Modeling the effect of climate change on suitable habitats for threatened medicinal plant, *Mahonia oiwakensis* Hayata in Taiwan

模擬氣候變遷對臺灣受威脅藥用植物阿里山十大功勞適宜棲地之影響

Ming-Lun Lu and Jing-Yi Huang*

呂明倫 黃靜宜*

Endemic Species Research Institute, Jiji, Nantou, Taiwan

行政院農業委員會特有生物研究保育中心 55244南投縣集集鎮民生東路1號

*Corresponding author: lily@tesri.gov.tw
*通訊作者：lily@tesri.gov.tw

Abstract

Climate change affects the geographical distribution of organisms significantly, particularly those of endangered plants. *Mahonia oiwakensis* is a medicinal plant endemic to Taiwan and is recognized as a vulnerable and endangered species by global and Taiwanese conservation assessment systems respectively. In this study, we applied maximum entropy (MaxEnt) to predict suitable habitats for this plant species both currently and in the future. The calculations used 85 occurrence points and ten environmental variables to simulate temporal and spatial changes in the species' suitable habitats in climate conditions under representative concentration pathways 2.6 (mitigated warming) and 8.5 (aggravated warming) now and in 2070. The results demonstrated that annual mean temperatures provide key contributions to the MaxEnt model, and the response curve indicated that annual mean temperatures 7–14 °C are the best ecological niche for this plant species. The simulations indicated that under conditions of mitigated or aggravated warming in the future, suitable habitats for *M. oiwakensis* will be reduced, especially for population at altitudes of 2,500 m and under, which will be unable to withstand the effects of global warming. We suggest that current plant conservation strategies and action plans should take into consideration the effects of climate change to avoid these plant species becoming extinct.

Key words: *Mahonia oiwakensis*, maximum entropy, climate conditions, ecological niche, conservation

摘要

氣候變遷會影響生物的地理分布，特別是對於受到威脅的植物，將可能面臨滅絕的危機。阿里山十大功勞(*Mahonia oiwakensis*)為臺灣特有的藥用植物，在全球及臺灣區域尺度的保育評估系統，分別被列為易受害與瀕危等級。本研究應用最大熵(maximum entropy; MaxEnt)預測了該物種現時和未來的適宜棲地，總計使用了85個出現點位與10個環境變項，模擬現時與2070年代表濃度途徑2.6(暖化減緩)和8.5(暖化加劇)兩種氣候情境下，物種適宜棲地的時空變化。研究結果顯示，年均溫為MaxEnt模型提供了重要的貢獻，從響應曲線可知，年均溫7~14°C範圍應為該物種最佳的生態棲位；而從模擬的結果發現，未來暖化減緩或加劇的情景，十大功勞的適宜棲地皆會縮減，尤其海拔2500 m以下的族群，將可能無法承受暖化的衝擊。因此，建議現有的植物保育策略與行動方案，應考量氣候變遷的衝擊，以避免該物種將來走向滅絕。

關鍵詞：阿里山十大功勞、最大熵、氣候情境、生態棲位、保育

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Introduction

The global population has continued raising drastically since the 19th century. During this period, humans have become overly reliant on fossil fuels, which destroy ecological environments and increase atmospheric greenhouse gas concentrations, resulting in rising global mean temperatures. The Intergovernmental Panel on Climate Change (IPCC) predicts that compared with the period from 1986 to 2005, the global mean temperature will rise by at least 0.3–1.7 °C and at most 2.6–4.8 °C by the end of the 21st century (2081–2100; IPCC 2013). Global warming will severely affect biodiversity, and because organism distribution and survival are closely related to climate, worsening climate conditions will cause certain species to vanish (Schloss *et al*. 2012; Randall and Woesik 2015). Studies have indicated that high-altitude plants are particularly sensitive to climate change and more fragile in comparison with the other species (Dirnböck *et al*. 2011; Dullinger *et al*. 2012); this includes alpine plants in Taiwan (Chou *et al*. 2011).

Species under the *Mahonia* genus are mostly identified as medicinal plants. Among these species, *M. oiwakensis* is used as traditional Chinese medicine and endemic to Taiwan. Originally discovered on Alishan, its roots, stems, leaves, and flowers all have medicinal properties, and the plant is said to have at least ten effects. *M. oiwakensis* has been scientifically proven to have antioxidant, analgesic, anti-inflammatory, and hepatoprotective effects (Chao *et al*. 2009; Wong *et al*. 2009; Chao *et al*. 2013), etc. The plant is primarily distributed in high-altitude mountainous regions on the main island of Taiwan (Lu and Yang 1996), and because of its medicinal effects and economic value, it may be affected by human interference. At present, the wild *M. oiwakensis* population is not large. Worldwide and Taiwanese conservation assessment systems have declared it to be vulnerable and endangered, respectively, among their threatened categories (International Union for Conservation of Nature 2001; Editorial Committee of the Red List of Taiwan Plants 2017).

As the climate warms, the high-altitude and threatened *M. oiwakensis* will inevitably be affected. Therefore, understanding the characteristics of its ecological niche and determining changes to suitable habitats under current and future climate conditions are necessary. Ecological niche modeling (ENM) predicts suitable habitat ranges based on the environmental conditions of the target species, and the maximum entropy (MaxEnt) model developed by Phillips *et al*. (2006) integrates statistical modeling and machine learning and is currently recognized as the most widely used modeling tool (Merow *et al*. 2013; Morales *et al*. 2017). In recent years, MaxEnt has often been used to model the effects of climate change on endangered and medicinal plants (Zhao *et al*. 2018; Abolmaali *et al*. 2018; Liu *et al*. 2019; Abdelaal *et al*. 2019).

At present, few studies in Taiwan have simulated the effects of climate change on medicinal plants. This study used data from biological surveys and ENM as basis to simulate suitable *M. oiwakensis* habitats, which are used to predict temporal and spatial population changes in conjunction with recent climate change developments. We hope the results can aid in promoting biodiversity conservation and sustainable use.

Materials and methods

Study Area

Taiwan is situated at the junction between continental Eurasia and the Pacific Ocean, across the Taiwan Strait with mainland China to the west (Fig. 1a). With a land area of approximately 36,000 km^2, Taiwan is the 38th largest island in the world. The island terrain fluctuates greatly, consisting mostly of mountains and hills. The average altitude is 660 m, with the tallest mountain being Yushan at 3,952 m. The plains are primarily distributed along the western coast (Fig. 1b), and the majority of Taiwan's population of approximately 23 million people congregate in metropolitan areas in the west. Taiwan is bisected by the Tropic of Cancer, with the northern half experiencing a subtropical monsoon climate and the southern half experiencing a tropical monsoon climate. Furthermore, the altitude differences from the high mountains form complex climate types of tropical, subtropical, temperate, and cold zones. Most of the land is covered by forest, and the diverse climate has formed rich vegetation ecologies, such as alpine vegetation, *Abies* forests, *Tsuga-Picea* forests, *Quercus* forests, *Machilus-Castanopsis* forests, and *Ficus-Machilus* forests.

Occurrence Data

Georeferenced occurrences about *M. oiwakensis* were acquired from the

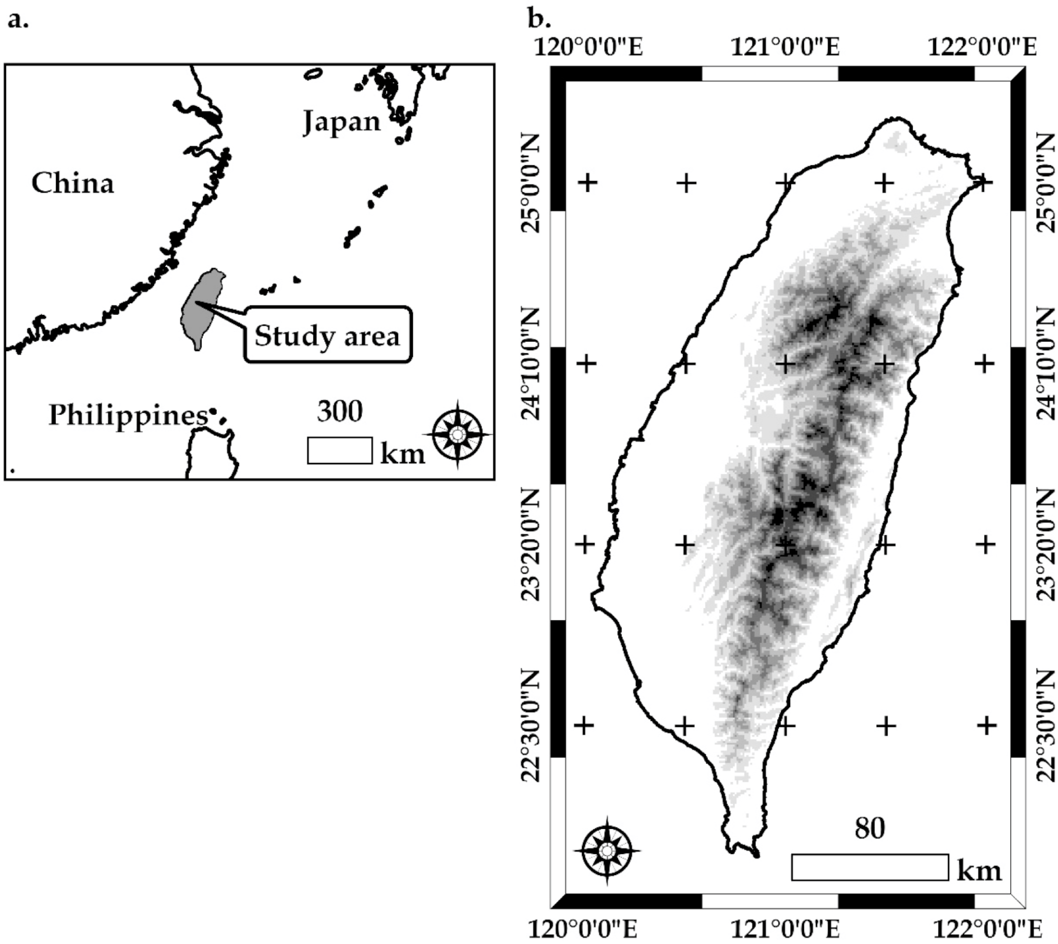

Fig. 1. (a) Geographical location of the study area; (b) digital elevation model, where darker colors indicate higher elevations.

圖**1**. (a) 研究區地理位置圖；(b) 數值高程模型(digital elevation model)，顏色愈黑，表示海拔愈高。

Ecological Survey Database of Taiwan's Forestry Bureau for the period from 1998 to 2008. The coordinates are expressed in longitude and latitude. In this study, the data were only retained to the third decimal place and uniformly converted to the Taiwan Datum 97 and 2-degree transverse Mercator coordinate formats. The subsequent environmental data used in the story were also stored in this system and format. The basic operation unit for the grid was configured as 1x1 km^2; duplicate records in a grid were calculated as a single entry, resulting in 85 counts of data for model construction.

Environmental data

The prediction variables in ENM include climate, topography, and land cover. The climate variables were downloaded from WorldClim, which was developed by Hijmans *et al*. (2005). This database converts data from the period 1950–2000 from meteorological stations worldwide through interpolation to generate at a nearly 1 by 1 km^2 minimum spatial scale. Furthermore, the database includes 19 bioclimatic variables that were specially designed to predict species distribution (Hijmans and Graham 2006). This study selected the following four variables for analysis: topographical variables were obtained from digital elevation models from the WorldClim database; slope images were created using the ArcGIS 10.6 software; and a compound topographic index representing humidity and heat load index representing the strength of solar radiation was acquired by referencing Gessler *et al*. (1995) and McCune and Keon (2002), respectively. Finally, we referenced the Terra-MODIS satellite imaging product MOD13Q, an enhanced vegetation index (EVI) obtained from the US Land Processes Distributed Active Archive Center, to acquire the land cover variables. This index can be used to describe vegetation coverage and to create six mapping types—maximum, minimum, average, median, full range, and standard deviation—for the same period. In the end, the predictive variables totaled 29. To avoid overfitting caused by the collinearity of variables, the variables were screened using Pearson correlation analysis; when the correlation coefficient for two variables exceeded 0.7, referencing previous practices, the research purpose, associativity with biology, and subsequent ease of interpretation were considered to select the appropriate variable (Kumar and Stohlgren 2009; Padalia *et al*. 2014).

Climate change conditions

The future suitable habitats for *M. oiwakensis* were simulated in different scenarios assuming that the variables would change in accordance with the climate change conditions announced by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Ar5). The AR5 defined change scenarios by representative concentration pathways (RCPs), with RCP 2.6 and 8.5 representing radiative forcing increases by 2.6 and 8.5 Wm^{-2}, respectively, from 1750 to 2100. In other words, RCP 2.6 is the ideal scenario under which global warming has been mitigated, whereas RCP 8.5 is a scenario of aggravated global warming (IPCC 2013). The WorldClim database also provides future climate data for use; this batch of data is first interpolated with actual current observations to obtain climate data for the base period, and then downscaled and revised with the future climate data projected by the Coupled Model Intercomparison Project, Phase 5 (Taylor *et al*. 2012). We collected 19 bioclimatic data items generated for the RCP 2.6 and 8.5 scenarios in 2070. To eliminate uncertainties that might be generated by different global climate models (GCMs), 14 GCM simulation results were selected to obtain their mathematic means. Both scenarios yielded 19 future bioclimatic variables each (Araújo and New 2007).

Ecological niche modeling

We used MaxEnt 3.3.3k to predict suitable habitats for species, first randomly selecting 75% of the species data as the training dataset and processing them ten times to obtain the mean value. The output results were set as the logistic probability, with a prediction value range from 0 to 1; values closer to 1 represent higher odds of *M. oiwakensis* appearing on the grid. The remaining 25% of the species data were the testing dataset, and the model's validity was evaluated based on the area under the curve (AUC) generated by the receiver operating characteristics. The AUC value was 0.5–1, with higher values indicating higher accuracy of model predictions; 0.7 is the standard for reliability (Swets 1988; Pearce and Ferrier 2000). The established ecological niche model could aid in understanding the importance of each predictive variable to the model through permutation importance, with higher values representing higher contributions. The response curves revealed the relationship between the variables and the logistic probability of the output, which aided in understanding the species' ecological niche traits.

To assess changes to suitable *M. Oiwakensis* habitats now and in 2070 under the RCP 2.6 and 8.5 scenarios, the resulting probability graphs for the three simulations were converted into binary graphs (1 as *yes* and 0 as *no*) using the 10^{th} percentile of training presence provided by MaxEnt. Grids represented as 1 were defined as suitable habitat ranges (Pearson *et al*. 2007; Koncki and Aronson 2015). Furthermore, by referencing the digital elevation model (Fig. 1b), the study area was divided into different altitude ranges of 500 m. This graph was further overlaid with the suitable habitats to analyze temporal and spatial changes in the different scenarios.

Results

The 29 predictors were simplified using Pearson correlation analysis. Through choosing correlation coefficients smaller than the 0.7 standard, ten variables were chosen. The results of calculations with MaxEnt based on these parameters showed that the mean AUC values for the training and testing datasets were 0.95 and 0.93, respectively, and the standard deviation was lower than 0.02, thereby demonstrating excellent simulation efficacy. Among the variables, annual mean temperature had the highest permutation importance—approximately 78%—indicating that it had the most obvious influence on the model. The remaining variables did not exceed 7% and had relatively less influence (Table 1).

Because annual mean temperatures are the most critical variable for predicting species suitable habitats, we referred to the response curves to understand the ecological habitat of *M. oiwakensis*. Fig. 2 indicates that the annual mean temperatures and the logistic probability of the output generated a bell curve. At a threshold greater than 0.5, the slope peak of the curve fell between 7 and 14 °C; this range is the optimal ecological niche for the species.

Our simulations revealed that under current and future climate change conditions, suitable *M. oiwakensis* habitats were mostly scattered in the central regions of higher altitudes. The area of current suitable habitats was estimated to be 4,276 km^2, and comparisons with the two climate change scenarios for 2070 indicated reductions in suitable habitats. The area of suitable habitats decreased to 3,130 km^2 under RCP 2.6 and to 2,159 km^2 under the more severe warming conditions of RCP 8.5. Using the current area of suitable habitat as the standard, the suitable habitat area size will decrease by 27% under RCP 2.6 and by 50% under RCP 8.5 (Fig. 3).

Table 1. Contribution of predictive variables on the MaxEnt model (by permutation importance)

表**1**. 環境預測變項對MaxEnt模型之貢獻度，以置換重要性百分比(permutation importance)表示

Variable	Permutation importance (%)
Annual mean temperature	78.54
Temperature seasonality	6.46
Annual precipitation	2.97
Slope	2.78
Mean diurnal range	2.53
EVI minimum value	1.89
Precipitation of warmest quarter	1.86
EVI average value	1.61
EVI standard deviation value	0.72
Heat load index	0.64

EVI= enhanced vegetation index

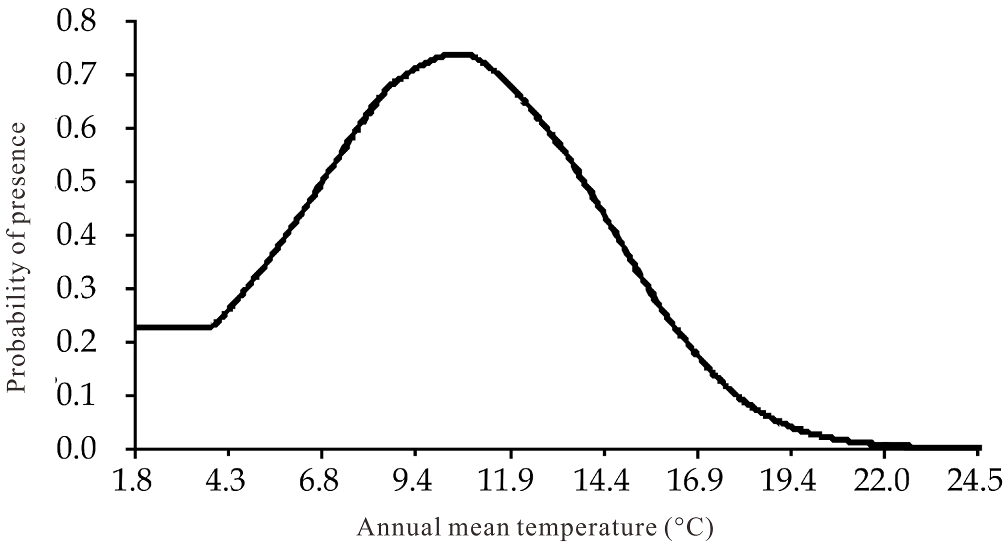

Fig. 2. Response curve for key annual mean temperatures in the suitable *M. oiwakensis* habitat prediction model.

圖**2**. 預測阿里山十大功勞適宜棲地模型中，重要預測變項(年均溫)之響應曲線。

Based on altitude gradation, current suitable habitats for *M. oiwakensis* on Alishan primarily fall in the mid-to-high-altitude ranges. The 2,001–2,500 m range has the most extensive area at 45% of the total area of suitable habitats; the 1,501–2,000 m and the 2,501–3,000 m ranges each account for 25%, and under the RCP 2.6 scenario for 2070, the 1,501–2,500 m range has a reduction in suitable habitat, resulting in a higher area ratio in the 2,500 m and higher ranges. A similar trend was also observed in the RCP 8.5 scenario but it was more drastic. This demonstrated that *M. oiwakensis* is influenced by climate change and will see declining populations, because it can only adapt to high-altitude areas.

Discussion

ENM is a critical approach to predicting the influences of climate change on suitable habitats of *M. oiwakensis*. The MaxEnt model we used is fit for calculating small sample sizes (Hernandez *et al*. 2006); however, if the sample size is too small, the model may be unstable or even overestimate AUC values (Jiménez-Valverde *et al*. 2008; Lobo *et al*. 2008). Among our study results, AUC values exceeded 0.9 and we had 85

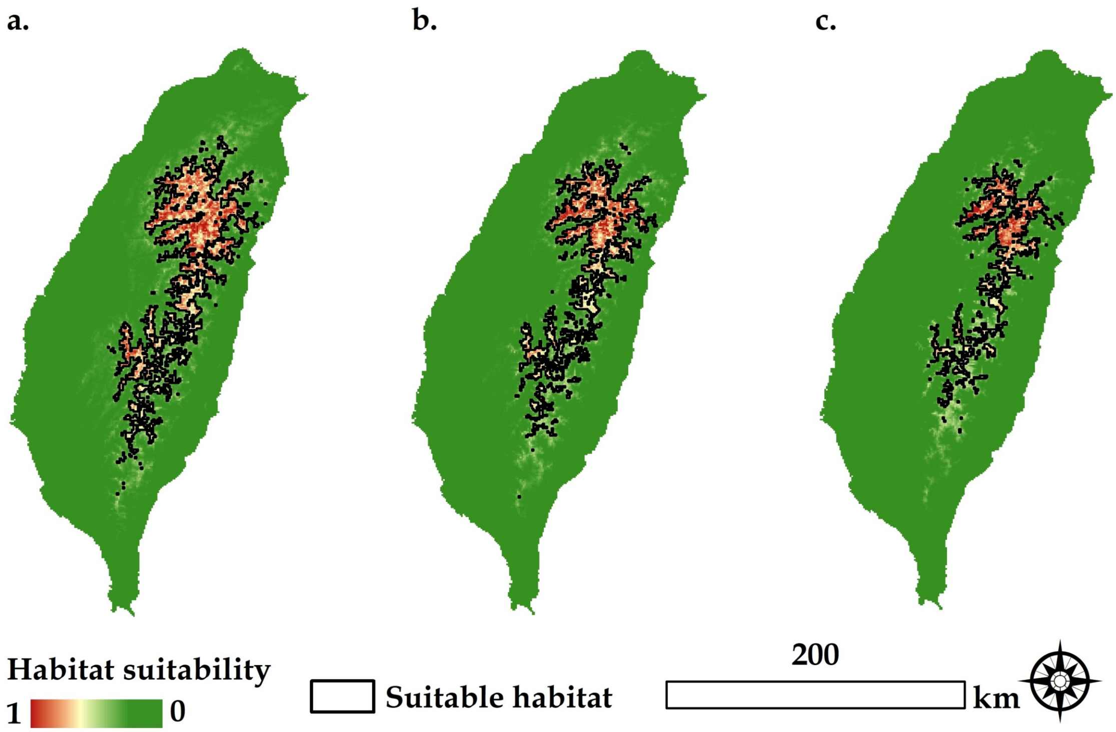

Fig. 3. Predictions of *M. oiwakensis* suitable habitats. (a) Current predictions; (b) predictions for 2070 under RCP 2.6; (c) predictions for 2070 under RCP 8.5.

圖3. 阿里山十大功勞適宜棲地之預測結果。(a) 現時的預測結果；(b) RCP 2.6情境下，2070年代預測結果；(b) RCP 8.5情境下，2070年代預測結果。

observed points for calculation when building the model. Our sample is considered a medium-sized one (Phillips and Dudík 2008; Wisz *et al*. 2008), thereby indicating that the predictions are reliable.

Among the model variables, annual mean temperature had the greatest contribution (Table 1). This is similar to the circumstances of many threatened plant species endemic to Taiwan (Huang 2019). Studies in other countries have also found that the effects of temperature were significantly greater than those of other environmental factors on endangered or medicinal plants that grow in mountainous regions, such as *Myristica dactyloides* in India (Remya *et al*. 2015), *Homonoia riparia* in China (Yi *et al*. 2016), *Gentiana lutea* in

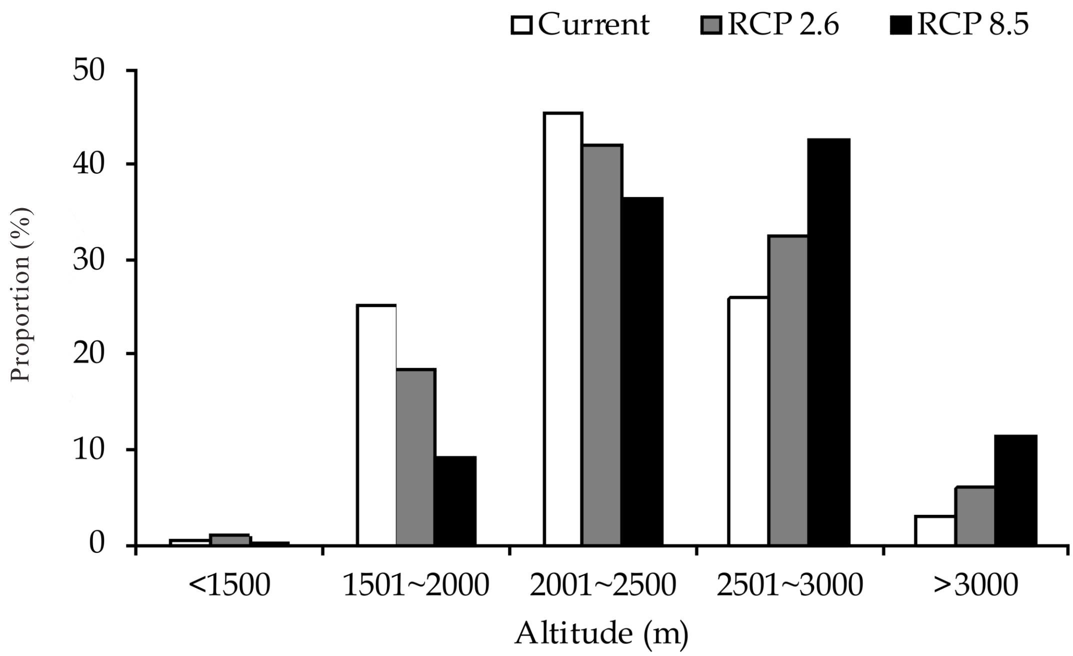

Fig. 4. Size of suitable *M. oiwakensis* habitats at different altitudes.
圖**4**. 阿里山十大功勞適宜棲地在不同海拔梯度之面積大小。

Italy (Cuena-Lonbraña *et al*. 2018), and *Rosa Arabica* in Egypt (Abdelaal *et al*. 2019). This signifies that annual mean temperature is the key indicator that influences the distribution of *M. oiwakensis*, and optimal ecological habitats have an annual mean temperature of 7–14 °C (Fig. 2); as a result, the ecological amplitude for this species is not high. *M. oiwakensis* prefers colder environments, and ecological amplitudes that exceed this range could inhibit plant growth.

Based on the suitable habitats predicted through MaxEnt modeling, current ranges for *M. oiwakensis* fall among mid-to-high-altitude mountainous regions (Fig. 3a). According to literature, suitable *M. oiwakensis* habitats are distributed approximately between elevations of 1,500 and 3,500 m on the main island of Taiwan (Lu and Yang 1996), which is similar to our results (Fig. 4). Under future climate change conditions, suitable *M. oiwakensis* habitats may be reduced (Fig. 3b and c) due to changes in original ecological habitats under elevations of 2,500 m that the plant cannot adapt to. Therefore, only ecological habitats at high altitudes will remain (Fig. 4).

Because of their different biological and phenological traits, plants respond to climate change differently (Parmesan and Hanley 2015). Species with narrower ecological amplitudes generally have unique ecological habitat needs and are less able to adapt to climate change compared with species of wider amplitudes (Yu *et al*. 2017). After referencing regions in the world on the same latitude as Taiwan, such as Southeast China (Huang *et al*. 2019), Pakistan (Khanum *et al*. 2013), Iran (Abolmaali *et al*. 2018), and Egypt (Abdelaal *et al*. 2019), we discovered that most medicinal plants with narrow ecological amplitudes face potential habitat loss as a result of climate change. In Taiwan, many threatened plant species have the same problems as the *M. oiwakensis* that we investigated (Huang 2019). Unlike countries on continental Asia, Taiwan is an island surrounded by seawater, and high-altitude plants have limited tractable space. Unique protozoa species in particular are often unable to adapt to abnormal climate conditions and have increased risk of extinction (Loarie *et al*. 2018; Cuena-Lombraña *et al*. 2018).

Conclusion

In this study, we successfully simulated changes in suitable habitats for *M. oiwakensis* under climate change conditions in the present day and in 2070. We concluded that in the future, whether in scenarios of mitigated or aggravated warming, suitable habitats for *M. oiwakensis* will shrink. Because of changes to original ecological habitats and its preference for colder environments, particularly in altitudes under 2,500 m, *M. oiwakensis* will be unable to withstand the effects of global warming. Consequently, we suggest that current plant conservation strategies and action plans consider climate change factors to protect populations in current habitats to prevent them from extinction.

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