Assessment of the Effects of Climate Change on the Invasiveness of Invasive Alien Plant in Taiwan

評估氣候變遷對臺灣外來入侵植物侵略性的影響

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Abstract

An effective understanding of the influence of climate change on the invasiveness of invasive alien plant species will contribute to the formulation and priority planning of control measures. In this study, climate change conditions were incorporated into a maximum entropy model to build a spatial invasiveness evaluation index for 49 invasive plant species. This index was used to assess the potential for population establishment and diffusion of invasive plant species under present day and future climate change conditions (RCP 8.5, 2060-2080). Furthermore, key invasive plants species that require reinforced precaution today and in the future were verified through quantifying and classifying their invasiveness. The results of this study indicated that temperature is a major driving factor in ecological niche for invasive plant species. Future climates may lead to habitat suitability for most species and increase the area size of suitable habitats and optimal habitats, while simultaneously reducing the distance between known populations and their optimal habitats. However, some species may be unable to adapt to climate change, thereby reducing their invasiveness. This study's classification of invasiveness indicated that 10 species of invasive plants, although not highly invasive at present, may become highly invasive in the future, and thus their effects on ecological habitats or agriculture production must be assessed. In summary, the influence of climate change on the invasiveness of invasive plants in Taiwan can be understood under the framework of this study, and the invasiveness index can serve as a reference when drafting future preventive strategies against invasive species.

Key words: biological invasions, ecological niche modeling, invasive species management, habitat suitability, risk assessment

摘要

有效掌握氣候變遷對外來入侵植物侵略性的影響，將有助於入侵防治措施的擬定及防治優先性的規劃。本研究將氣候變遷資料納入最大熵模式(MaxEnt)，建立49種入侵植物空間侵略性評估指標，評估當前與未來氣候變遷情境下(RCP8.5, 2060~2080)下，入侵植物族群建立與擴散潛勢。此外，藉由入侵植物侵略性的量化與分級，確認當前與未來需要加強防範的關鍵物種。研究結果顯示，溫度是改變入侵植物生態棲位的主要驅動因子，未來氣候可能導致

多數物種之棲地適宜性、適宜棲地面積及最適棲地面積將所有提升，同時縮減已知族群與最適棲地間的距離，但仍有部份物種因無法適應氣候改變，致使侵略性下降。侵略性分級結果顯示，當前有10種入侵植物屬非高侵略性，但未來可能轉為高侵略性，有必要著手進行該些物種對生態環境或農業生產力的影響評估。總結而言，本研究的架構下可瞭解氣候變遷對臺灣入侵植物侵略性的影響，過程所建立之侵略性指標，亦可提供未來入侵防治策略制定之參考。

關鍵詞：生物入侵、生態棲位建模、入侵物種管理、棲地適宜性、風險評估

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Introduction

Invasive plants often have high capacities for dispersal and establishment. In addition to their rapid growth, they exhibit remarkably high environmental tolerance and adaptability (Murray and Phillips 2010; Davidson *et al*. 2011). Once a habitat has been invaded, existing ecological processes—vegetation composition, disturbance regimes, and biological interactions—may change accordingly (Hejda *et al*. 2009; Pyšek *et al*. 2012; Wu *et al*. 2017), further posing direct and indirect threats to original ecosystems, social economies, and human health (Dukes and Mooney 2004; Pratt *et al*. 2017; Stone *et al*. 2018). Climate change has been proven as a major driving factor for species migration and distribution (Mainka and Howard 2010; Chen *et al*. 2011). In the past, the general understanding was that invasive species may benefit from climate change and spread to areas where they were previously unable to survive or propagate (Walther *et al*. 2009; Bradley *et al*. 2010). However, recent studies have proposed a different view, that climate change will not exclusively favor invasive plants (Parker-Allie *et al*. 2009; Gallagher *et al*. 2013). Whether climate change will benefit invasive plants remains inconclusive (Thuiller *et al*. 2008). However, in the face of rapidly changing climates, effectively predicting and understanding the potential distribution or dispersal risks for invasive plants are often the key processes and significant issues in whether preventive strategies succeed (Leung *et al*. 2012; Sheley *et al*. 2015).

Ecological niche modeling (ENM) is a common method for predicting species habitat suitability and spatial distribution. Among the ENM models, maximum entropy (MaxEnt) models are the mostly widely used, including in the exploration of invasive plant species. Panda *et al*. (2019) studied habitat suitability and invasion risk ranges for *Chromolaena odorata* and *Tridax procumbens*, 2 invasive plants in India, under climate change conditions, and then proposed solutions for preventing invasion by these 2 species based on the resulting data. Thapa *et al*. (2018) modeled the influence of climate change on the potential distributions for 11 invasive plants in the western Himalayas, indicating that most plants will spread under climate change conditions and may pose threats to the native ecosystem. Yang *et al*. (2018) predicted the extent of the invasive harm of *Galinsoga quadriradiata* in China, and their study results showed that under climate change conditions, suitable habitats for the species in central and eastern China may shrink and even disappear, but may expand their distribution range in the northeast. These case studies applied MaxEnt to model the potential spatial distribution and habitat suitability of invasive species, which can be used as references for establishing preventive strategies against invasive plants. Taiwan is situated at the junction between continental Eurasia and the Philippine Sea plate. The unique geographical location was originally at high risk of being invaded by invasive alien plants (Usher 1988; Macdonald *et al*. 1989). According to data from the Taiwan Invasive Alien Species Database built by the Taiwan Forestry Research Institute, 76 species of invasive plants are currently listed. In this age of facing climate change challenges, how to determine priority levels in invasive species prevention based on spatial distribution data is critical. Relevant Taiwanese studies on invasive plants have been made on a regional scale (Lu and Chung 2007; Wang *et al*. 2007; Wu *et al*. 2009; Liu and Kuo 2011; Lu 2016) and, along with studies evaluating invasion risk (Chang *et al.* 2008, Lee and Wang 2012) have failed to consider climate change and spatial data. Thus, this study included climate change scenarios in ENM and integrated spatial evaluation criteria to quantify and classify the spatial invasiveness of invasive plants in Taiwan. We anticipate that the invasiveness assessment method constructed in this study can be used to assess the possibility of invasive plants establishing and dispersing in current and future climates and further confirm which species need to be listed for elevated monitoring or priority prevention. The results of this study aims to serve as a reference for future projects on the prevention of invasive alien plants and conservation-related projects.

Materials and Methods

Study area

The island of Taiwan is situated to the east of the Asian continent and west of the Pacific Ocean, and its western coast lies adjacent to the Taiwan Strait. The island has approximately 36,000 km^2 land area and a population of 23 million. Most of its steep terrain consists of mountains and hills, and its flatland and urban land are mainly concentrated on the western side along the coast, resulting in terrain that is high in the east and low in the west. The 5 major mountain ranges are the Central Mountain Range, the Yushan Range, the Alishan Range, the Xueshan Range, and Coastal Range, with Yushan being the tallest peak at 3,952 m. Most of the rivers originate in the Central Mountain Range, and the water systems are densely distributed in the western half of the island. The Zhuoshui River has the longest river basin, and the Gaoping River has the widest surface area. According to Taiwan's Central Weather Bureau, from 1981 to 2010, the island received an average of 2,474 mm of rainfall per year and had an average temperature of 21.5°C. The winter season is marked by continental cold, high-pressure systems from Siberia, with the northeast monsoon, whereas the summer is characterized by high-pressure systems from the Pacific Ocean and the southwest monsoon. Based on the Forestry Bureau's fourth forest resource survey, forests are the primary type of land cover and account for 61% of the island (Forestry Bureau 2014). By vertical differentiation of altitude, the forests can be divided into the alpine vegetation zone, the *Abies* zone, the *Tsuga-Picea* zone, the *Quercus* zone, the *Machilus-Castanopsis* zone, and the *Ficus-Machilus* zone.

Species occurrence data

Distribution data were analyzed using the Taiwan Forestry Research Institute's Taiwan Invasive Alien Species Database as the basis for identifying invasive alien species, and based on data from the Forestry Bureau's Ecological Survey Database, 49 invasive alien plants with high quality and adequacy for subsequent analysis were selected as target species. The species belong

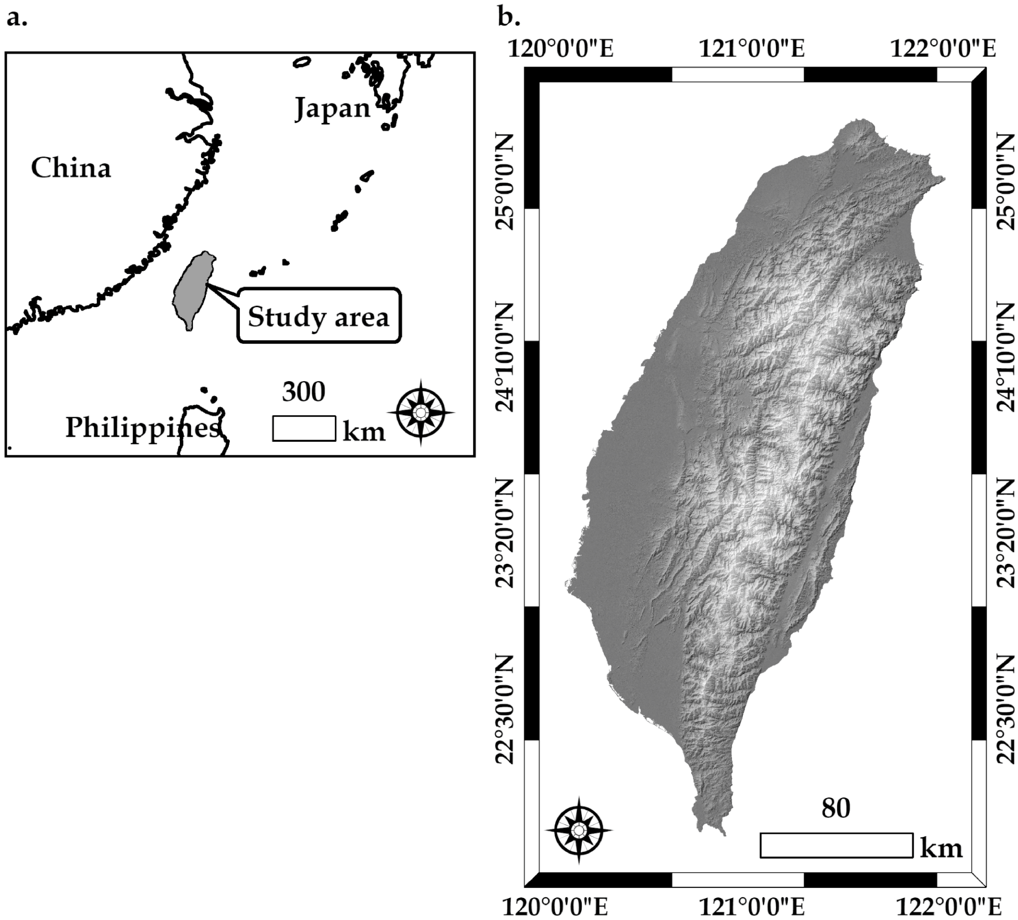

Fig. 1. (a) Geographical location of the study area; (b) elevation of the study area; lighter colors indicate higher elevations, and darker colors indicate lower elevations.

圖1. (a)研究區地理位置圖、(b)研究區海拔高，顏色愈淺為海拔愈高，反之則愈低。

to 17 families (Table 1), with Compositae, Fabaceae, and Poaceae accounting for 67.35% of the species in the study. The survey period of the data was 1998-2008, and the coordinate format was longitude-latitude. In this study, data were only retained to the third decimal place and uniformly converted to the Taiwan Datum 97 and the 2-degree transverse Mercator coordinate formats. Subsequent environmental data were also stored in this system and format. The basic operation unit

Table 1. Family, species number, and proportion of target invasive species
表1. 本研究選擇目標種之科別、種數與比例

Family	Species number	Proportion (%)
Araceae	1	2.04
Asteraceae	17	34.69
Balsaminaceae	1	2.04
Basellaceae	1	2.04
Brassicaceae	1	2.04
Capparaceae	1	2.04
Chenopodiaceae	1	2.04
Convolvulaceae	2	4.08
Crassulaceae	1	2.04
Cyperaceae	1	2.04
Euphorbiaceae	1	2.04
Fabaceae	9	18.37
Malvaceae	1	2.04
Onagraceae	1	2.04
Passifloraceae	2	4.08
Poaceae	7	14.29
Sapindaceae	1	2.04

for the grid was configured as 1×1 km^2; duplicate records of the same species within a grid were excluded.

Environment data

Environmental data are key factors that influence habitat suitability and the predictive variables in this study's ENM. The variables included climate, topographical, and vegetation conditions. Climate variables were downloaded from the WorldClim database, which was built by Hijmans *et al.* (2005). This database converts data from 1950-2000 from meteorological stations around the world through interpolation to generate at a nearly 1×1 km^2 minimum spatial scale. The database has 19 bioclimatic variables that were specially created to predict species distribution (Hijmans and Graham 2006). Topographical variables were obtained from digital elevation models from the WorldClim database, with ArcGIS 10.6 software used to create altitude slope images; furthermore, Gessler *et al*. (1995) and McCune and Keon (2002) were referenced to create a compound topographic index and heat load index, respectively, for a total of 4 variables. Vegetation conditions were extracted from the Terra-MODIS satellite imaging product MOD13Q, an enhanced vegetation index (EVI) obtained from the US Land Processes Distributed Active Archive Center. This index can be used to describe vegetation coverage and to create 6 mapping types—maximum, minimum, average, median, full range, and standard deviation—from 2000-2008. The MOD13Q products had a spatial resolution of 250×250 m^2. All EVI data were resampled in ArcGIS to 1×1 km^2 spatial resolution using the nearest neighborhood algorithm to match the resolution of other predictors. In the end, the predictive variables totaled 29 (Table 2). To

Table 2. Ecological niche modeling predictive variables in this study
表2. 本研究建立生態棲位建模所使用的預測變項

Variables	Description
Bioclimatic	
Bio1	Annual mean temperature
Bio2	Mean diurnal range (Mean of monthly (max temp - min temp))
Bio3	Isothermality (BIO2/BIO7) (* 100)
Bio4	Temperature seasonality (standard deviation *100)
Bio5	Max temperature of warmest month
Bio6	Min temperature of coldest month
Bio7	Temperature annual range (BIO5-BIO6)
Bio8	Mean temperature of wettest quarter
Bio9	Mean temperature of driest quarter
Bio10	Mean temperature of warmest quarter
Bio11	Mean temperature of coldest quarter
Bio12	Annual precipitation
Bio13	Precipitation of wettest month
Bio14	Precipitation of driest month
Bio15	Precipitation seasonality (Coefficient of variation)
Bio16	Precipitation of wettest quarter
Bio17	Precipitation of driest quarter
Bio18	Precipitation of warmest quarter
Bio19	Precipitation of coldest quarter
Topographic	
Elevation	Elevation
Slope	Slope
CTI	Compound topographic index
HLI	heat load index
Vegetation	
EVI1	EVI maximum value
EVI2	EVI minimum value
EVI3	EVI mean value
EVI4	EVI median value
EVI5	EVI standard deviation value
EVI6	EVI range value

EVI= enhanced vegetation index

avoid overfitting caused by the collinearity of variables, the variables were screened using Pearson correlation analysis; when the correlation coefficient for 2 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 scenarios

Subsequently, ENM was conducted assuming that the variables will change in accordance with the climate change conditions announced by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5). The AR5 defines change scenarios by representative concentration pathways (RCPs), with RCP 8.5 being the scenario of aggravated warming, with radiative forcing increasing by 8.5 Wm^{-2} from 1750 to 2100. Sometimes called the “business as usual” scenario, it represents a worst case that is fossil-fuel intensive and excludes any climate mitigation policies, leading to nearly 5 °C of warming by the end of the century (Riahi *et al*. 2011; IPCC 2013). The WorldClim database also provides future climate data for use; this batch of data was first interpolated with current, actual 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). From the 19 bioclimatic data items generated for RCP 8.5 scenarios during 2060-2080, 14 global climate model (GCM) simulation results were selected to obtain their mathematic means (Araújo and New 2007) after eliminating uncertainties that might be generated by different GCMs.。

Analysis of habitat suitability

MaxEnt 3.3.3k, developed by Phillips *et al*. (2006), was used to establish ecological niche models for the present day and future (2060-2080). This tool takes known distribution grids for species as sample points, and based on the environmental variables of the sample point, uses machine learning to predict habitat suitability for the species; it is the mostly widely used tool today and has been rated as an excellent software package (Kumar and Stohlgren 2009; Trisurat *et al*. 2011). For each species, 75% of the species data were randomly selected as the training dataset, before being processed 10 times to obtain the mean value. The output results were set as the logistic probability, with the prediction value ranging from 0 to 1; values closer to 1 represented higher odds of the plant species appearing on the grid and the grid being a suitable habitat. 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 values range 0.5-1, with higher values indicating higher accuracy of model predictions and the value greater than 0.7 indicating a reasonable discrimination ability appropriate for many uses (Swets 1988; Pearce and Ferrier 2000).

Building the invasive plants invasiveness evaluation index

The invasiveness of different invasive plants in present day and future climate change scenarios were quantified referencing Roger *et al*. (2015). The index comprises 5 indicators: (1) known population count, (2) habitat suitability, (3) area of suitable habitats, (4) area of the optimal habitat, and (5) distance between known populations and optimal habitats. Table 3 presents a definition for each indicator.

Known population count refers to the total number of grids in the study area in which an invasive species has actually been observed. This can be considered the population count of that invasive species. Habitat suitability is the measurement of that grid's habitat quality, which can indicate the probability of an invasive species growing or spreading its population in that grid. If a known population falls in a grid with high suitability, then that population will have a high probability of growing in the future. To calculate the area size of suitable habitats,

Table 3. Invasive plant invasiveness evaluation index
表**3**. 本研究建立入侵植物侵略性評估指標

Indicator	Description
Known population count	Number of grids with the target species observed in the study area
Habitat suitability	Average value of habitat suitability for all observed grids with the target species
Area of suitable habitats	Area size of areas with suitability greater than or equal to the threshold set by the model
Area of optimal habitat	Area size of areas with suitability greater than 0.5
Distance between known populations and optimal habitats	Shortest distance (average value) of all known populations to the optimal habitat

Note: Suitability refers to the distribution probability of each analysis unit derived from MaxEnt calculations.

the suitability of each grid was converted into a binary graph—suitable and unsuitable—using the 10th percentile of training presence provided in the MaxEnt model (Pearson *et al*. 2007; Koncki and Aronson 2015), and the number of suitable grids was tallied to estimate the largest possible range that the invasive species can spread. The area of optimal habitat uses 0.5 as the binary threshold value to predict the size of the region most suited to the survival of that invasive species. Finally, the distance between known populations and optimal habitats was calculated by taking the average value of shortest distances from grids with known populations to optimal habitats. This indicator can express the probability of known populations establishing a population in the optimal habitat or expanding their habitat; shorter distances indicate higher probabilities.

Quantifying and classifying the invasiveness of invasive plants

The results obtained from the invasiveness index were converted into percentiles by individual items and then given a score according to which of the 5 grades they were classified into based on set intervals. Known population, habitat suitability, area of suitable habitats, and area of optimal habitats were given the following scores and grades: 1 point for 0-5, 2 points for 6-25, 3 points for 26-75, 4 points for 76-95, and 5 points 96-100 (Roger *et al.* 2015). The indicator for distance between known populations and optimal habitats was given a score that was inverse to its level. Subsequently, the index scores for each time were tallied to obtain the invasiveness score for 49 invasive plants species; higher scores indicated higher invasiveness. Finally, using the Jenks natural breaks method, the 49 invasive plants species were divided into low, medium, and high levels of invasiveness, and this classification method was applied to quantify results of future climate scenarios for subsequent comparative analysis. In the study process, spatial analyses were run through the Spatial Analysist module of the Arc GIS 10.6 software package.

Results

With Pearson correlation coefficients less than 0.7 as the threshold, 11 out of 29 environmental factors were chosen to be predictors in subsequent MaxEnt models to build ecological niche models for each species. The AUC fell between 0.70 and 0.95, and the mean AUC was 0.85 with a standard deviation of 0.01, indicating favorable modeling overall. Figure 2 presents the different levels of contribution for the 11 variables toward each of the species. Annual mean temperature (BIO1) had the greatest mean contribution to each species model (average 44.79%) and was the most critical variable to model building for 36 species (73.47%); temperature seasonality (BIO4) and mean diurnal range (BIO2) accounted for 16.86% and 12.07% of the contribution, respectively and each had the greatest contribution to the modeling of 4 species. The remaining 8 predictors—annual precipitation (BIO12), slope, precipitation of warmest quarter (BIO18), EVI standard deviation value (EVI5), EVI minimum value (EVI2), EVI mean value (EVI3), HLI, and CTI—had lower importance (less than 7%) and were the most critical variables for few (1-2) or no species, thereby having relatively no overall influence on the models. These results indicated that climate variables have the greatest explanatory power for models predicting suitable habitats for invasive plants species, especially variables concerning temperature, which may be the primary reason influencing habitat suitability for invasive plants.

Based on the invasiveness evaluation index values for each invasive plant under current climate conditions, calculations and comparisons of change rates for each invasiveness indicator under future climate change conditions (Table 4) demonstrated that climate warming can increase habitat suitability, the area of suitable habitats, and the area of optimal habitats for numerous species and also lower the distance between known populations and optimal habitats for the most species. Climate change will

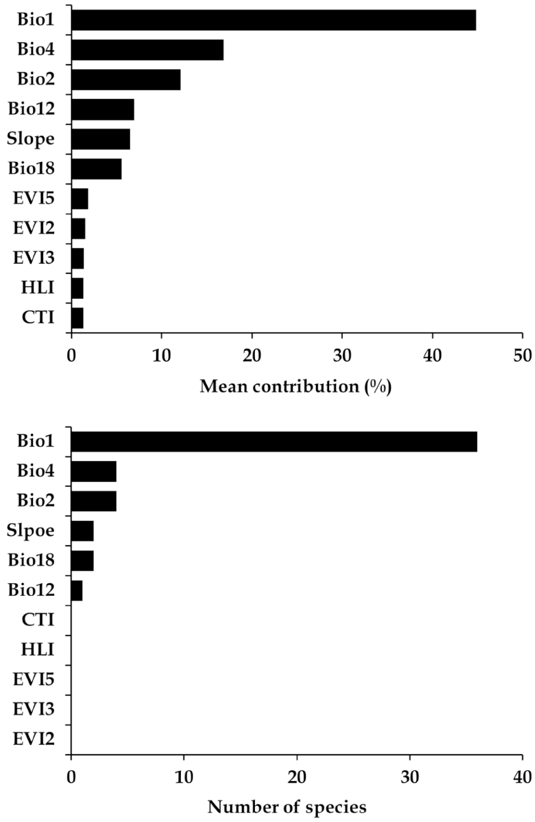

Fig. 2. (a) Mean contribution of predictive variables; and (b) number of species for which the predictive variable is the greatest contributor.

圖2. (a)預測變項的平均貢獻度與(b)最大貢獻度變項之物種數。

increase habitat suitability for 28 species, have no effects on suitability for one species, and lower suitability for the remaining 20 species. Under current climate conditions, the average area of suitable habitats for 49 species is 10,150.31 km^2, and under future climate conditions this area will increase for 37 species (75%). Area size of suitable habitats will increase by 51% and more for 13 species, resulting in the overall average area of suitable habitats increasing to 13,446.96 km^2. Further comparisons of the area of optimal habitats for each species under current and future climate conditions revealed that the optimal habitat for 35 species will increase in area, with 24 species having their optimal habitats increase in area by 51%. Furthermore, 5 of the 14 species with shrinking optimal habitats will see over 51% of optimal habitat area shrinkage. Future climates will also reduce the average distance between known populations for 33 species and their optimal habitat; the distance will increase for the other 16 species.

The quantified cumulative value of each species' invasiveness index was divided using the Jenks natural breaks method into low (≤ 13), medium (14-16), and high (≥ 17) levels of invasiveness. Under current climate conditions, 12 invasive plant species were evaluated with high invasiveness (Table 5),

Table 4. Variations in the invasiveness evaluation index under climate change conditions
表4. 氣候變遷情境下入侵植物侵略性評估指標的變化量

Variation		Habitat suitability	Area of suitable habitats	Area of optimal habitats	Distance to optimal habitat
Increase	≥ 51%	0	13	24	10
	26-50%	10	14	6	5
	11-25%	8	8	2	0
	1-10%	10	2	3	1
No change	0%	1	0	0	0
Decrease	1-10%	4	1	2	1
	11-25%	5	6	4	4
	26-50%	7	4	3	9
	≥ 51%	4	1	5	19

Note: numbers in parentheses are number of species.

and the effects of climate change will lower invasiveness for 5 of these species; the remaining 7 species will maintain their level of invasiveness. While 10 out of the 49 species—including Malabar spinach (*Basella alba*), *Mimosa pudica*, *Mimosa diplotricha*, umbrella sedge (*Cyperus involucratus*), and Natal grass (*Melinis repens*)—may not be highly invasive plant species under current climate conditions, they may become highly invasive under future climate conditions, with the arrowhead plant (*Syngonium podophyllum*) transforming from low to high invasiveness. Overall, under future climate change conditions, the number of highly invasive plant species will increase from 12 to 17; that of medium-invasive plant species will decrease from 27 to 17; and that of low-invasive plant species will increase from 10 to 15.

Table 6 presents the top 3 species with increased or decreased cumulative invasiveness index scores. The 2 species with the greatest cumulative increase—arrowhead plant (*Syngonium podophyllum*) and cutleaf evening primrose (*Oenothera laciniate*)—are both low-invasive plant species, but under future climate change conditions their invasiveness index will increase to high and medium invasiveness, respectively. Malabar spinach will see increases in habitat suitability and area of optimal habitats and shortened distances between known populations and optimal habitats; its invasiveness will increase from medium to high. The species that will see the greatest decrease are the Peruvian daisy (*Galinsoga quadriradiata*), white clover (*Trifolium repens*), and grazing brome (*Bromus catharticus*), in that order. The most obvious result of climate change on these 3 species is the decrease in habitat suitability; the invasiveness of grazing brome will stay the same, whereas the invasiveness of Peruvian daisy and white clover will decrease from high and medium to low, respectively.

Discussion

The application of ENM to invasion prevention topics can provide quantified and spatialized data on invasion risks, thereby serving as a critical tool in invasion prevention. This study conducted ENM using climate, topography and vegetation data. Based on the mean AUC value the predictive results achieved ideal standards. Climate factors accounted for 5 of the 11 variables selected for the model and made high contributions to model building (Fig. 3); the cumulative contributions were 86%, with temperature variables being the major driving factor in the location of ecological

Table 5. Highly invasive plant species under current and future climate change conditions
表5. 當前及未來氣候變遷情境下高侵略性入侵植物種

Species	Family	Invasiveness level	
		Current	RCP8.5(2070s)
Passiflora suberosa	Passifloraceae	High	High
Bidens pilosa var. *radiata*	Asteraceae	High	High
Panicum maximum	Poaceae	High	High
Tithonia diversifolia	Asteraceae	High	High
Conyza canadensis	Asteraceae	High	High
Crassocephalum crepidioides	Asteraceae	High	High
Ageratum houstonianum	Asteraceae	High	High
Conyza bonariensis	Asteraceae	High	Medium
Chenopodium ambrosioides	Amaranthaceae	High	Medium
Pennisetum purpureum	Poaceae	High	Medium
Malvastrum coromandelianum	Malvaceae	High	Medium
Galinsoga quadriradiata	Asteraceae	High	Low
Basella alba	Basellaceae	Medium	High
Mimosa pudica	Fabaceae	Medium	High
Mimosa diplotricha	Fabaceae	Medium	High
Cyperus involucratus	Cyperaceae	Medium	High
Melinis repens	Poaceae	Medium	High
Chamaesyce hirta	Euphorbiaceae	Medium	High
Impatiens walleriana	Balsaminaceae	Medium	High
Pennisetum polystachion	Poaceae	Medium	High
Cuscuta campestris	Convolvulaceae	Medium	High
Syngonium podophyllum	Araceae	Low	High

habitats for invasive species changing. Other studies (Sheppard and Stanely 2014; Yang *et al*. 2018) have had similar results, indicating that the 49 species of invasive plants analyzed in this study are highly likely to experience the effects of temperature changes in the future and the expansion, loss, or transference of their habitats.

Model results simulating RCP 8.5 scenarios in the years 2060-2080 (Tables 4 and 5) indicated that invasive plants will have different responses to climate change based on their biological traits and the invasion environment conditions (Leishman

Table 6. Top 3 species in terms of increasing and decreasing cumulative invasiveness index scores under future climate change conditions

表6. 未來氣候變遷情境下侵略性指標得分累計增加或減少最多的前3種物種

Species	Score variation	Previous score	Difference between future and current invasiveness index scores			
			Habitat suitability	Area of suitable habitats	Area of optimal habitats	Distance to optimal habitats
Syngonium podophyllum	7	13	1	1	2	3
Oenothera laciniata	7	9	1	2	2	2
Basella alba	6	15	2	0	2	2
Galinsoga quadriradiata	-9	17	-4	-1	-2	-2
Trifolium repens	-5	16	-2	-1	-1	-1
Bromus catharticus	-5	12	-2	-1	-1	-1

and Gallagher 2015; Ramesh *et al*. 2017). Habitats currently unsuitable for most invasive plant species will become suitable under new climate conditions, and the distance between known populations and optimal habitats will be shortened; thereby suggesting that most species of invasive plants will be more likely to establish populations in the future or expand current populations to other ecosystems. Table 6 indicates that under future climate conditions, the 3 pantropic species with the greatest increase in invasiveness are the arrowhead plant, cutleaf evening primrose, and Malabar spinach. The native range of arrowhead plant is in Central America (GISD 2020). It has been observed invading native ecosystems in Singapore, South Africa, and other countries (Chong *et al*. 2010; Foxcroft *et al.* 2008). The cutleaf evening primrose is native to North, temperate and subtropical America. At present cutleaf evening primrose is considered naturalized in much of the world, including south-western Europe, China, Japan and other countries and potentially harmful by its invasive nature (Dietrich 1977; Liu and Dong 2010; Mito and Uesugi 2004; Mahklouf 2016). The cutleaf evening primrose is exceedingly strong at expanding and can grow in dry, hot coastal sand and on cool, shady mountains over 1000 m in altitude (Chen *et al*. 1997). The Malabar spinach native to tropical Asia and thrives well in tropical and subtropical climates

(Grubben and Denton 2004). It prefers high temperatures and is highly adaptive to its environment, particularly in humid and hot environments (Grubben and Denton 2004; Reddy *et al*. 2014; Chu and Lin 2018). If these plant species continue to establish or expand new population ranges without supervision, they may bring inestimable damage to native ecosystems, agricultural production, and human health (Simberloff *et al*. 2013). The modeling results (Table 4) also indicated that few species will decrease in invasiveness from climate and environmental changes, which was consistent with the results of many studies (Parker-Allie *et al*. 2009; O'Donnel *et al*. 2012; Bellard *et al*. 2013; Gallagher *et al*. 2013; Roger *et al*. 2015). The invasiveness of Peruvian daisy is predicted to decrease obviously because the optimal germination temperature of this species is 16-24°C, and the highest germination rate is reached at 16°C (Hsu *et al*. 2012). We infer that the future climate warming condition should be disadvantageous to seed germination. In terms of maladjustment to warming, white clover and grazing brome are similar to Peruvian daisy (Table 6). The two species are temperature zone species (Archer and Robinson 1989; Williams *et al*. 2011), and their seed germinations must undergo alternating temperatures (Alshallash 2018) or dormancy breaking at low temperatures in winter (Bewley and Black 1994). These species may be more easily prevented in the future, thereby offering new opportunities in invasion management (Pyke *et al*. 2008; Bradley *et al*. 2009; Bellard *et al*. 2013).

Invasive plant species evaluated as highly invasive under current and future climate conditions (Table 5) have advantages in establishing populations and expanding habitat ranges, which may pose a threat to current or future suitable regions. An impact assessment on ecological environments and agriculture production should be conducted, especially for the 10 species that are not currently highly invasive but may become so in the future. Studies (Davis *et al*. 2000; Vila and Ibáñez 2011; González-Moreno *et al*. 2013; Jauni *et al*. 2015) have shown that alien plants will most likely establish populations in disturbed or fragmented environments. However, even if climate change adds many suitable habitats for invasive plants, it would not signify that invasive plants must exist in their suitable habitats—known populations must still pass through geographical obstructions to reach new suitable habitats before establishing new populations (Bellard *et al*. 2013). Therefore, prevention strategies might involve interventions or preventions using landscape measures, such as maintaining the integrity of current floristics to avoid creating more marginal environments or deteriorating habitats with poor resilience, as preferred by invasive species (Vila and Ibáñez 2011; Bennett 2013; Bennett *et al*. 2013; Leishman and Gallagher 2015), or landscape connectivity, which identifies key areas that can inhibit the spread of invasive plants through a connectivity model (Minor and Gardner 2011; Glen *et al*. 2013; Roy *et al*. 2016). A successful grasp of the relationship between landscape patterns and invasive spread may aid in future priority planning and strategy formulation for the prevention of invasive species (Rodewald and Arcese 2016).

This study assumed that climate change is the only factor that drives the distribution of ecological habitats for invasive plant species, and therefore, changes in land use and the ability of invasive plant species to spread and interact with other species were not taken into account However, the key to biological invasion is actually determined by the comprehensive effects of biological and nonbiological factors (Roura-Pascual *et al*. 2011; Gallardo and Aldridge 2013), which may be subjected to changes due to the effects of climate change, thereby adding further uncertainty to the invasion process (Leishman and Gallagher 2015). Furthermore, although the invasiveness evaluation index established in this study cannot provide an absolute rubric based on invasiveness, it can provide scores based on clear ranking in percentiles. This ranking can be used to objectively derive the relative invasiveness of invasive plants, which can provide a reference for the future management or prevention priority planning for invasive plants.

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