project'. These programs have notably increased forest cover and enhance ecological benefits (Wei et al. 2024). Other examples of the initiatives of China's national strategy to enhance carbon sequestration and restore degraded lands, particularly in southern and eastern regions is the ‘Grain-for-Green Program’ (Deng et al. 2014; Chen et al. 2019). These programs demonstrated 35% increases in carbon sequestration from converted croplands (Lu et al. 2018). However, large-scale afforestation still faces challenges in selecting climate-resilient species communities that can sustain biodiversity and ecosystem functions under future climate scenarios (Hua et al. 2018; Zastrow 2019).

Recent studies have advanced understanding of afforestation potential and climate-smart forestry, particularly in China. For example, Song et al. (2024) mapped future afforestation distribution under national policy and climate constraints using downscaled climate data and the Holdridge life zone model, while Bi et al. (2024) simulated afforestation potential in Yunnan under multiple development scenarios using a multi-indicator PLUS model. Xu et al. (2024) and Xu (2025) focused on site-level climate-smart tree species selection and ecological niche modeling to ensure plantations are resilient to future climate conditions, and Wang et al. (2024a, b, c, d) proposed AI-enabled forestry solutions to enhance monitoring and carbon sequestration. In addition, Cai et al. (2024) provided the first national-scale assessment of forest fragmentation and restoration trends, highlighting pressures from agriculture and urbanization. Despite recent advances, practical community-level modeling frameworks to guide species assemblage planning remain limited.

Afforestation initiatives not only contribute to the conservation of valuable forests unique ecosystems, but also ensure the continued provisioning of vital services that benefit both local communities and the global environment (Zhao et al. 2014; You et al. 2024). Identifying suitable regions for new forest establishment involves assessing areas with high potential for ecological restoration and biodiversity conservation. A study focusing on optimizing protected areas in China identified 26 priority regions that, if designated as protected areas, could enhance the conservation of key species and ecosystems (Mi et al. 2023). Hence, it is crucial to identify potential areas suitable for establishing forests like those of the Qinling Mountains.

The Qinling Mountains in China are recognized as a significant global biodiversity hotspot, characterized by diverse natural forest ecoregions, including temperate conifer forests and broadleaf and mixed forests (Tang et al. 2006; Chai and Wang 2016; Zhang et al. 2017a, b). This unique combination of ecoregions creates a mosaic of habitats supporting endemic species such as the Qinling panda (*Ailuropoda melanoleuca qinlingensis*) and the golden snub-nosed monkey (*Rhinopithecus roxellana*), alongside numerous other plant and animal species (Zhao et al. 2014). The region is home to over 2600 plant species and 300 animal species, making it one of the key areas of global biodiversity (Zhang et al. 2010). Their dense canopy and undergrowth contribute to water conservation by maintaining the hydrological cycle, ensuring clean water supply to millions of people downstream (Zhou et al. 2020). Furthermore, the Qinling Mountains act as a natural barrier, regulating climate between northern and southern China, which is essential for agricultural stability and food security (Zhang et al. 2010). The ecological services provided by the Qinling forests extend beyond environmental benefits (Zhiyuan et al. 2003). They are integral to soil conservation, reducing landslide risks and enhancing soil fertility, which supports sustainable agriculture in surrounding areas (Biao et al. 2010; Wang et al. 2024a, b, c, d). The forests’ biodiversity and scenic landscapes also contribute to ecotourism, generating significant economic revenue and fostering environmental awareness (Zhang et al. 2019). A study estimated the total economic value of terrestrial ecosystem services in the Qinba Mountains, which include the Qinling range, to be approximately 968.33 billion renminbi per year (Li et al. 2006). The Qinling Mountains exemplify the importance of forest ecoregions in maintaining environmental and ecological balance (Zhiyuan et al. 2003; Zhao et al. 2014, 2016; Mori 2017; Zhang et al. 2017a, b; Zhang et al. 2019).

Conserving these areas through the creation of new protected areas will contribute to both enhancing ecological services provisioning and biodiversity conservation. Expanding such protected areas within the newly formed forests through afforestation efforts can contribute to climate adaptation and mitigate the adverse impacts of deforestation and land degradation (Zhang et al. 2017a, b). Additionally, these efforts will promote sustainability and notably contribute to achieving Sustainable Development Goals (SDGs) particularly SDG1(Zero Hunger), SDG113 (Climate Action), and SDG115 (Life on Land).

Building on previous foundation, our study introduces a new community-level approach by integrating an ensemble stacked species distribution model (S-SDM) with non-metric multidimensional scaling (NMDS). Species Distribution Models (SDMs) have traditionally relied on climatic variables to predict species distributions (Guisan et al. 2017). However, incorporating a broader range of predictors such as soil properties, land cover, and human influence can enhance the models' accuracy and ecological relevance. This comprehensive approach provides a better understanding of the factors influencing species distributions and ecosystem structures (Mod et al. 2016; Dakhil et al. 2021a, b).

To identify habitat suitability for multispecies, stacked species distribution models (S-SDMs) can be employed (Bedair et al. 2023). The non-metric multidimensional scaling (NMDS) is an ordination technique that facilitates the recognition and interpretation of patterns and differences among plant communities (Wu et al. 2022). Guided by previous work that demonstrates the value and efficacy of S-SDMs for predicting diversity patterns (Del Toro et al. 2012; Bedair et al. 2023), which supports our use of this method to project shifts in species assemblages; and the feasibility of integrating SDMs with NMDS for climate-smart community classification (e.g., Xu et al. 2024). We hypothesize that integration of stacked species distribution models (S-SDMs) with Non-Metric Multidimensional Scaling (NMDS) can provide information on the suitability of agricultural land use for afforestation efforts of dominant tree communities. The integration of the outcomes from S-SDMs with NMDS provides comprehensive insights into the suitability of habitats for various species assemblages, facilitating the identification of areas that can support diverse biological communities (Zellmer et al. 2019). The outcome of these models can help inform afforestation initiatives (e.g., Zellmer et al. 2019; Zwiener and Alves 2023). This approach is particularly effective when woody multispecies dominate the communities, as they reflect the structure and function of forest ecosystems (Gaston et al. 2013).

This framework goes beyond single-species suitability or broad forest potential by identifying dominant tree species communities that reflect likely co-occurrence patterns under current and future climates. This is critical for designing afforestation projects that establish functionally coherent, resilient communities instead of isolated monocultures. By providing spatially explicit guidance on suitable species assemblages, our study offers actionable insights for transforming marginal agricultural landscapes, enhancing biodiversity and ecosystem services, and delivering a practical, scalable tool for climate-smart afforestation planning and implementation. Therefore, we sought to (1) Identify the most important environmental and human factors explaining the potential distribution of target dominant tree communities; (2) Identify the main dominant tree associations based on soil, climate, and human influence; and (3) Explore the potential species richness and endemicity to identify the most suitable areas for afforestation of target communities or group of the dominant tree communities.

Methods

Study area and field sampling

We conducted field work in which 625 sampling plots with size of 20 × 20 m were surveyed in the temperate broad-leaved forests in the global biodiversity hotspot "Qinling Mountains. The detection of the dominant tree communities was determined using NMDS ordination technique based on the number of individuals (> 1000 individual/plots). We obtained 26,173 occurrence records from the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/), the Chinese Virtual Herbarium (CVH, http://www.cvh.ac.cn), and the National Specimen Information Infrastructure (NSII, http://www.nsii.org.cn/2017/home.php). We verified the taxonomic status and synonyms to get the accepted names of 20 target species (Table S1, Supplementary Material) according to Catalogue of Life (https://www.catalogueoflife.org/). Then, we removed the duplicates, erased points located outside the border of China and cleaned the data using the package "CoordinateCleaner" (Zizka et al. 2019) in R 4.4.1.

Environmental and anthropogenic predictors

For identification of the target dominant tree association data collected from the Qinling Mountains and surrounding region served as the illustrative case for of broader afforestation policy relevance; however the study's actual modeling extent covers China's whole low-forest-cover and agricultural transition zones. For application of ensemble stacked species distribution models (S-SDMs) to predict the potential distribution of target dominant tree communities across China, key environmental variables were utilized in addition to climatic factors, including edaphic, and anthropogenic factors. We obtained the merit digital elevation model (MERIT-DEM) from the Japan Agency for Marine-Earth Science and Technology (http://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_DEM/) (Yamazaki et al. 2017) which has better accuracy than the SRTM DEM in ecological modelling (Moudrý et al. 2018). We used the 19 bioclimatic predictors representing the current climate WorldClim v2.1 (Fick and Hijmans 2017) downloaded from https://www.worldclim.org/data/ at a gain size of 30 arc-seconds. Also, aridity index (AI) is identified as the ratio of annual precipitation to annual potential evapotranspiration. The AI and potential evapotranspiration data were acquired from the Global Aridity Index and Potential Evapotranspiration (ET0) Climate Database v3 (Zomer et al. 2022).

The edaphic factors were exemplified by ten variables downloaded from the ISRIC-World Soil Information database (Hengle et al. 2017) at a spatial resolution of 30 arc seconds. We downloaded the soil nitrogen and phosphorus data from (http://globalchange.bnu.edu.cn/; Shangguan et al 2013). Human influence data were downloaded from the NASA Socioeconomic Data and Applications Center (SEDAC) at 1 km^2 spatial resolution (Kennedy et al. 2020). This database comprises 13 anthropogenic stress indicators encompassing agriculture and infrastructure. Finally, all the environmental and human influence variables were resampled into resolution ~ 2 km^2 using the terra package in R 4.4.1. To avoid model overfitting, we checked for multicollinearity and assessed the variance inflation factor (VIF) that estimates how greatly each variable can explain the remaining of the variables (Naimi and Araújo 2016). To carry out the VIF analysis, we used the package "usdm" (Naimi 2015) in R 4.4.1., and then we removed the variables with VIF values > 5 and a correlation threshold of 0.75 (Guisan et al. 2017).

Species distribution modeling

We applied ensemble modelling of two common algorithms: generalized linear model (GLM) and random forest (RF) to compute the habitat suitability maps from species presence data and ecological-human predictors using the SSDM-stacked species distribution model package (Schmitt et al. 2017). The conversion from habitat suitability to a binary format of presence or absence was executed using the threshold that optimized the True Skill Statistics (TSS; Allouche et al. 2006). The TSS is defined as the sum of sensitivity and specificity, subtracted by one, where sensitivity and specificity represent the ratios of correctly predicted presences and absences, respectively. The model's fit was evaluated using the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) plot and the kappa statistic (Allouche et al. 2006). Each of the two algorithms was applied three times on current-day variables, and the resulting six models were consolidated into an ensemble Ecological Niche Model (ENM) using the ensemble_modelling function from the 'SSDM' package (Schmitt et al. 2017). The model's cross-validation was conducted by dividing the occurrence data set into a training set (comprising 70% of the records) and an evaluation set (the remaining 30%).

NMDS ordination and detection of tree species associations

To identify the similar or associated groups of the dominant tree communities in the study area, we applied the non-metric multidimensional scaling (NMDS) analysis using the function metaMDS in Vegan R package (Oksanen et al. 2013) in R 4.4.1. The stressplot function was used to create a Shepard diagram, which is a plot of the observed dissimilarities against the NMDS distances and used to assess the NMDS goodness of fit (Clarke 1993).

Spatial prioritization and land cover adjustment

To visualize the suitability classes of the model's outputs, we reclassified all the predicted output maps of the species richness and endemicity in ArcGIS Pro 3.3.0. The suitability maps were then modified or adjusted using the global land cover's mosaic vegetation classes of the global land cover map (Tuanmu and Jetz 2014). This was done to remove unsuitable areas like urban regions and bodies of water.

Finally, based on the output of NMDS output, we merged the binary maps of species of each tree group and produced a mosaic map of the three main tree group in ArcGIS Pro 3.3.0, representing the dominant communities. The produced map was then adjusted to the global cropland cover map (Potapov et al. 2022) to identify agricultural landscapes which could be helpful tool for afforestation planning.

Results

Ensemble model accuracy and relative importance of the predictor variables

We observed 20 tree taxa representing the dominant tree communities, with > 1000 individuals, which accounted for 80% of the total individuals. The cleaning of the distribution datasets resulted in 5,117 occurrence records (Fig. 1). The multi-collinearity test resulted in 16 predictor variables with VIF < 5 (Table 1). Overall, the ensemble models showed good performance in predicting the potential distribution of dominant communities with AUC > 0.8 and TSS > 0.5 (Table 1). The most important predictor variables with a high value of relative importance explaining the potential distribution of dominant tree communities in China are Bio2 (15.5%), human influence (15.3%), Bio15 (7.5%), Bio18 (6.4%), PET (6.1%), and soil organic carbon content (6.1%).

Potential richness and endemicity

The potential richness maps of the dominant communities showed that southeast and south-central China are the most suitable areas supporting the presence of the target forest vegetation, particularly in provinces

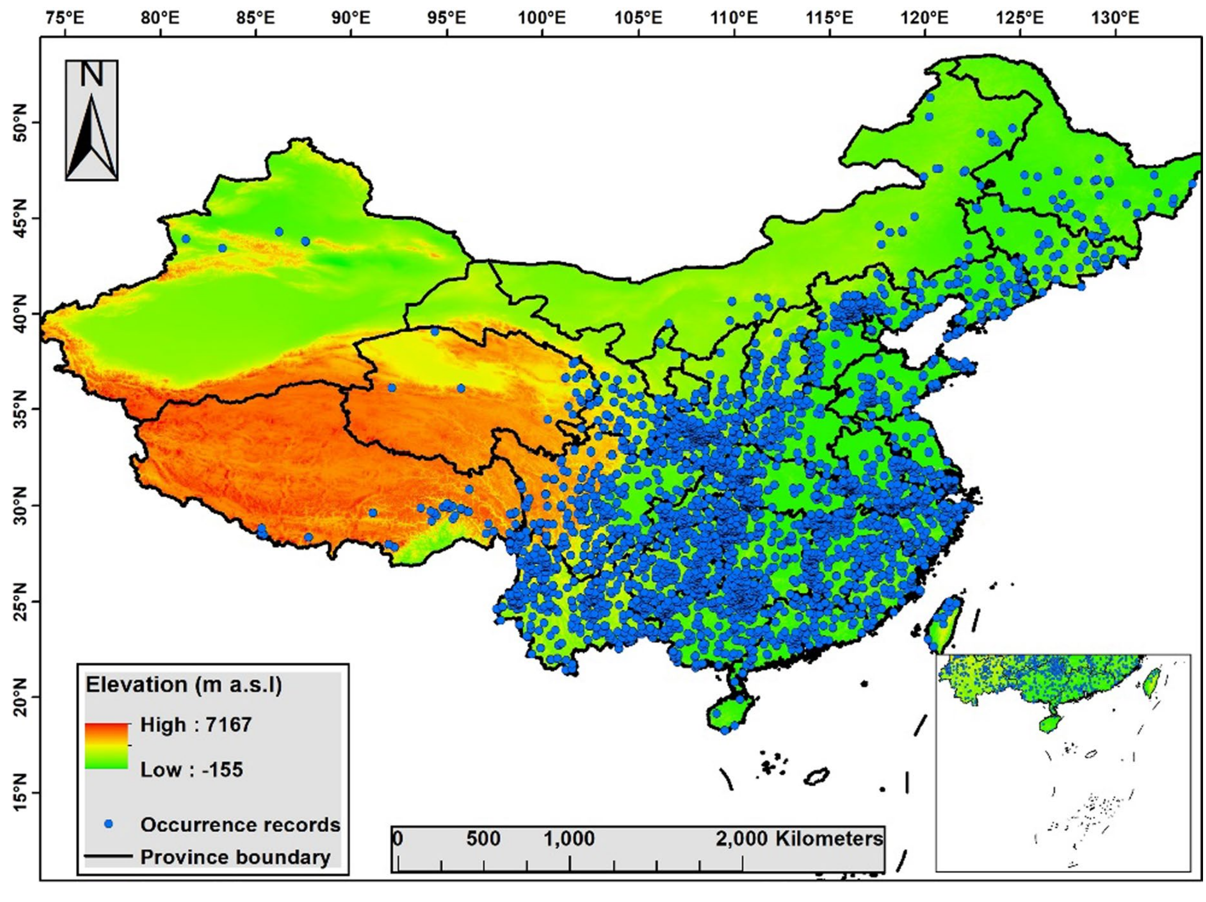


Fig. 1 National distribution of the occurrence points of target species on the elevation map of China

Table 1 The relative importance of the selected predictor variables explaining potential distribution of dominant species

Variable	Code	Description	Unit	Relative Importance	VIF
Climate	ai	Aridity index	–	4.3	2.31
	pet	Potential evapotranspiration	mm/year	**6.1**	3.50
	bio2	Mean diurnal range	°C	**15.3**	3.64
	bio3	Isothermality	%	4.7	2.69
	bio8	Mean temperatures of the wettest quarter	°C	4.0	2.79
	bio15	Precipitation seasonality	%	**7.5**	2.29
	bio18	Precipitation of the warmest quarter	mm	**6.4**	2.63
Soil	aN	Available nitrogen	mg/kg	4.8	1.56
	aP	Available phosphorus	mg/kg	3.9	1.33
	carbon	**Organic carbon content**	g/kg	**6.1**	2.33
	clay	Soil texture fraction clay in percent	%	5.3	4.50
	coarse	Coarse sand fragments volumetric in percent	%	5.3	2.29
	sand	Soil texture fraction sand in percent	%	3.5	4.42
	silt	Soil texture fraction silt in percent	%	4.9	3.98
	pH	Soil pH $\times$ 10 in H_2O	–	4.4	1.78
Human Influence	**human**	Human Modification System (influence index)	–	**13.5**	1.70
	Threshold and model accuracy metrics				
	GLM	**RF**		**Mean**	
AUC	0.79	0.83		0.81	
Sensitivity	0.72	0.75		0.73	
Specificity	0.72	0.74		0.73	
Kappa	0.42	0.48		0.4	
TSS	0.51	0.62		0.56	
Threshold	0.34	0.76		0.55	

The most important variables and their values are in bold

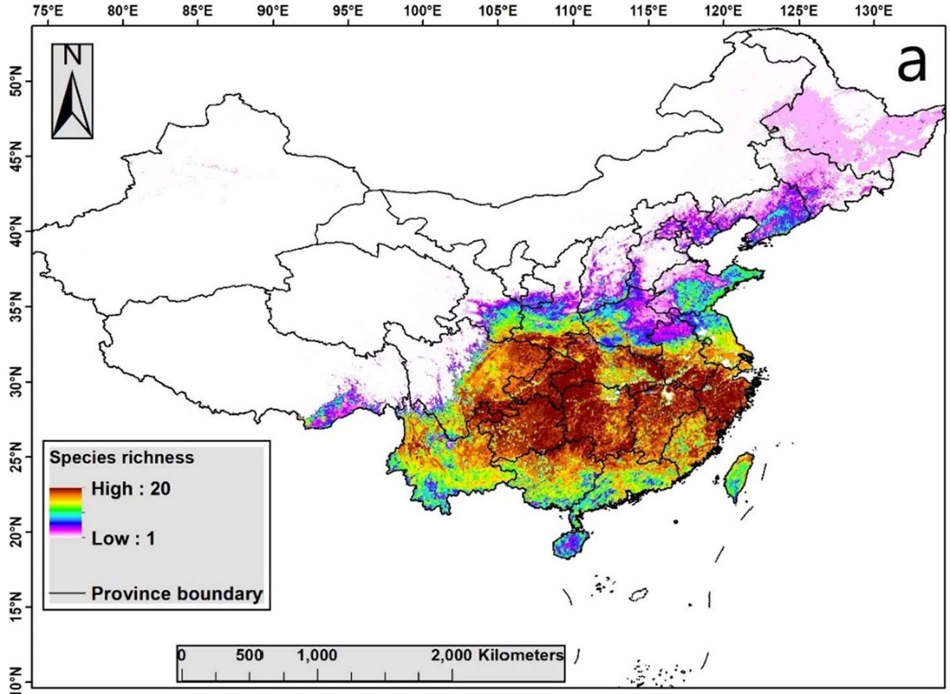
VIF Variance inflation factor (VIF), *TSS* True skill statistic, *AUC* Area under the curve, *MTS* Maximum training sensitivity plus, specificity threshold

Chongqing, East Sichuan, Guizhou, the south parts of Henan and of Shaanxi, Hubei, Hunan, Jiangxi, Anhui, and Zhejiang (Fig. 2a and b). The northeast parts of China showed less suitability for the richness of these dominant communities particularly in Liaoning, Jilin, and Heilongjiang. Moreover, the lower parts of the south China including the Hainan and Taiwan Islands showed high suitability for 10 species of the total dominant communities (Fig. 2a and b). However, these south parts showed suitability for 10 species, it showed high suitability for most endemic species or endemism (Fig. 2 c) which could be assumed as refugia for most of these dominant communities.

Tree species associations and potential agricultural landscapes for afforestation

The NMDS showed three main associations of dominant tree species influenced by the environmental factors as well as human impact. Association 1 of the dominant tree species (*Corylus chinensis*, *Sorbus folgneri*, *Castanea mollissima*, *Quercus ali*, *Platycarya strobilacea*, and *Diospyros lotus*) showed negative associate with the human influence, bio15 (precipitation seasonality), bio2 (mean diurnal range), and soil pH (means increase in soil pH (towards alkaline) decrease the potential presence of dominant species in association 1 (Fig. 3a).

Association 2 of the dominant tree species, comprising *Pinus armandii*, *Elaeagnus henryi*, *Elaeagnus lanceolata*, *Philadelphus incanus*, and *Euonymus*



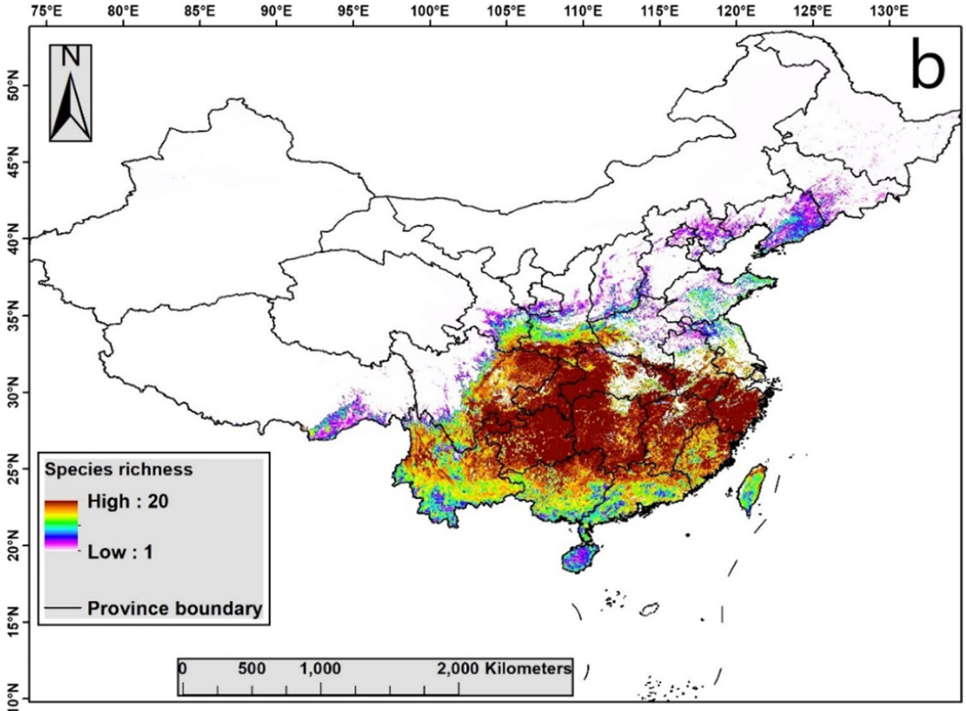


Fig. 2 Potential species richness of the dominant 20 tree species: **a** Unadjusted richness (not constrained by land cover); **b** adjusted richness (constrained by land cover); **c** potential endemicity map

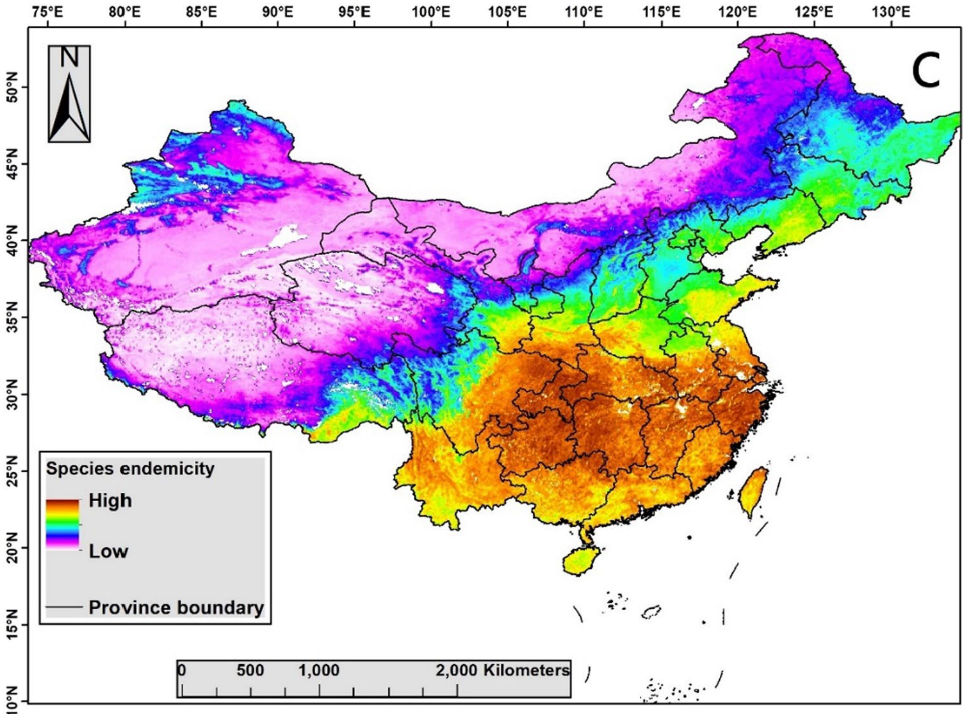


Fig. 2 (continued)

alatus, showed positive correlation with the aridity index (means increase in aridity index (towards humid) increase the potential presence of these dominant tree species (i.e., increase in humidity makes the environment suitable for the presence or growth of these dominant tree species of association 2 (Fig. 3a)). Also, association 2 showed a positive correlation with the precipitation of the warmest quarter (bio18) (Fig. 3a). Finally, the association 3 of the dominant tree species of *Pinus tabuliformis*, *Sunhangia elegans*, *Symplocos paniculata*, and *Carpinus turczaninovii*; showed positive correlation with soil clay fraction (Fig. 3a). In Fig. (3b), the non-metric fit value ($R^2=0.99$) and the linear fit value ($R^2=0.97$) are both close to 1 and this indicates that the NMDS ordination effectively maintains the original distances. The combined suitable maps for the three main tree species associations showed in Fig. (4), and the interactive map, supplementary information, revealed that the most suitable agricultural landscapes for all three tree species associations are in provinces: Henan, Anhui, Shandong, and Jiangsu (Fig. 4). These four provinces could be assumed as potential regions to support the afforestation and hence conversion of cropland to forest which provide more ecosystem services particularly carbon storage and enhance the achievement of SDG sustainable development goals. The tree association 3 showed the highest area of 125,000 km^2 compared to association 1 or 2, both < 50,000 km^2 each (Fig. 4, bar-chart).

Discussion

This study aimed to identify potential habitat zones and agricultural landscapes for afforestation based on modelling the distribution of the dominant tree communities in temperate broad-leaved forests in China. Through an integrated approach involving field surveys that focused on the Qinling Mountains- a global biodiversity hotspot- and the surrounding region, species distribution modeling, and tree species association, the results provide valuable insights for forest ecosystem restoration, and agricultural sustainable land use planning.

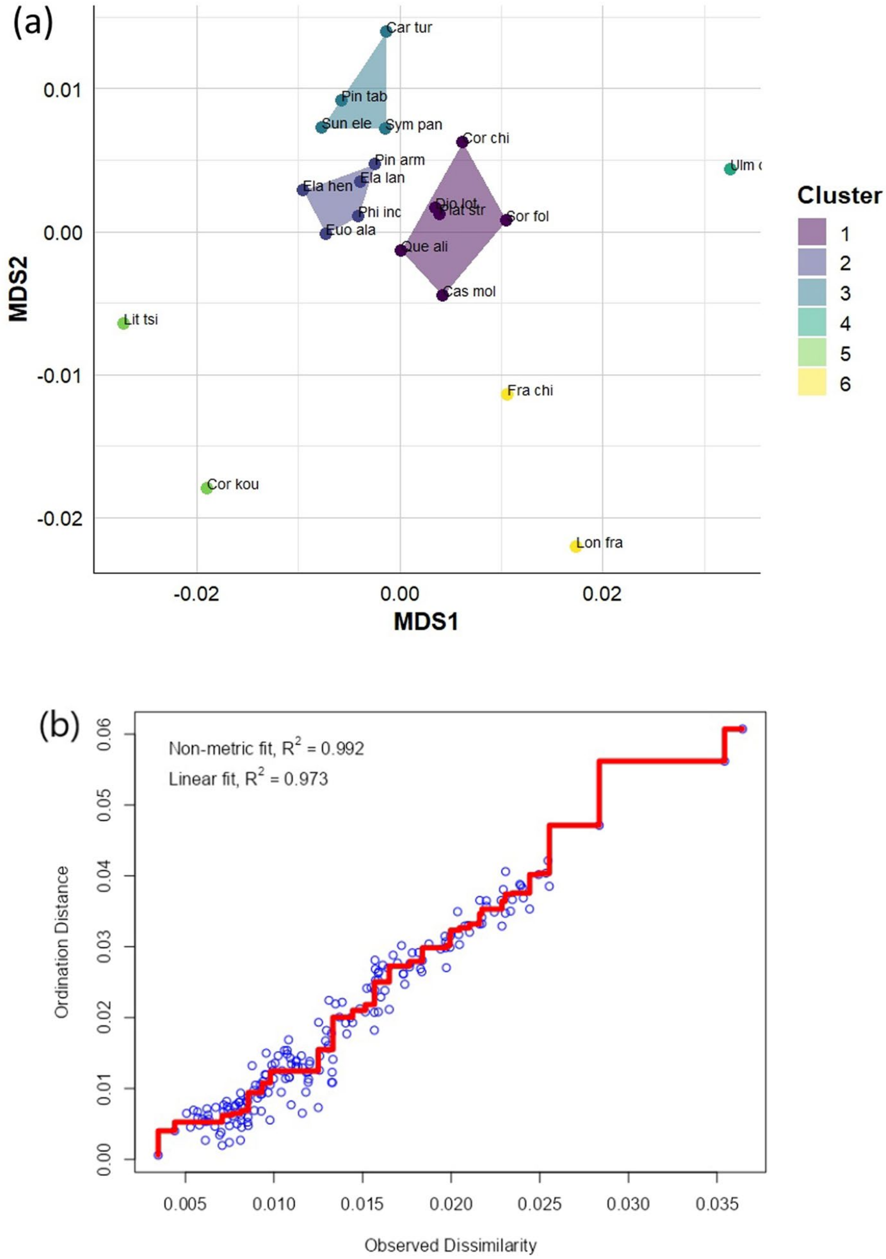


Fig. 3 Ordination for the dominant tree species using non-metric multidimensional scaling revealing: **a** the association of the tree species in relation to soil, climate, and human influence. **b** Shepard diagram showing the observed dissimilarities against the NMDS distances

Model accuracy and predictor variables

The ensemble models demonstrated high performance in predicting suitability of habitat for dominant tree associations. These metrics confirm the reliability of the ensemble modeling framework in estimating the potential distribution of tree taxa (Engler et al. 2013; Kocev and Džeroski 2013). The AUC value shows good discriminatory power, and the Kappa reflects fair agreement between predicted and observed values (Liu et al. 2011; Pottier et al. 2013; Duan et al. 2014). These metrics indicate that the model is robust and reliable for ecological applications, particularly in understanding the spatial distribution of tree taxa under varying environmental conditions.

The dominant trees' potential distribution is primarily influenced by variability of the mean diurnal range, precipitation seasonality, and precipitation

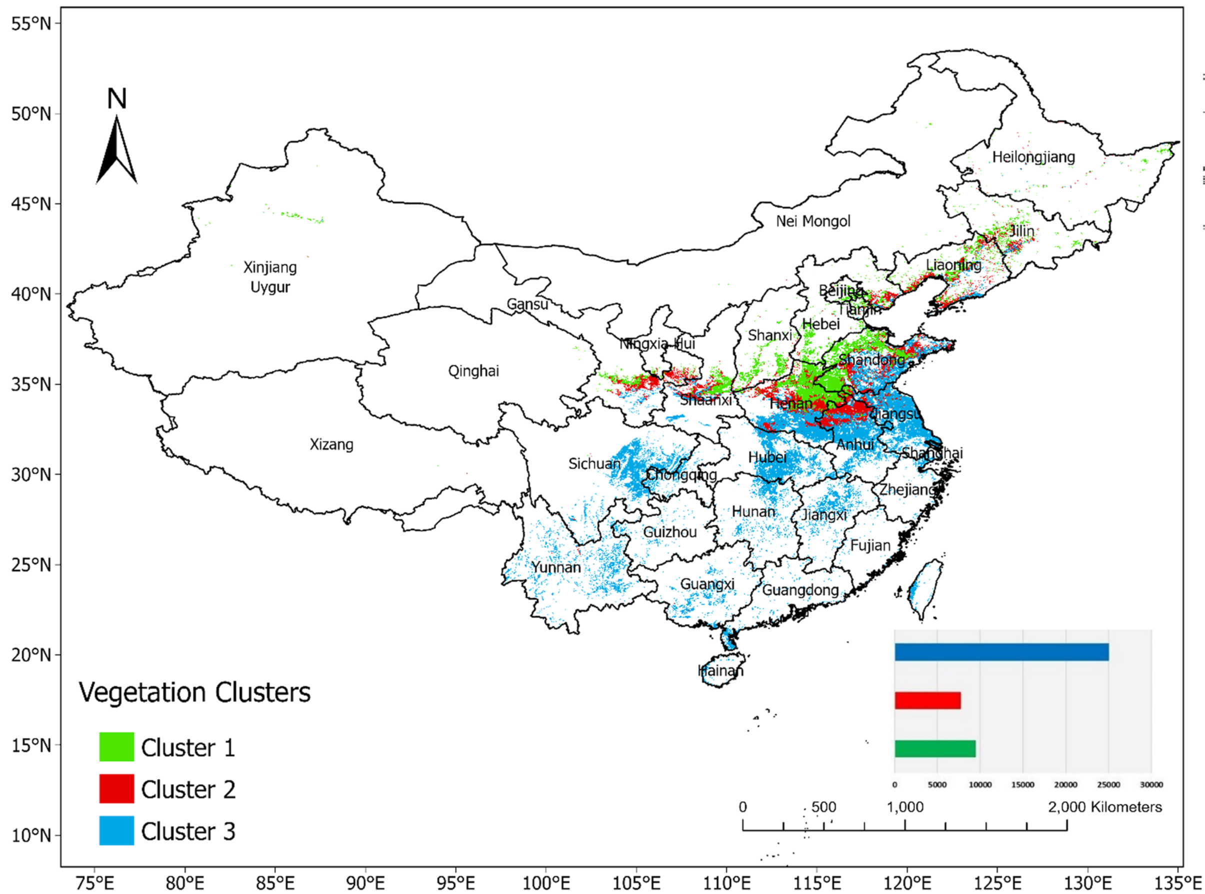


Fig. 4 Adjusted Suitability maps to agricultural landscapes (~5 km^2 spatial resolution) of the three main dominant tree species associations based on NMDS output. For more details on the dominant species of each association, see Fig. 3a. Barchart showing the area (* 5 km.^{2}) of suitable habitat zones for the dominant tree communities cluster 1: *Corylus chinensis*, *Sorbus folgneri*, *Castanea mollissima*, *Que ali*, Platycarya strobilacea, and Diospyros lotus; cluster community 2: *Pinus armandii*, *Elaeagnus henryi*, *Elaeagnus lanceolata*, *Philadelphus incanus*, and *Euonymus alatus*; cluster community 3: *Pinus tabuliformis*, *Sunhangia elegans*, *Symplocos paniculata*, and *Carpinus turczaninovii*)

of the warmest quarter, as well as human modifications. The prominence of the temperature mean diurnal range underscores the sensitivity of tree species to fluctuations in daily temperature, which might influence physiological processes such as photosynthesis and respiration (Gallou et al. 2023). Studies have found an inverse relation between the mean diurnal range and the probability of plant species occurrence (e.g., Ngarega et al. 2022; Yang et al. 2023a, b; Gallou et al. 2023; Dakhil et al. 2024). Similarly, the high relative importance of human influence reflects the pervasive impact of land-use changes, urbanization, and other human activities on natural ecosystems in the area. The inclusion of human influence as a key predictor highlights the necessity of addressing anthropogenic stressors when formulating afforestation strategies. Precipitation seasonality and warmest quarter precipitation likely influence water availability during critical growth periods (El-Barougy et al. 2023; Dakhil et al. 2024). Studies revealed the contribution of human activities and climate change as dominant factors in influencing vegetation pattern in China particularly for endemic tree species (e.g., Zhu et al. 2021; Guo et al. 2022; Xu et al. 2023). The contribution of precipitation seasonality and warmest quarter precipitation to the distribution of mountain tree species in China has been reported by other investigation (e.g., Dakhil et al. 2021a, b, 2024; Yang et al. 2023a, b). Soil variables play a secondary but noteworthy role particularly soil organic carbon, clay and silt. The contribution of soil organic carbon content in predicting the tree species distribution reflects the role of nutrient availability and soil health, both of which are vital for tree establishment and growth of the tree species in the area. These results underscore the strong influence of climatic variability, human activity, and soil quality on the distribution of tree species in the study region.

The ensemble model's ability to integrate multiple predictor variables and accurately predict species distributions provides valuable insights for conservation planning and ecosystem management (Meller et al. 2014). By identifying the key drivers of tree community distributions, this study offers a foundation for targeted conservation efforts, particularly in regions facing rapid environmental change due to climate variability and human activities.

Richness and endemicity patterns

The potential richness maps produced reveal distinct spatial patterns in the suitability of different regions in China for supporting dominant tree communities. Southeastern and south-central China, including provinces such as Chongqing, Sichuan, Guizhou, Henan, Shaanxi, Hubei, Hunan, Jiangxi, Anhui, and Zhejiang, emerged as the most suitable areas for these communities. This aligns with the known ecological characteristics of these regions, which are characterized by favorable climatic conditions, such as moderate temperatures, ample precipitation, and diverse topography, creating ideal habitats for a wide range of tree species (e.g., Liu et al. 2014; Guo et al. 2017). These findings are consistent with previous studies that have identified southern China as a biodiversity hotspot due to its complex geography and climate, which support high levels of species richness and endemism (López-Pujol et al. 2011; Zhao et al. 2016; Mi et al. 2021; Yang et al. 2021).

In contrast, northeastern provinces such as Liaoning, Jilin, and Heilongjiang showed lower suitability for dominant tree communities. This is likely due to the colder climate and shorter growing seasons, which limit the establishment and growth of many tree species (Liu et al. 2022; Xiaojie et al. 2022). However, these regions still support unique forest ecosystems adapted to cold conditions, such as larch plantations that are highly resistant to low temperatures (Luo et al. 2020; Mahardika et al. 2023).

The southernmost parts of China, including Hainan and Taiwan Islands, also showed high suitability for several dominant and endemic tree species. Their tropical and subtropical climates provide favorable conditions for species that thrive in warm and humid environments, suggesting these regions may serve as important refugia for biodiversity (Huang et al. 2011; Zhu et al. 2021; Xiaojie et al. 2022; Wang et al. 2024a, b, c, d). Identifying such potential refugia is critical for conservation, especially under climate change, as these areas can provide stable habitats for species persistence despite shifting conditions elsewhere.

Overall, these spatial patterns highlight the need for targeted conservation strategies to safeguard biodiversity in high-suitability regions and to enhance the resilience of marginal habitats.

Tree species associations and afforestation potential

The NMDS ordination revealed three distinct tree species associations shaped by climate, soil, and human influence. The NMDS plot shows clear differentiation based on environmental drivers, with soil texture, pH, and human impact appearing as significant factors. These results offer valuable insights into the ecological preferences of dominant tree communities and their potential for afforestation in agricultural landscapes.

Association 1 negative correlations with human influence, precipitation seasonality, mean diurnal temperature range, and alkaline soil pH; suggests that the species in this association thrive in areas with minimal human disturbance, stable precipitation, and acidic soils. Acidic conditions can enhance nutrient availability and support specific soil microbial communities that benefit plant health (Wang et al. 2019; Coughlin et al. 2021; Xiong et al. 2024). A preference for stable precipitation patterns indicates vulnerability to seasonal droughts or waterlogging, while a narrow diurnal temperature range suggests sensitivity to large temperature fluctuations, which can affect plant physiology (Chen et al. 2020; Yang et al. 2023a, b; Gallou et al. 2023; Xian et al. 2024). The ecological requirements of this group highlight the importance of conservation strategies that minimize human impact and maintain suitable soil conditions.

Association 2 positive correlation with humid conditions and precipitation in the warmest quarter indicates that the species in this association are well adapted to regions with high moisture availability, especially during warm seasons when evapotranspiration is high (Wei et al. 2010; Zhang et al. 2017a, b; Chi et al. 2017; Qi et al. 2022). These traits make them suitable candidates for afforestation in areas with similar climatic conditions.

Association 3 positive correlation with clay-rich soils, may be due to the higher water retention and nutrient-holding capacity that this soils tend to have, supporting species adapted to these conditions (Osman and Osman 2013; Kang et al. 2017; Yang et al. 2023a, b). This indicates that Association 3 species could be prioritized in afforestation projects targeting regions with clay-rich soils.

The Qinling Mountains served as a reference for model validation and ecological representation. However, model projections highlight that southern and eastern China, including Henan, Anhui, Shandong, and Jiangsu, should be prioritized, as they contain extensive degraded or marginal lands targeted for afforestation under national strategies (Chen et al. 2019). These provinces, dominated by agricultural landscapes, hold great potential for conversion to forests, which would deliver ecosystem services such as carbon sequestration, biodiversity conservation, and soil restoration (Bing et al. 2011; Hu et al. 2014; Huang et al. 2023; You et al. 2024; Wang et al. 2024a, b, c, d; Ju et al. 2025).

Identifying these provinces as afforestation hotspots underscores the importance of integrating ecological data into land-use planning. By aligning species-specific requirements with local environmental conditions, afforestation initiatives can maximize ecological and socio-economic benefits. The outcomes of this study can help guide afforestation strategies aimed at enhancing carbon storage, supporting biodiversity, and contributing to Sustainable Development Goals, particularly SDG 13 (Climate Action) and SDG 15 (Life on Land).

While the results provide a useful foundation for conservation and afforestation planning, several limitations should be noted. The reliance on available occurrence and environmental data may not fully capture local microhabitat variability, species interactions, or future land-use changes. Furthermore, projections under climate change scenarios were not explicitly evaluated in this study, which constrains the ability to assess temporal shifts in species distributions.

Future research should assess the socio-economic feasibility of large-scale afforestation in these areas and monitor long-term project outcomes to adapt management strategies as needed.

Conclusion

This study provides insights into the potential distribution, richness, and dominant tree species associations in China using ensemble species distribution models and NMDS vegetation ordination. The ensemble models showed good predictive performance, supporting the reliability of the findings; however, the results should be interpreted with caution given the inherent uncertainties in modeling approaches. The NMDS analysis, based on data from the Qinling Mountains, a temperate broad-leaved forest and recognized biodiversity hotspot, highlighted three distinct dominant tree species associations structured by environmental gradients such as precipitation, soil properties, and human influence. Ecological niche modeling further identified temperature mean diurnal range, precipitation seasonality, soil organic carbon, and human influence as important predictors shaping these distribution patterns. Spatial patterns of richness and endemicity suggested that southeast and south-central China are particularly suitable for sustaining diverse and endemic tree associations, with southern provinces emerging as priority areas. Additionally, provinces such as Henan, Anhui, Shandong, and Jiangsu were indicated as potential agricultural landscapes where afforestation could be explored, though this finding requires further field validation. Future research should therefore integrate dynamic climate projections, land-use change scenarios, and biotic interactions to refine predictions and ensure adaptive management strategies. Such efforts would strengthen the application of this work in conservation planning and ecosystem restoration, supporting sustainable land management and contributing to broader environmental goals such as biodiversity conservation and climate change mitigation.

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Data availability Data will be made available on request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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