Predicting the potential distribution of pine wilt disease in China under climate change

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Abstract

Pine wilt disease (PWD) cause by pine wood nematodes (PWN, Bursaphelenchus xylophilus) is an epidemic forest disease that seriously threatens the world's forest resources and human ecological environment. Predicting the potential geographical distribution of PWD in China under climate change and studying the impact of climate change on the distribution of PWD using the MaxEnt model can provide a basis for high - efficiency quarantine, supervision, and timely prevention and control. In our study, the ENMeval data package was used to optimize the parameter setting of the MaxEnt model based on 647 geographical distribution locations of PWD and seven climate factors, the potential distribution areas of PWD under current and future climate conditions (2050s, 2070s) were simulated and predicted, and the dominant environmental factors affecting the geographical distribution of PWD were analyzed. The results showed that the value of AICc of the Akaike information criterion was 0, and the prediction accuracy was good when the feature combination (FC) was LQHPT and the regularization multiplier (RM) was 0.5. The results showed that the main climate factors affecting the distribution of PWD were temperature (max temperature of warmest month (bio5), mean temperature of driest quarter (bio9), rainfall (coefficient of variation of precipitation seasonality (bio14) and precipitation of wettest quarter (bio16). The prediction results of the MaxEnt model showed that the area of the total suitable habitat and highly suitable habitat will expand significantly in 2050 and 2070, and the potential distribution of PWD will tend to spread to high latitude and altitude.

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Abstract. Pine wilt disease (PWD) cause by pine wood nematodes (PWN, *Bursaphelenchus xylophilus*) is an epidemic forest disease that seriously threatens the world's forest resources and human ecological environment. Predicting the potential geographical distribution of PWD in China under climate change and studying the impact of climate change on the distribution of PWD using the MaxEnt model can provide a basis for high - efficiency quarantine, supervision, and timely prevention and control. In our study, the ENMeval data package was used to optimize the parameter setting of the MaxEnt model based on 647 geographical distribution locations of PWD and seven climate factors, the potential distribution areas of PWD under current and future climate conditions (2050s, 2070s) were simulated and predicted, and the dominant environmental factors affecting the geographical distribution of PWD were analyzed. The results showed that the value of AICc of the Akaike information criterion was 0, and the prediction accuracy was

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Key words : Pine wilt disease, potential geographical distribution, climate change, MaxEnt model, climate factors

INTRODUCTION

Climate is one of the decisive factors affecting species distribution (Willis & Bhagwat, 2009). In recent years, the process of urbanization has accelerated, and the natural ecological environment is facing rapid fragmentation (Qi et al. , 2014). In the fifth assessment report (AR5), the United Nations Intergovernmental Panel on climate change stated that the global climate will continue to warm, and the average temperature of the earth will increase by 0.3 to 4.5 by the end of the 21st century (Li et al. , 2019). The seasonal variation of potential evapotranspiration and other climate variables will also change with climate warming (Stocker et al. , 2013). The change in ecological environments will directly affect the geographical distribution pattern of species and the structure, function, and stability of the ecosystem (Dieleman et al. , 2015).

Predicting the distribution of suitable habitats under climate change has become a major research endeavor (Fitzpatrick et al. , 2008; Li et al. , 2013). There are many models for species' potential distribution prediction, such as climate change experiment(CLIMEX), genetic algorithm for rule - set production(GARP), ecological niche factor analysis (ENFA) and maximum entropy species prediction model (MaxEnt) (Sutherst & Maywald, 1985). MaxEnt has the highest accuracy (Padalia et al. , 2014). MaxEnt is a niche species distribution prediction method that simulates the distribution probability of species based on actual distribution points of species combined with ecological variables in the target distribution area (Phillips & Dudík, 2008). Its advantage is that the accuracy of its results is high even if the species distribution data are incomplete (Elith et al. , 2011). It has been widely used in potential planting area prediction, invasive plant distribution area prediction, quarantine pest prediction, and so on (Kroschel et al. , 2013; Qin et al. , 2015; Sanchez et al. , 2010). Recent studies have found that when the MaxEnt model is used to simulate the potential distribution area of a species, it offers high complexity and is not conducive to model transfer. After the parameters of the MaxEnt model are adjusted by ENMeval packet, it can better predict potential suitable areas of species (Yan et al. , 2021).

Pine wood nematode (PWN, *Bursaphelenchus xylophilu*) causes pine wilt disease (PWD), a worldwide plant disease (Mamiya, 1983). So far, PWD has occurred in at least eight countries: Canada, Mexico, and the United States in North America; China, Japan, and South Korea in Asia; and Portugal and Spain in Europe. In Asia, PWD is causing great damage to the ecological environment and may cause major ecological disasters in the future (Abelleira et al. , 2011). Since PWD was first reported in Nanjing in 1982 (Liu et al. , 2021), more provinces have reported PWD, such as Jiangsu, Anhui, Guangdong, and Zhejiang (Zhao et al. , 2009). If a tree is infected with PWD, it can die within a few months (Mamiya, 1983). PWD has caused billions of dollars in losses annually, severely threatening pine resources (Tan et al. , 2013). In the future climate, the geographical distribution pattern of pine PWD may change. Its potential distribution area and important environmental factors affecting its distribution should be urgently understood for the prevention and control of PWD.

Herein, the optimized MaxEnt model and ArcGIS V10.5 software were used to simulate and predict potential PWD distribution in China. In our study, we aimed to (1) determine the potential habitats of PWD, (2) identify the dominant climate factors affecting the geographical distribution of PWD, and (3) predict PWD's distribution shift in future climate scenarios to provide a basis for formulating quarantine measures and monitoring management and timely control of PWD.

2 MATERIALS AND METHODS

2.1 Occurrence data of PWD

Data on the epidemic areas of pine wilt disease were obtained from the National Forestry and Grassland Administration (*http://www.forestry.gov.cn/main/5461/20220114/221304653870544.html*). Duplicate data points and specimen details with unknown geographic coordinates were removed. For available records lacking coordinates, latitude and longitude information corresponding to the place names was obtained using Baidu tools (http://api.map.baidu.com/lbsapi/getpoint/index.html). A total of 646 points of PWD were selected and saved as a ".csv" file for later use (Fig. 1).

Fig. 1. Occurrence records of PWD in China.

2.2 Selection and comparison of climate variables

Table 1. 19 Bioclimatic variables in the study.

A total of 19 environmental variables for the current (1971–2000s) and future (2041–2060s, 2061–2080s) were downloaded from WorldClim (http://www.worldclim.org/) with a resolution of 2.5' (Table 1). Data of BCC - CSM2 - MR from Coupled Model Intercomparison Project phase 6 were selected for future climate data, including three scenarios in shared socioeconomic pathways: sustainable development SSP1-2.6, moderate development SSP2-4.5, and conventional development SSP5-8.5 (Riahi et al. , 2017). The multilinearity of the 19 environmental factor variables related to PWD can affect the accuracy of MaxEnt model prediction results, so Pearson correlation analysis was used to test the correlation of variables. First, 19 climate variables and 647 pine wood nematode distribution points were loaded into the MaxEnt model. The importance of 19 climate factors was determined using the knife-cutting method and ranked according to the contribution rate of the factors. Additionally, correlation analysis of 19 climate factors was conducted. If the correlation coefficient of two related variables is greater than 0.8, the lower contribution rate of the variables should be deleted to avoid the impact of multicollinearity on the model results (Zhang*et al.* , 2016). Finally, seven variables were obtained through screening: isothermality (bio2/bio7) (*100) (bio3), temperature seasonality of warmest month (bio4), max temperature of warmest month (bio5), mean temperature of driest quarter (bio9), coefficient of variation of precipitation seasonality (bio14), precipitation seasonality (bio15), and precipitation of wettest quarter (bio16). China's administrative division vector map was obtained from the national basic geographic information system (http://mail.nsdi.gov.cn).

2.3 Optimization of model parameters and model building

Because the MaxEnt model is sensitive to sampling deviation and prone to overfitting, directly running the default parameters of the MaxEnt model may lead to unreliable prediction results. Therefore, the regulation magnification (RM) and feature combination (FC) parameters of the MaxEnt model were adjusted using the ENMeval data package developed by R language (Phillips *et al.* , 2006). The values of RM were set to 0.5, 1, 1.5, 2, 2.5, 3, 3.5, and 4. There are five types of FC: linear (L), quadratic (Q), hinge (H), product (P), and threshold (T) and it was set as L, LQ, H, LQH, LQHP, and LQHPT 6 combinations. The minimum value of AICc was selected as the optimal setting and the final model was set (Muscarella et al. , 2014).

After 647 pine wood nematode distribution points were collected and imported into the MaxEnt model software, 75% of the samples were selected as the training subset, and the remaining 25% of the samples were used to verify the model. The maximum number of iterations was set to 10,000, and the operation was repeated 10 times for modeling. The contribution rate obtained by the MaxEnt model and knife-cutting test was used to evaluate the importance of environmental factors limiting the potential geographical distribution of PWD in China. The area under the receiver operating characteristic curve (AUC) was used to evaluate the accuracy of the model. The value of AUC was 0 - 1. The closer the AUC value is to 1, the more accurate the prediction result of the model is (Yan et al. , 2021). Documents containing the prediction results of PWD were reclassified using ArcGIS 10.5. Jenks natural breaks were used (Zhao et al. , 2021). The suitable area of PWD can be divided into four levels: highly suitable habitat (values ranging from 0.50 to 1.00), moderately suitable habitat (values ranging from 0.30 to 0.50), poorly suitable habitat (values ranging from 0.10 to

0.30), and unsuitable habitat (with values < 0.10). The area of each suitable area was counted. After 0.14 was set as the threshold, a suitable grade distribution map of PWD was transformed into binary format. Based on the binary map of PWD distribution under the current and future climate change scenarios, the COGravity function in the SDMTools package of R language was used to calculate the centroid position of the highly suitable area of PWD disease under current and future climate change, and the changes in the centroid in the highly suitable area of PWD under different climate scenarios were compared.

2.4 Analysis of multivariate environmental similarity surface

We used the multivariate environmental similarity surface (MESS) to analyze the degree of ecological change of PWD in the distribution area in the future. The reference layer of bioclimatic factors was determined using MESS analysis. The similarities among bioclimatic factors under different climatic conditions and the set points of bioclimatic factors in the refence layer (similarity, S) were calculated. Because the value of S was positive, the smaller the value, the more significant the climate difference was; no difference existed because the value of S was 100. The value of S for at least one bioclimatic factor was beyond the refence range because the value of S was negative. The environmental change at the point was good (Elith et al. , 2010). The prediction was made by running the "Density. Tools. Novel" tool in the MaxEnt .jar file in the command window.

3 RESULTS

3.1 MaxEnt model evaluation

Table S1 . Evaluation results of MaxEnt model under different parameter settings.

The MaxEnt model was used to simulate the potential distribution area of PWD in China. When the model is the default parameter, RM = 1, FC of operation are H and L; and RM = 0.5, FC = LQHPT, delta, and AICc = 0, the model is optimal (Table S1). Therefore, FC = LQHPT and RM = 0.5 were set as modeling parameters (Fig.2). The optimized parameters were used to remodel and simulate the suitable area of PWD in China. The model was repeated 10 times, and the training data of AUC were 0.940, indicating that the prediction results of the MaxEnt model were accurate (Fig.S1).

Fig. 2. Evaluation metriies of MaxEnt model generated by ENMeval

Fig.S1. ROC response curve under the MaxEnt model.

3.2 Main environmental factors affecting distribution of PWD

Table 2. Contributions of the climatic factors to the MaxEnt model.

The contribution rate of climate factors to the adaptability of PWD in China is shown in Table 2. The greater the contribution value is, the greater the influence of this variable on the existence probability of species. The climate factor with the largest contribution rate was precipitation of the wettest quarter (bio16, 45.7%), followed by max temperature of the warmest month (bio5, 27.5%), and coefficient of the variation of precipitation seasonality (bio14, 16.1%). The cumulative contribution rate was 89.3%, showing that these factors had the greatest influence on predicting the probability of PWD. The relative importance of each variable for predicting the probability of species existence was obtained based on the jackknife of regularized training gain in MaxEnt (Fig. 3). When only a single climatic factor was used, the three climatic factors that had the greatest impact on regularized training were coefficient of variation of precipitation seasonality (bio14), precipitation of the wettest quarter (bio16), and mean temperature of the driest quarter (bio9). In conclusion, the main climatic factors affecting the potential geographical distribution of PWD were temperature (max temperature of warmest month and mean temperature of driest quarter), rainfall (coefficient of variation of precipitation seasonality and precipitation of the wettest quarter). To understand the relationship between existence probability of PWD distribution and dominant environmental factors, a logistic curve suitable for only a single environmental factor (max temperature of the warmest month, mean temperature of the driest quarter, coefficient of the variation of precipitation seasonality, and precipitation of the wettest quarter) was drawn in the MaxEnt model (Fig. 4). The suitable range was the probability of existence > 0.5. The suitable range of max temperature of the warmest month was 31 - 33, the suitable range of mean temperature of the driest quarter was 5.1 - 20, the suitable range of the coefficient of variation of precipitation seasonality was 21 - 64, and the suitable range of precipitation of the wettest quarter was 450 - 950 mm.

Fig 3. Jackknife test result of climatic factors for PWD.

Fig. 4. Response curves of the main environmental variables affecting distribution of PWD.

3.3 Current potential distribution

Table 3. The potential distribution areas of PWD under current climatic conditions.

The potential distribution of PWD mainly distributes in central and southeast China under the current climate scenario (Fig. 5). According to the classification of suitable habitats, the areas of suitable habitat in each province were calculated (Table 3). The suitable distribution area of PWD was 197.26 x 10^4km^2, the area of highly suitable habitat was 44.11 x10^4 km^2, the area of moderately suitable habitat was 55.27x10^4 km^2, and the area of poorly suitable habitat was 97.88 x10^4km^2 (Table 4). Hunan, Jiangxi, Hubei, Guangdong, Anhui, Chongqing, and Guangxi have relatively large areas of highly suitable habitat. The area of highly suitable habitat in Jiangxi is 7.84 x10^4 km^2, ranking first in China. Guangxi, Hunan, Sichuan, Jiangxi, and Hubei have moderately suitable habitat areas than other provinces. There is no suitable distribution area of PWD in Gansu, Ningxia, and Xinjiang.

Fig. 5. Current suitable climatic distribution of PWD.

3.4 Changes in spatial distribution of habitat suitability in the future

Table 4. Suitable areas for PWD under different climatic conditions.

Under SSP1-2.6, SSP2-4.5, and SSP5-8.5 for the 2050s and 2070s, predictions of potentially suitable distributions of PWD in the future were illustrated (Table 4). The main distributions were in South China, East China, and Central China. There were also distributions in some parts of the Southwest, Northwest, and Northeast (Fig. 6). Under SSP1-2.6, the total suitable area of PWD was 240.36 x 10^4 km^2, 21.77% more than the current distribution area. The highly suitable area increased by almost three times its current amount, whereas the moderately suitable and lowly suitable areas decreased by 36.36% and 44.65%, respectively, in 2050. Under SSP2-4.5, the total suitable area of PWD was 246.99 x 104 km^2, an increase of 25.13% compared to the current distribution area. The highly suitable area increased by almost two times, whereas the moderately suitable and lowly suitable areas decreased by 35.42% and 36.80%, respectively, in 2050. Under SSP5-8.5, the total suitable area of PWD was 267.23 x 104 km^2, an increase of 35.38% compared to the current distribution area. The highly suitable area increased by almost four times, and the moderately suitable and lowly suitable areas decreased by 40.14% and 37.24%, respectively, in 2050. Under SSP1-2.6, in 2070, the total suitable area of PWD was 243.72 x 10^4 km^2, an increase of 23.47% compared to the current distribution area. The highly suitable area increased by almost three times, and the moderately suitable and lowly suitable areas decreased by 44.09% and 42.06%, respectively, in 2070. Under SSP2-4.5, the total suitable area of PWD was 261.97 x 10^4km^2, an increase of 32.72% compared to the current distribution area. The highly suitable area increased by almost three times, and the moderately suitable and lowly suitable areas decreased by 38.75% and 38.03%, respectively, in 2070. Under SSP5-8.5, the total suitable area of PWD was 286.29 x 10^4 km^2, an increase of 45.4% compared to the current distribution area, the highly suitable area increased by almost four times, and the moderately suitable and lowly suitable areas decreased by 29.12% and 24.51%, respectively, in 2070.

Fig. 6. Changes in current potential distribution to future distribution under different future climate change scenarios in China.

Table 5. Changes in the potential geographic distribution of PWD.

According to Table 5, by the 2050s, the total suitable area will increase to 44.01 x 10^4m^2 (SSP1-2.6), 50.72

x 10^4m^2 (SSP2-4.5), and 69.92 x 10^4m^2 (SSP5-8.5). The increased areas were the largest under SSP5-8.5 compared with the other climatic scenarios, and the increased areas were mainly distributed in parts of Hebei, Liaoning, Shanxi, Shaanxi, Hainan, Hunan, and other regions (Fig. 7). By the 2070s, the areas will increase to 48.17 * 10^4m^2 (SSP1-2.6), 55.24 * 10^4m^2 (SSP2-4.5), and 90.47* 10^4m^2 (SSP5-8.5) (Table 5). The increased areas were the largest under SSP5-8.5 compared with the other climatic scenarios, and the increased areas were mainly distributed in parts of Jilin, Liaoning, Hebei, Shandong, Shanxi, Shaanxi, Hunan, Jiangxi, Guangdong, Guangxi, and Hainan (Fig. 7).

Fig. 7. Potentially suitable changes in PWD under different climate change scenarios in China.

3.5 Highly suitable area centroid distributional shifts under climate change for PWD

The current centroid of highly suitable habitat for PWD was 113.37 E, 29.49 N. The centroid of highly suitable habitat shifted to the position 113.74 E, 30.58 N in 2050 and to 113.59, 30.54 in 2070 under SSP1-2.6. The centroid of highly suitable habitat shifted to the position 113.87 E, 30.84 N in 2050 and to 114.04 E, 30.99 N in 2070 under SSP2-4.5. The centroid of highly suitable habitat shifted to the position 114.15 E, 31.41 N in 2050 and to 115.06, 32.33 in 2070 under SSP5-8.5. In general, under different climate change scenarios, the highly suitable area for PWD is migrating to the Northeast. The highly suitable area centroid distributional shifts will migrate to Hubei and Henan in the future (Fig. 8).

Fig. 8. Highly suitable area centroid distributional shifts under climate change for PWD.

3.6 Analysis of MESS of potential area of distribution of PWD under future climate change scenarios.

The distribution of the climate anomaly area (S [?] 0) in the entire potential distribution area was low under the future climate scenarios (Fig. 9). No suitable habitat area for PWD was predicted in the climate anomaly area compared with the potential distribution area under the same climate scenarios (Fig.9). The average similarity values of the 647 modern effective distributional points for PWD were 7.73, 6.08, 9.13, 9.15, 5.74, and 5.12, respectively, under SSP1-2.6, SSP2-4.5, and SSP5-8.5 in the 2050s and under SSP1-2.6, SSP2-4.5, and SSP5-8.5 in the 2070s. This indicated that the degree of anomaly was higher in the 2070s SSP5-8.5 climate scenario. The abnormal degree of the other five climate scenarios was low.

Fig. 9. Analysis of MESS of potential area of distribution of PWD under future climate change scenarios.

4. DISCUSS

In this study, the distribution of PWD was predicted based on the MaxEnt model. Environmental factors and actual geographical distribution spaces of species were combined when this model was used to study the potential distribution of species (Yuan et al. , 2020). The actual geographical distribution of species and the environmental factors of species have a stable state when the state parameters obtained through the operation of the system obtain the maximum entropy to determine the potential geographical distribution of the species (Rong et al. , 2019). The MaxEnt model is easy to overfit when simulating the potential distribution of species, resulting in unreliable prediction results. This can seriously affect its application in global change biology and other research fields (Liu et al. , 2018). Therefore, the ENMeval data package was used to adjust the MaxEnt model parameters in the study. The parameters with the lowest complexity were selected to predict the potential distribution areas of PWD disease by analyzing model complexity under various parameter conditions (Muscarella et al. , 2014). The average value of training AUC reached 0.940, indicating that the prediction results of the model had high accuracy and feasibility.

The main climatic factors affecting the potential geographical distribution of PWD were temperature (max temperature of the warmest month [bio5], mean temperature of the driest quarter [bio9]), rainfall (coefficient of the variation of precipitation seasonality [bio14], and precipitation of the wettest quarter [bio16]). Kobayashi et al. (1970) studied precipitation as a crucial factor affecting damage caused by PWD, including the many pine trees killed by PWD during a summer drought. Naoko et al. (2001) studied pine forests in the warm temperature zone of Japan, which PWD had seriously damaged. The maximum temperature in the warmest month affected the diffusion of adult*Monochamus alternatus* (*M.alternatus*), the vector of pine wood nematodes. The population density of *B.xylophilus* was significantly increased by drought (Zhao et al. , 2003).Currently, researchers agree that the climate conditions of high temperature and drought are conducive to the occurrence of PWD (Kanzaki & Giblin-Davis, 2018).

Under the next six greenhouse gas emission scenarios, the potential distribution area of PWD predicted by MaxEnt will shift to the Northeast, and the potential suitable area will expand significantly under the 2070s SSP5-8.5 scenario. Climate is the key factor affecting the distribution area of species. Climate change will have a far-reaching impact on the distribution of pests, and global warming will be the trend of climate change in the future (Volney & Fleming, 2000; Walther et al. , 2009). Previous studies have reported that the suitable distribution area of PWD in China will expand nearly twice by 2100 with the intensification of climate change, showing a trend of acceleration of the diffusion rate to the North and West (Cheng et al. , 2015). The results of the correlation between temperature and *B.xylophilus* showed that low temperature may inhibit the spread of *B.xylophilus* by affecting the reproduction and activity range of *M.alternatus* (Jikumaru et al., 2008). Global warming is conducive to the activity of the nematode vector *B.xylophilus* , which significantly enhances the damage caused by PWD (Jikumaru & Togashi, 2000). However, predictions of the potential distribution area of PWD also need to be combined with host plants, topography, soil, and human activities. Abiotic factors, biological factors, and species migration affect the distribution of species during their long-term evolution, and the distribution range of species is different in different historical periods (Soberon, 2007).

If effective prevention and control of PWD is not realized as soon as possible, this major disease may soon spread across a larger area in China, causing hundreds of millions of pine tree deaths every year. This will be an ecological disaster (Lee, 2014). The techniques adopted to control PWD in China mainly include disease quarantine and epidemic situation monitoring, diseased wood removal, and vector insect control. Further, there is an active disease prevention measure, namely, trunk injection. Trunk injection involves injecting effective components into the tree and exerting a drug effect by distributing the chemicals based on the transpiration of the tree. It has advantages of accurate application and high control efficiency, and it is environmentally friendly (Byrne et al. , 2014; Takai et al. , 2000b) (Aćimović et al. , 2014; VanWoerkom et al. , 2014). Emamectin benzoate is a semi-synthetic second-generation avermectin-derived insecticide found to have the strongest nematicide activity against *B.xylophilus* among different chemical substances (Takai et al. , 2000a). Therefore, it can be considered a strong candidate for use as a preventive trunk injection against pine wilt disease.

5 CONCLUSION

Based on the actual distribution data of PWD and current (1950–2000) and future (2050 and 2070) climate data, the MaxEnt model was used to predict the potential distribution area of PWD in China. The prediction results showed that, under current climate and environmental conditions, moderately and highly suitable habitats are mainly distributed in Anhui, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, Sichuan, and other places. In 2050 and 2070, the area of total suitable habitat and highly suitable habitat will expand significantly and spread to the Northeast. The main climatic factors affecting the potential geographical distribution of PWD are temperature (max temperature of the warmest month (bio5), mean temperature of the driest quarter (bio9), rainfall (coefficient of the variation of precipitation seasonality (bio14), and precipitation of the wettest quarter (bio16). By predicting PWD's potential geographical distribution, a basis for quarantine, supervision, and timely prevention and control can be obtained.

Contribution of authors

Xianheng Ouyang: concept and design the research; acquire the data; analysis the data; statistical analysis; draft the manuscript; Anlliang Chen: revise the manuscript and design the research; Haiping Lin: revise the manuscript and design the research. All authors read and approved the final manuscript.

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Conflict of Interest

The authors declare no conflict of interest.

Data availability statement

All authors agreed to deposit data from this manuscript to a public repository. Data are submitted to Dryad, and DOI number is https://doi.org/10.5061/dryad.msbcc2g12.

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Figure Legends

Fig. 1. Occurrence records of PWD in China.

Fig. 2. Evaluation metriies of MaxEnt model generated by ENMeval

Fig 3. Jackknife test result of climatic factors for PWD.

Fig. 4. Response curves of the main environmental variables affecting distribution of PWD.

Fig. 5. Current suitable climatic distribution of PWD.

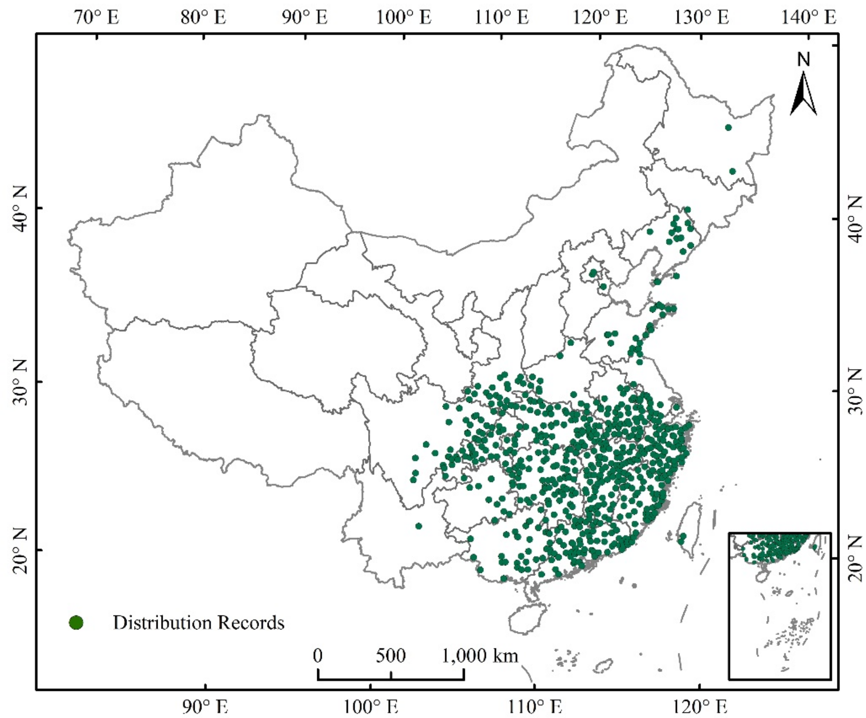
Fig. 6. Changes in current potential distribution to future distribution under different future climate change scenarios in China.

Fig. 7. Potentially suitable changes in PWD under different climate change scenarios in China.

Fig. 8. Highly suitable area centroid distributional shifts under climate change for PWD.

Fig. 9. Analysis of MESS of potential area of distribution of PWD under future climate change scenarios.

Fig. S1. ROC response curve under the MaxEnt model.



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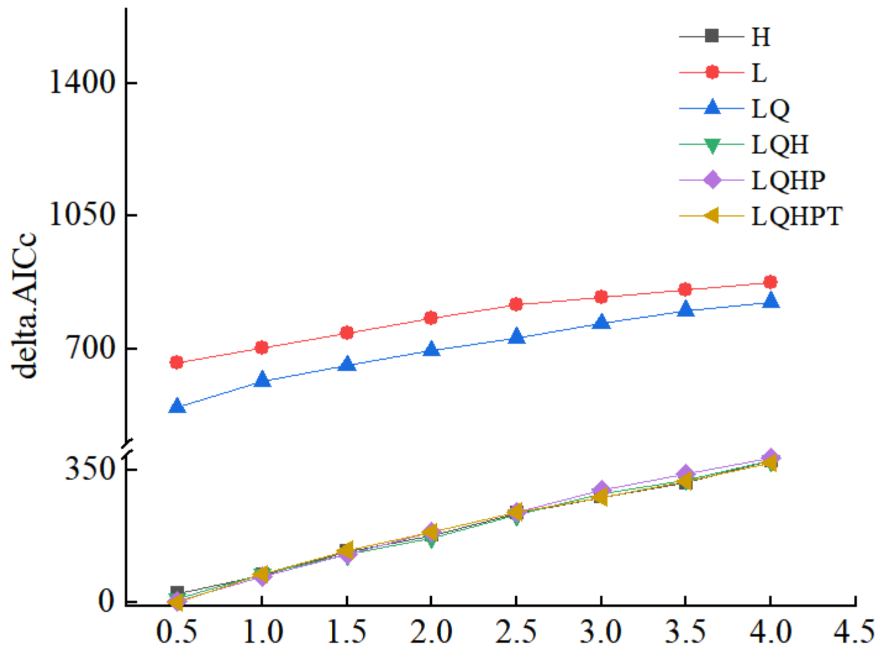


Fig. 2. Evaluation metriies of MaxEnt model generated by ENMeval

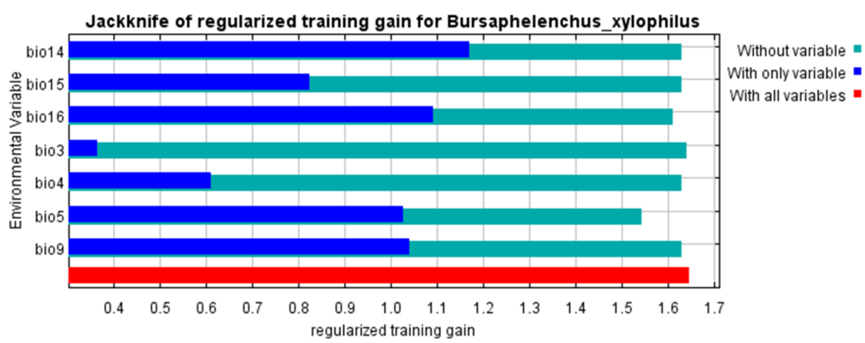
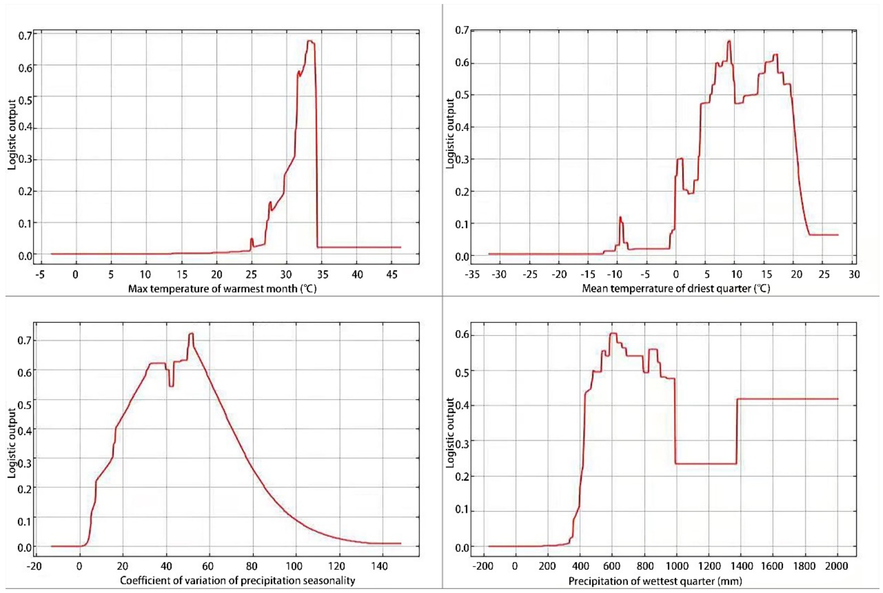


Fig 3. Jackknife test result of climatic factors for PWD.



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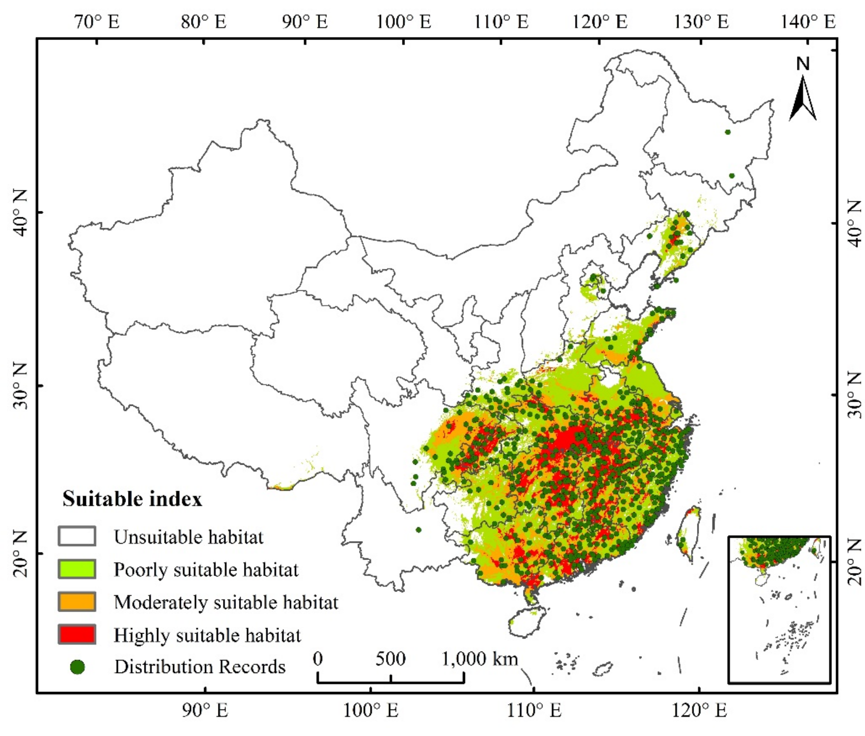


Fig. 5. Current suitable climatic distribution of PWD.

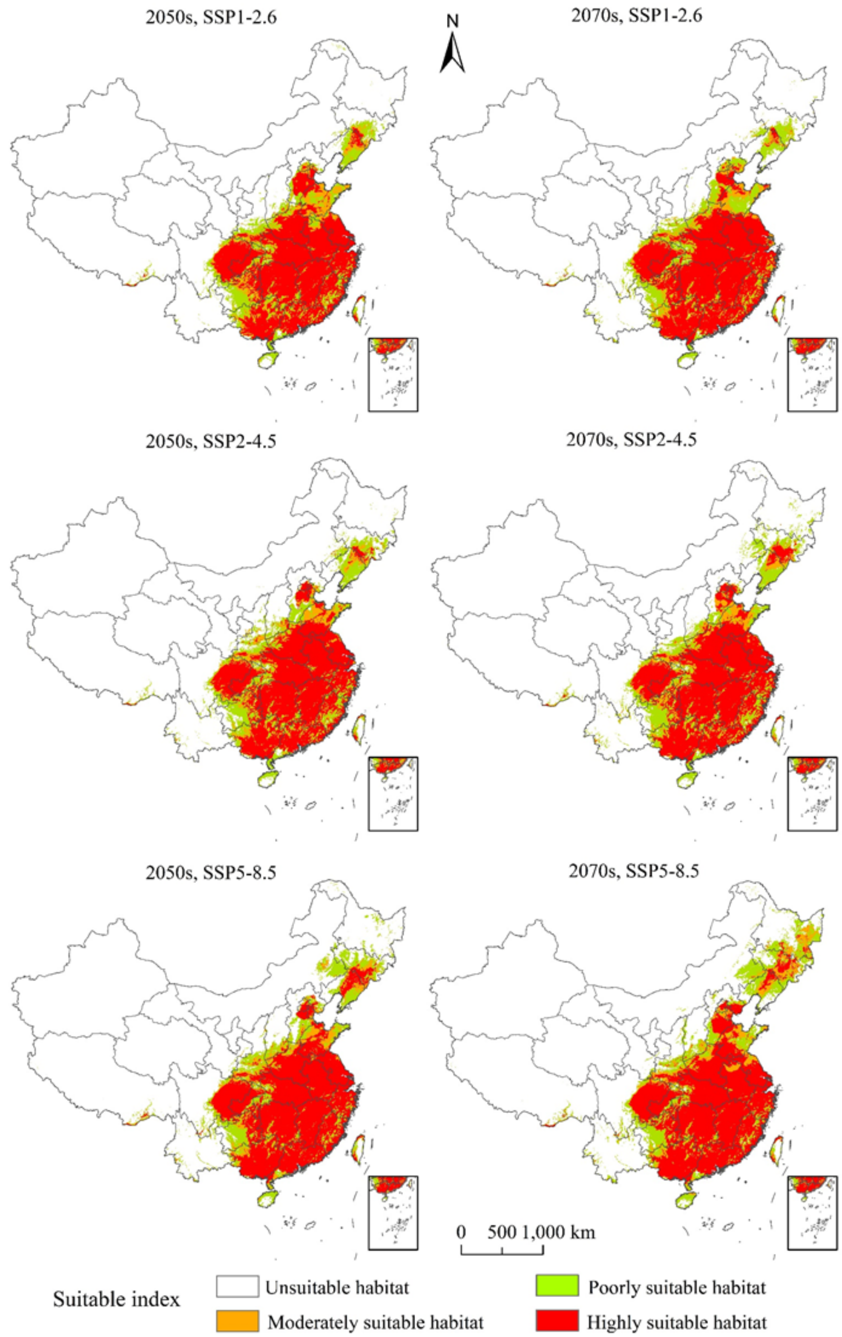


Fig. 6. Changes in current potential distribution to future distribution under different future climate change scenarios in China.

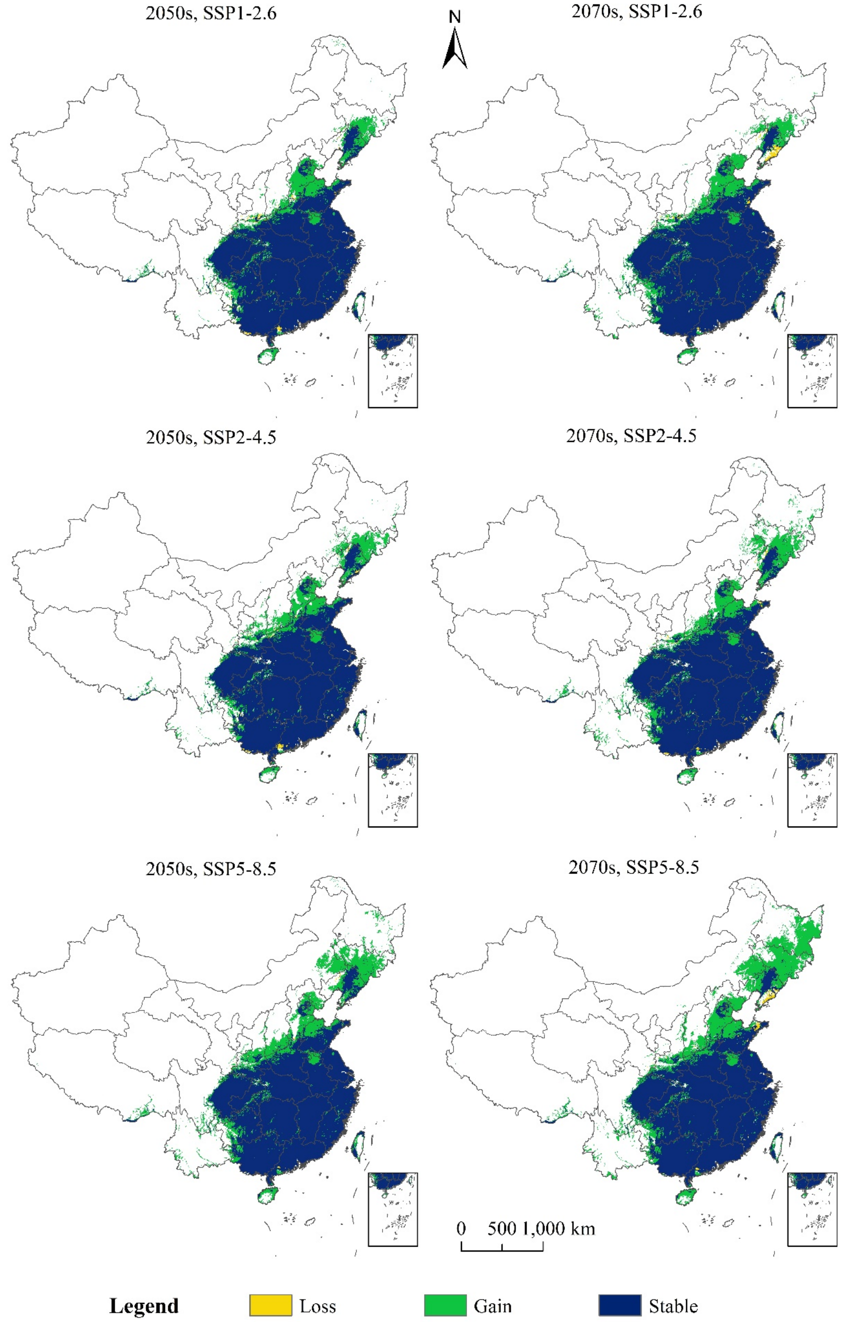
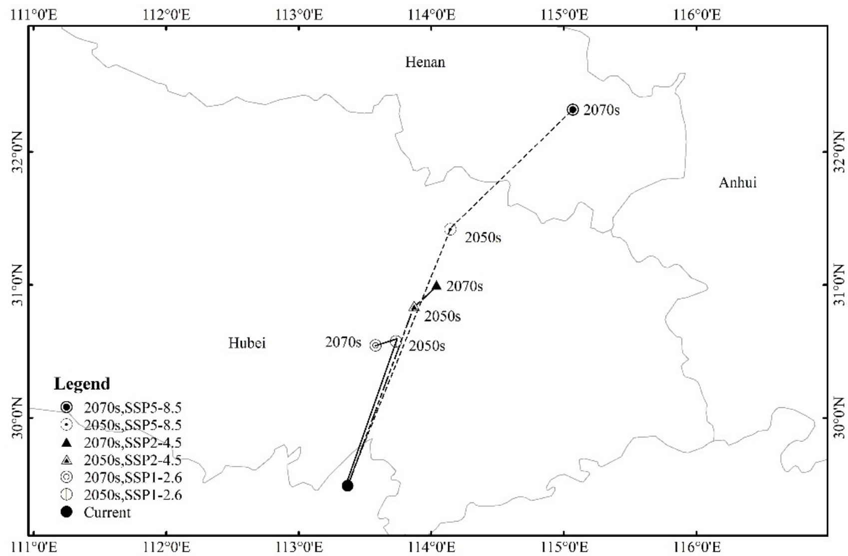


Fig. 7. Potentially suitable changes in PWD under different climate change scenarios in China.



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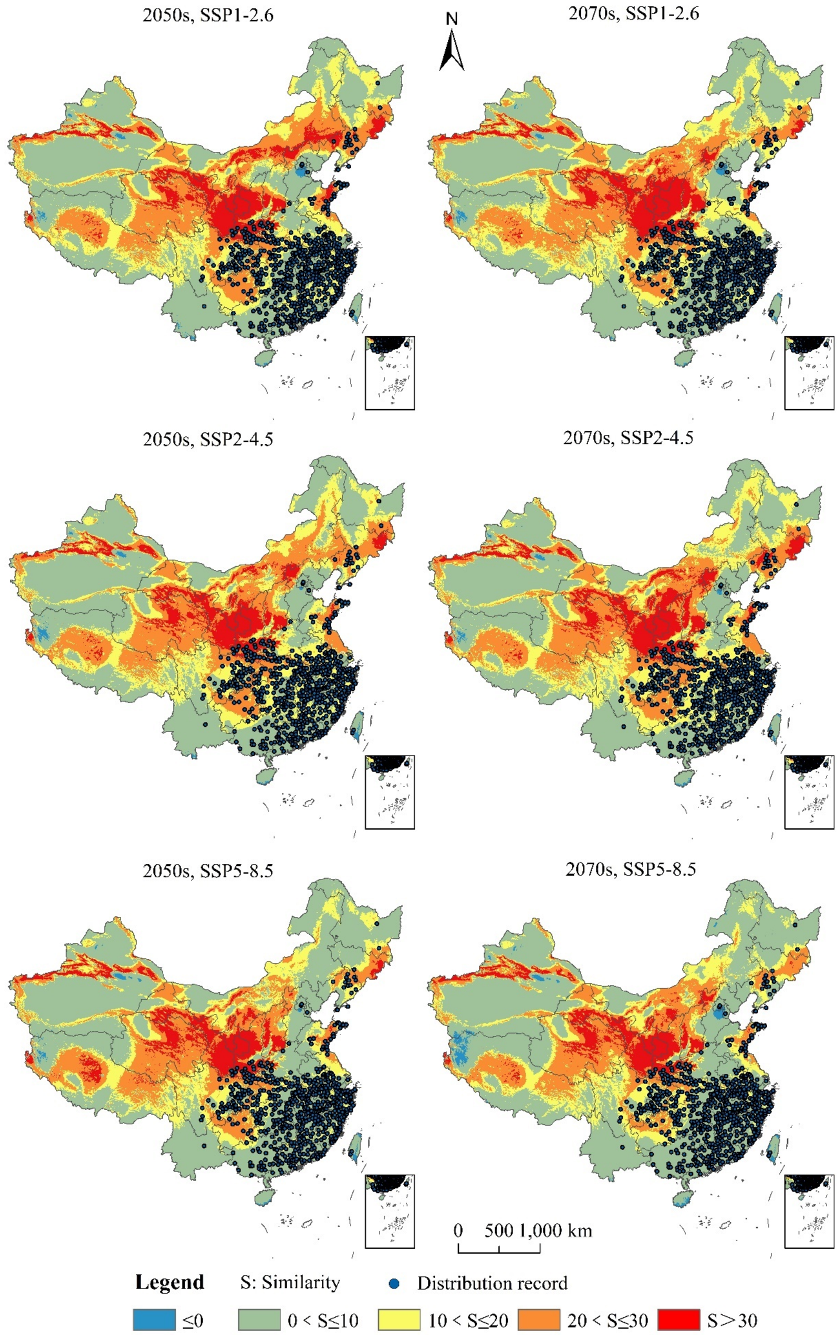

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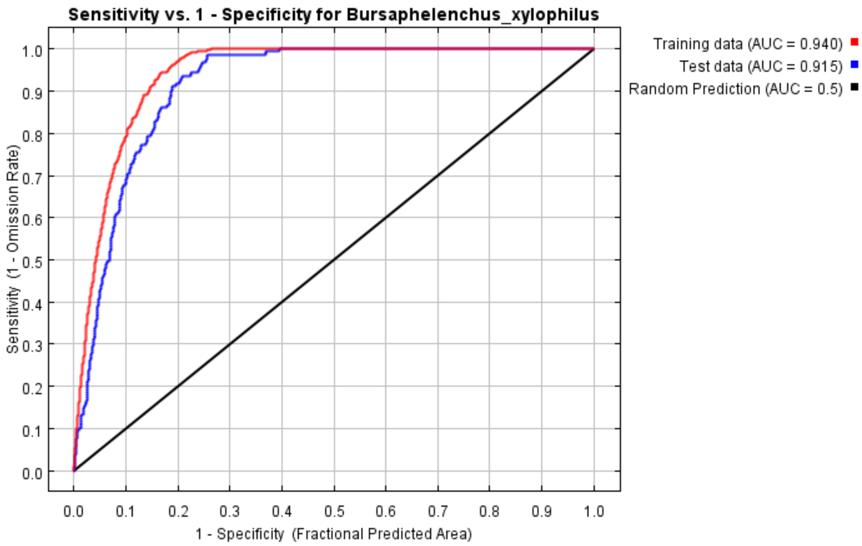

Appendix

Fig. S1. ROC response curve under the MaxEnt model.

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