Response of Asian citrus psyllid *Diaphorina citri* Kuwayama (Hemiptera: Liviidae) to climate change

Owusu Fordjour (ofaidoo@uesd.edu.gh)
University of Environment and Sustainable Development https://orcid.org/0000-0003-3332-0943

Philipe Guilherme Corcino Souza
Universidade Federal dos Vales do Jequitinhonha e Mucuri

Ricardo Siqueira da Silva
Universidade Federal de Vicosa

Paulo Antonio Santana Jr,
Universidade Federal dos Vales do Jequitinhonha e Mucuri

Marcelo Coutinho Picanço
Universidade Federal dos Vales do Jequitinhonha e Mucuri

Rosina Kyerematen
University of Ghana

Mamoudou Sètamou
Texas A and M University: Texas A&M University

Sunday Ekesi
International Centre for Insect Physiology and Ecology

Christian Borgemeister
University of Bonn

Research Article

Keywords: Asian citrus psyllid, ACP, climate change, Diaphorina citri, invasive species, MaxEnt

Posted Date: September 9th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-862117/v1

Abstract

The Asian citrus psyllid (ACP) Diaphorina citri Kuwayama (Hempitera: Liviidae) is a destructive, invasive species which poses a serious threat to the citrus industry worldwide. The psyllid vectors the phloem-limited bacteria “Candidatus Liberibacter americanus” and “Candidatus Liberibacter asiaticus”, causal agents of the incurable citrus greening disease or huanglongbing (HLB). It is essential to understand which regions and areas are suitable for colonization by ACP to formulate appropriate policy and preventive measures. Considering its biology and ecology, we used a machine learning algorithm based on MaxEnt (Maximum Entropy) principle, to predict ACP’s potential global distribution using bioclimatic variables and elevation. The model predictions are consistent with the known distribution of ACP and also highlight the potential occurrence outside its current ecological range, i.e. primarily in Africa, Asia, and the Americas. The most important abiotic variables driving ACP’s global distribution were annual mean temperature, seasonality of temperature, and annual precipitation. Our findings highlight the need for international collaboration in slowing the spread of invasive pests like *D. citri*.

Highlights

• We modeled and mapped the potential global distribution of *Diaphorina citri*.

• MaxEnt model consisted of bioclimatic variables and elevation.

• Annual mean temperature, seasonality of temperature, and annual precipitation were the most significant environmental variables.

• The model predicts suitable areas in Africa, Australia, Asia, and the Americas.

• There model predicts expansion of suitable areas from SSP1-2.6 to SSP5-8.5, and either marginal contraction or expansion from 2040 to 2060 time periods.

1. Introduction

Invasive species (IS) introduced outside their native range through human activities are increasing worldwide at unprecedented rates (van Kleunen et al. 2020; Saul et al. 2017). If not effectively handled, IS can pose a serious threat to the global economy and biodiversity. Global trade and transportation have opened up new entry pathways for IS such as farm machinery and escapes or introductions. The introduction, establishment and spread of IS in new habitats are often associated with irreversible ecological changes, and serious consequences for agriculture and food security (Linders et al. 2019). Frequently, crop production is under the combined threats from IS and climate change, both of which are affecting biodiversity and ecosystem functioning (García et al. 2018; Sala et al. 2000). The total cost of IS to agriculture is estimated at $3.66 billion/year in Africa (Eschen et al. 2021), $120 billion/year in the USA (Fish and Wildlife Service U.S. 2012), 13.6 billion/year in Australia (Hoffmann and Broadhurst 2016), and $14.45 billion/year in China (Xu et al. 2006).

The invasive Asian citrus psyllid (ACP) *Diaphorina citri* Kuwayama (Hemiptera: Psyllidae), is one of the economically most important pests of citrus worldwide. It vectors the phloem-limited bacteria “Candidatus Liberibacter americanus” (*C*Lam) and “Candidatus Liberibacter asiaticus” (*C*Las), causal agents of the incurable citrus greening or huanglongbing (HLB) disease, which has been associated with huge economic losses to citrus wherever it occurs (Bové 2006). Although the rate of *C*Las and *C*Lam transmission by ACP individuals is usually low, HLB can quickly spread through citrus groves (Hall et al. 2013). This often leads to an expansion of the geographic distribution of the disease, rendering many citrus fruits unmarketable. In California, economic losses associated with a lack of HLB management regime are estimated annually at $2.7 billion, and even under an aggressive disease management regime at $2.2 billion per year (Durborow 2012). Attempts by citrus growers, researchers, and regulatory officers to eradicate HLB in citrus groves have focused on the ACP vector, which involves intensive applications of insecticides (Hall et al. 2013). Yet, this strategy is expensive, unsustainable, ineffective and is a threat to human and environmental health. Insecticide resistance in field populations of ACP has been reported in Florida (Chen and Stelinski 2017), Punjab (Naeem et al. 2016), and Guangdong (Tian et al. 2018). The scientific community is working hard to develop ecological friendly solutions to HLB, though it could be years before they are fully implemented (Hall et al. 2013), highlighting the importance of proper policy formulation and prevention measures against the disease.

ACP is listed as an A1 quarantine pest by European and Mediterranean Plant Protection Organization, Caribbean Plant Protection Commission and Organismo Internacional Regional de Sanidad Agropecuaria (CABI 2020). The putative center of geographical origin of the psyllid is Asia (Mead 1977), but it has spread to almost all citrus-growing regions of the world, causing economic havoc for citrus growers. In the Americas, it was first reported in Brazil around the 1940s (Costa Lima 1942). In East Africa, ACP was first reported in Tanzania in 2016 (Shimwela et al. 2016), and more recently also in Nigeria, West Africa (Oke et al. 2020). Thus to date, ACP is present in all leading citrus-producing countries in the world, i.e. China, Brazil, Mexico, India, and the USA (FAOSTAT 2019).

In order to mitigate or even avoid the ecological and socio-economic impacts caused by ACP invasions, a thorough understanding of the habitat suitability for the vector is fundamental for appropriate risk assessment and decision making. Biological invasion prevention is far less expensive than post-entry control (Mack et al. 2000). Hence, a detailed understanding of a species’ geographical and biological distribution is essential for conservation planning and forecasting (Lawler et al. 2011).

Climate change has a significant impact on the distribution of species, causing either the expansion or contraction of suitable habitats (Ajene et al. 2020). Anthropogenic activities are increasing the amounts of pollutants in the atmosphere, particularly atmospheric CO_2 and tropospheric O_3, which play important roles in ecosystem functioning (Couture and Lindroth 2013). These global changes are expected to impact the ecological range of crop pests (Das et al. 2011). For instance, increased CO_2 levels in leaves can lead to an increase in simple sugars and a decrease in nitrogen content, leading to higher damage by insect herbivores (Gely et al. 2020).

The recent introductions of ACP into West and East Africa (Oke et al. 2020; Shimwela et al. 2016), as well as to other citrus-growing regions in the world, has highlighted the need for forecasting potential new areas of habitat suitability of this pest to enable monitoring and surveillance of such potential routes of invasion. Previous studies have successfully used species distribution models (SDMs) to predict the potential distribution of agricultural pests (Rank et al. 2020; Santana et al. 2019). The method computes the degree of similarity between the environmental conditions at a particular site and the conditions at locations where a species is known to exist (Hijmans and Elith 2013). SDMs are classified into two types: correlative models such as Maximum Entropy (MaxEnt), Genetic Algorithm for Rule Set Production, and Ecological Niche Factor Analysis, and process-based distribution models like CLIMEX (Srivastava et al. 2019). MaxEnt is a machine learning algorithm that is useful for makings predictions or inferences from few data points (Rank et al. 2020). It can be used to find correlations between the occurrence of species and background data points from geographical environmental variables to produce estimates about potential regions for a species to occur (Rank et al. 2020; Phillips et al. 2006). It enables researchers to investigate the implications of climate change on areas that are suitable for future spread and has provided significant insights into prospective colonization behavior (Santana Jr et al. 2019).

In order to prevent the detrimental consequences of global warming on insect pests, researchers must get a deeper understanding of particular species' responses as well as the complex ecological systems that underpin these systems (Lehmann et al. 2020). Although information on the influence of climate change on pests of horticulture crops has expanded significantly, information on the impact of climate change on the global distribution of ACP, essential for future mitigation measures, are often inadequate. Hence we utilized MaxEnt to assess the response of ACP to climate change to develop information for quarantine measures and emphasize the need for policy implementation.

2. Materials And Methods

2.1 Occurrence datasets

Occurrence data for ACP were collected in Kenya and Tanzania using yellow sticky traps, visual observations of eggs, nymphs, adults, and symptomatic leaves between October 2015 and April 2018. The information gathered consisted of georeferenced coordinate points with the latitude and longitude of locations where ACP presence had been confirmed. This was complemented by additional global distribution data from the literature (Aidoo et al. 2021; Abreu et al. 2020; Ajene et al. 2020; Oke et al. 2020; Wulff et al. 2020; Fuentes et al. 2018; Halbert and Núñez 2004; Cornejo and Chica 2014; Boykin et al. 2012; Teck et al. 2011; Davis et al. 2005) and from the databases of the Global Biodiversity Information Facility (GBIF – https://www.gbif.org). A total of 386 data points were obtained (Table S1), and Fig. 1 illustrates the current distribution of ACP in Africa, the Americas, and Asia.

We applied spatial filtering using spThin, an R package that reduces spatial autocorrelation (Aiello-Lammens et al. 2015). The degree of the spatial association present in the datasets is known as spatial autocorrelation, and it can prevent the points used for testing from being separated. After this filtering

process, all 286 remaining points of occurrence were at least 10 km apart (Boria et al. 2014). This distance ensures that each cell has only a single point of occurrence. The data were then transformed into MaxEnt-compatible formats.

2.2 Environmental data layers

Initially, we considered 20 variables as potential predictors for estimating ACP habitat suitability. Nineteen (19) standard WorldClim Bioclimatic variables and one elevation data derived from the Shuttle Radar Topographical Mission (SRTM) (Farr and Kobrick 2000) were used. These datasets were obtained from the WorldClim version 2.1, released on January 2020 (https://www.worldclim.org/). The data layers employed had a 2.5 min spatial resolution (about 5 km), which was suitable for supporting climatic variables on a global scale because they covered all global land surfaces. High spatial resolution climate data are often necessary for ecological and modeling studies (Ramos et al. 2019). WorldClim projects current climatic conditions based on observations gathered from different weather stations between 1970 and 2000; the point datasets are interpolated using a thin plate smoothing spline algorithm to create a seamless raster dataset (Hijmans et al. 2005).

Table 1
Nineteen environmental variables used for the model with code and units. The variables that were used in the final model as predictor variables are highlighted in bold

Code	Environmental variable	Unit
Bio_1	**Annual average temperature**	°C
Bio_2	**Average variation of day time temperature**	°C
Bio3	Isothermality	°C
Bio_4	**Seasonality of temperature (SD x 100)**	SD × 100
Bio_5	Highest temperature of the hottest month	°C
Bio_6	Lowest temperature of the coldest month	°C
Bio_7	Annual temperature variation	°C
Bio_8	Average temperature of the rainy quarter months	°C
Bio_9	Average temperature of the driest quarter months	°C
Bio_10	Average temperature of the hottest quarter months	°C
Bio_11	Average temperature of the coldest quarter months	°C
Bio_12	**Annual precipitation**	mm
Bio_13	Precipitation of the rainiest month	mm
Bio_14	Precipitation of the driest month	mm
Bio_15	**Precipitation seasonality**	CV
Bio_16	Precipitation of the rainiest quarter months	mm
Bi0_17	Precipitation of the driest quarter months	mm
Bio_18	Precipitation of the hottest quarter months	mm
Bio_19	Precipitation of the coldest quarter months	mm
20	**Elevation**	m

We used the SDM toolbox 2.4 (Brown et al. 2017) in the ArcGIS software (version 10.8.1) to remove variables with high correlation ($r \geq |0.70|$), and only one variable from a group with correlation was included based on Pearson's correlation coefficient (Rank et al. 2020; Kumar et al. 2014).

2.3 The future projections of suitable areas for *Diaphorina citri*

Our study focuses on two predictions under two different scenarios (SSP1-2.6 and SSP5-8.5) of the upcoming 2021 Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (AR6). The SSP1-2.6 represents a scenario that assumes climate protection measures are being taken. However, the SSP5-8.5 scenario represents the upper boundary of the range of scenarios described in the literature (Riahi, et al. 2016). The Global Climate Model (GCM) we employed was the Model for Interdisciplinary Research on Climate (MIROC-6). The model was developed as a result of a collaboration among the Atmosphere and Ocean Research Institute (The University of Tokyo), the National Institute for Environmental Studies, and the Japan Agency for Marine-Earth Science and Technology (Japan). It is a newly developed climate model, with updates to its physical parameterizations in all sub-modules (Tatebe et al. 2019).

2.3 Development and model validation

The global distributions of ACP were obtained from the model based on the MaxEnt version 3.4.4 (Steven et al. 2021), which is best suited to the current study, for it has been based on the presence-only data and background points of the organism under consideration (Phillips et al. 2006; Kumar et al. 2009). MaxEnt generates a suitability index of the species ranging from 0 (for unsuitable) to 1 (for optimum suitability) per grid cell. Our model for ACP was based on adjusting to the MaxEnt default settings combining different feature classes (FC), and the regularization multiplier (RM) to find the best setting for the species (Kumar et al. 2014). To adjust the number of parameters, and, hence, the model's complexity, we selected the linear (L), quadratic (Q), product (P), threshold (T), and hinge (H) sets of MaxEnt FC with RM (Table 3) (Elith et al. 2011). As this is a global ecological niche modeling, we tested two RM values, i.e., 1.0 and 2.0. We chose these values because models are very restricted when the RM is < 1, which is inadequate for global predictions. An RM value > 1 generates models with a broader potential distribution (Phillips et al. 2006).

To eliminate extrapolations from the environmental range, we used the MaxEnt ‘fade by-clamping’ (Owens et al. 2013). The predictive contribution of variables was estimated using the Jackknife technique; thus, we assessed the importance of each variable. Response curves were generated in MaxEnt, and we chose only the environmental variables that represented strong relationships between the probabilities of the presence for the species with each environmental predictor. All the response curves were evaluated in terms of providing powerful biological logic. This indicates that the probability of the presence of a species does not display many ups and downs as the environmental variables increases, which is not expected to occur with living organisms.

To validate the models, we selected the criteria of test sensitivities of 0% and 10% training Omission Rates (OR) (Kumar et al. 2014) and the AUCcv (area under the receiver operating characteristic [ROC] curve) (Peterson et al. 2008). To calculate the AUCcv and OR, 10-fold cross-validation was run in MaxEnt. An AUCcv value of 0.5, indicates that model predictions are no better than random; values < 0.5 are less than random; values between 0.5 and 0.7 indicate poor performance; values between 0.7 and 0.9 indicate moderate performance, and values > 0.9 indicate high performance (Peterson et al., 2011). In the case of the OR, its value determines whether the model omitted the existence of locations where the target

species occurs. The expected value at 0% OR is 0, and at 10% it is 0.10; models show poor performance when value deviates from expected ORs (Boria et al. 2014). The model ranking was based on 10% training OR, 0% training OR, and AUCcv in this order, respectively (Kumar et al. 2014). ArcGIS 10.8 software was used to extract the MaxEnt outputs to project areas suitable for ACP. The Maximum Test Sensitivity Plus Specificity (MTSPS) threshold, considered simple and effective and at least as good as other more complicated approaches (Ramos et al. 2019), was chosen to extract from the predictive model four suitability classes for ACP (unsuitable: 0-MTSPS; low: MTSPS-0.5; medium: 0.5–0.7 and high: 0.7–1.0).

3 Results

3.1 Modeling performance

All the performance statistics of the ACP MaxEnt models are provided in Table 2. The average AUCcv values ranged from 0.931 to 0.948. These models displayed low test ORs with values varying from 0.0035 to 0.0139 at a 0% training OR and from 0.1050 to 0.1887 at 10%. The best model comprised six environmental variables with Linear, Quadratic, Product (LQP) features and RM equal to 2. Based on the tenfold cross-validation, this model exceeded a random distribution, had an AUC value of 0.931, and low ORs.

Table 2
Summary of the performance statistics of the *Diaphorina citri* MaxEnt models. The best model is highlighted in bold.

Model rank	Variables	MaxEnt settings		Test AUCcv	OR	
		Features	RM		0%	10%
1	**bio1,bio2,bio4, bio12, bio15, elevation**	**LQP**	**2**	**0.931**	**0.0035**	**0.1050**
2	Same as above	LQPTH	2	0.947	0.0036	0.1298
3	Same as above	LQPT	2	0.947	0.0069	0.1475
4	Same as above	LQPT	1	0.945	0.0070	0.1887
5	Same as above	LQP	1	0.933	0.0070	0.1157
6	Same as above	LQPTH	1	0.948	0.0139	0.1504

Note: Variable full names (see Table 1). L, Q, P, T and H are linear, quadratic, product, threshold and hinge features, respectively. RM is the regularization multiplier. OR is the test omission rate. Test AUCcv is the MaxEnt 10-fold cross-validation Area Under the ROC curve.

3.2 Contribution of environmental variables

The Jackknife test was used to identify the environmental variables that most influenced the ACP distribution. The test of the importance of variables showed that annual mean temperature (bio1) was the most useful information by itself than bio2, bio4, bio12, bio15, elevation. The variable that most decreased the gain when omitted was seasonality of temperature (bio4), which, therefore, seems to have the greatest amount of information that is not present in the other variables (Fig. 2). Values shown are averages over replicated runs.

3.3 Response of variables to the suitability

The probability of occurrence of ACP has an average annual temperature of around 20 ºC (Fig. 3a) and annual precipitation about 2,000 mm (Fig. 3b). Values mean variation in daytime temperature that differs from 10 ºC also reflects a decrease in the probability of ACP occurrence. The greater this variation, the lower the probability of the species' presence (Fig. 3c). The probability of the presence of ACP was higher in areas with low altitudinal gradients (Fig. 3d).

Annual mean temperature (Bio1; ºC), seasonality of temperature (SD × 100) (bio4), and Annual precipitation (bio12; mm) were the environmental variables that contributed more than 90% to the pest distribution (Tables 3). Therefore, to the observed occurrences, ACP occurs in areas with a mean annual temperature of 21.67º C and a mean annual precipitation range of 77-5076 mm with a mean of 1,411.69 mm.

Table 3

Environmental variables considered in the *Diaphorina citri* niche models and mean percentage contribution of environmental variables in the distribution model; values were averaged over ten repeated runs. General statistics were calculated using all occurrences (n = 166). (Min. = minimum, Max. = maximum, Avg. = Average and SD = standard deviation).

Variable	Percentage contribution	Permutation importance	Min.	Max.	Mean.	SD
Annual mean temperature (Bio1; ºC)	**56.4**	**67.1**	**14.59**	**28.78**	**21.67**	**3.27**
Seasonality of temperature (SD × 100) (bio4)	**19.3**	**10.8**	**31.55**	**876.87**	**459.59**	**251.28**
Annual precipitation (bio12; mm)	**17.7**	**13**	**77**	**5076**	**1411.69**	**660.73**
Mean variation of daytime temperature (bio2; °C)	**4.4**	**3.1**	**5.31**	**18.84**	**9.10**	**2.61**
Precipitation seasonality (CV) (bio15)	**2**	**5.2**	**14.63**	**154.99**	**65.10**	**25.51**
Elevation (m)(bio20)	**0.1**	**0.8**	**0**	**2,221**	**338.77**	**403.52**
Precipitation of the driest quarter months	-	-	-	-	-	-
Isothermality	-	-	-	-	-	-
Precipitation of the coldest quarter months	-	-	-	-	-	-
Highest temperature of the hottest month	-	-	-	-	-	-
Lowest temperature of the coldest month	-	-	-	-	-	-
Annual temperature variation	-	-	-	-	-	-
Average temperature of the rainy quarter months	-	-	-	-	-	-
Average temperature of the driest quarter months	-	-	-	-	-	-
Average temperature of the hottest quarter months	-	-	-	-	-	-

Variable	Percentage contribution	Permutation importance	Min.	Max.	Mean.	SD
Average temperature of the coldest quarter months	-	-	-	-	-	-
Precipitation of the hottest quarter months	-	-	-	-	-	-
Precipitation of the rainiest month	-	-	-	-	-	-
Precipitation of the driest month	-	-	-	-	-	-
Precipitation of the rainiest quarter months	-	-	-	-	-	-

3.4 Global Predicted areas at risk of distribution of *Diaphorina citri* spread

The model predictions are in agreement with the known occurrence records of ACP (Fig. 4A and B). Yet, the adjusted model in MaxEnt for ACP habitat suitability exceeded the current distribution of the pest. The model identified low habitat suitability in regions including parts of Ghana, Côte D'Ivoire, and Democratic Republic of Congo (DRC) in Africa; China and India in Asia; Brazil, Paraguay, Bolivia, Argentina in South America; USA and Mexico in North America; Papua New Guinea and Australia in Oceania. The areas identified to have medium suitability for ACP include some regions of Brazil, Paraguay, Bolivia, Argentina, the United States of America, Ghana, Burma, Bangladesh, Bhutan, and China. The regions identified with high habitat suitability include parts of Southeast Asia.

3.5 Predicted areas at risk of Diaphorina citri spread for 2040 and 2060 under the SSP1-2.6 scenario

Under the low scenario (SSP1-2.6), our model predicts expansion of habitat suitability of ACP, with regions that are presently suitable for ACP will become highly suitable in the future (Figs. 5A and B). These regions include some parts of the USA, Brazil and Southeast Asia. Areas that will be marginally affected by the future predictions from 2040 to 2060 under the SSP1-2.6 includes Ghana, Brazil and China. These areas are forecasted to experience either slight expansion or contraction of suitable areas. In Australia, there will be a marginal expansion of habitats with low suitability. However, areas in Asia with presently high habitat suitability will continue to be highly suitable from 2040 to 2060.

3.6 Predicted areas at risk of Diaphorina citri spread for 2040 and 2060 under the SSP5-8.5 scenario

Under the extreme socio-economic pathways (SSP5-8.5) from 2040 to 2060 (Figs. 6A and B), the model predicts expansion of habitat suitability of ACP from the low scenario, with parts of Brazil becoming highly suitable for the pest. In addition, parts of Brazil that were suitable under the low scenario will have medium habitat suitability. In Africa, areas in Ghana and Côte D'Ivoire with presently low suitability are

forecasted to become medium suitability for ACP in the future. Some areas that are presently unsuitable in North Africa are predicted to have a low suitability for ACP in the years to come. In Asia, there will be a marginal expansion of areas with high suitability. Present areas with low suitability in Australia are forecasted to expand inwards to cover almost half of the country from 2040 to 2060.

3.7 Impacts of climate change on potential distribution *Diaphorina citri* in the world's three largest citrus-producing regions.

The suitability classes for ACP and their projections in the SSP1-2.6 and SSP5-8.5 scenarios for the world's three largest citrus-producing regions, i.e., Brazil, China, and the USA, show that more areas in Brazil, China, and the USA will experience an expansion of habitat suitability across the different periods (Figs. 7 and 8).

4 Discussion

In the present study, we used SDM to establish the global distribution of ACP under different climate change scenarios. Although there are existing information on the distribution of ACP from Brazil, Australia, Mexico, China, the USA and Africa (Oke et al. 2020; Wang et al. 2020, 2019; Rwomushana et al. 2017; Shimwela et al. 2016; Narouei-Khandan et al. 2016; Torres-Pacheco et al. 2013; Costa et al. 2010), most of these studies focused on small-scale ranges. Hence, there is a paucity of data examining the possible geographic spread of the pest on larger scales and modeling future niches under climate change scenarios. In addition, most of the studies only used bioclimatic variables whereas we used in addition elevation. Our model predictions were consistent with the current occurrence areas of ACP, including Nigeria (Oke et al. 2020), Kenya and La Réunion (Wang et al. 2021; Aidoo et al. 2021; Aidoo et al. 2020; Ajene et al. 2020; Narouei-Khandan et al. 2016), Malaysia (Sule et al. 2014), Mexico (Fuentes et al. 2018), China (Wang et al. 2020, 2019), Uganda, Tanzania and Ethiopia (Rwomushana et al. 2017), and the USA (Sétamou and Bartels 2015). Our study provides updated and detailed maps of the occurrence and potential global distribution of ACP under climate change. These predictions are essential for policy formulation and quarantine measures because they will put areas that have not reported the pest on regular surveillance and monitoring to prevent a possible invasion. We also show environmental variables that influence the global distribution of ACP and how climate change influences the spread of the pest. In addition, our findings are highly relevant for the successful management of invasive species.

Although previous studies have modelled the potential distribution of ACP under climate change using MaxEnt (Wang et al. 2019; Narouei-Khandan et al. 2016) and CLIMEX (Wang et al. 2020), these works focused on a specific geographical area, i.e., China and the USA, whereas our research aimed at global distribution modelling. MaxEnt is a machine learning algorithm that uses presence and background points for the prediction of areas suitable for a pest (Sillero & Barbosa 2021). MaxEnt models are distinguished from other models because of their high accuracy in predicting the possible spread of species (Merow et al. 2013). Furthermore, even with few occurrence records, they can provide maximum outputs. The projected suitable areas of our MaxEnt model are consistent with ACP occurrence records,

reflected by the high AUC value, implying a close association between the model and the biology and ecology of the pest.

Previous studies have used bioclimatic variables for modelling the distribution of ACP in China (Wang et al. 2019). Here, we used one topographical and five climatic variables in the final model for prediction of ACP suitable areas. The environmental variables that contributed most to our predictions were annual mean of temperature, followed by seasonality of temperature, annual precipitation, and mean variation of daytime temperature. This suggests that thermal much more than rainfall conditions play a critical role in the spread of ACP which would explain why low winter temperatures have such a detrimental effect on the survival and reproduction of ACP, hence affecting the geographical spread and potential ACP dispersal to new areas (Hall et al. 2013). Also, the peak of *D. citri* activity appears to occur in the spring and summer months, when temperatures are warmer and citrus flushing is at its maximum (Martini et al. 2016). During the colder winter months, ACP activity is significantly decreased and movement is constrained, providing an opportunity to target populations with dormant winter sprays (Qureshi and Stansly 2010). As a result, the environmental variables we chose to study are crucially governing the biology of the pest.

Our model predicts Portugal as a suitable habitat for ACP. With the African citrus psyllid *Trioza erytreae* Del Guercio (Hempitera: Triozidae) already present in Portugal (Cocuzza et al., 2016), this suggests that the combined effects of the two vectors of HLB could pose a serious threat to the local citrus industry. The impact of climate change on ACP's distribution across the major citrus growing regions in the world require urgent attention on the development of sustainable management strategies. For instance, the economic losses associated with HLB in Florida and California alone are estimated at $1 to $2.7 billion/year (Farnsworth et al. 2014; Durborow 2012).

Invasive species reacts to climate change such as rising temperatures and variations in precipitation (Kariyawasam et al. 2021), as shown in the current study. In addition, climate variables are known to impact both native and invasive species' presence, absence, distribution, reproductive success, and survival (Finch et al. 2021). As a result of the limited environmental conditions suitable for ACP, long-term climate change possibly will have a considerable impact on the spread of the pest. Hence the urgent need to develop now effective control and preventive measures to curb the present and future spread of ACP. Identifying potential areas at risk of ACP invasion and detecting invasion patterns in the future are critical components of climate-smart pest management plans (Heeb et al. 2019). We have predicted and mapped worldwide areas at risk of ACP spread, which may be useful for plant protection and regulatory officers. In addition, our model has established a global approach for future studies at the local level. Moreover, the findings from our study will be valuable for future surveying and monitoring activities, as well as the development of surveillance and monitoring plans to safeguard local citrus industries.

Models for assessing suitable areas of a specific insect pest can be developed using the maximum entropy principle, and/ or bioclimatic and topographical data. In the present study, we successfully predict the occurrence and future global distribution of ACP. We used global models with a spatial

resolution of 5 km^2, and identified present regions at risk as well as regions that could be invaded by ACP in the future under two different climate change scenarios. These predictions exceeded the current distribution of ACP, with highly suitable areas in Southeast Asia, Brazil, and the USA. Our findings can be used by decision-makers and quarantine authorities in accelerating present and future pest control efforts for ACP.

Declarations

Acknowledgement

We thank the Universidade Federal dos Vales do Jequitinhonha e Mucuri (UFVJM) and the University of Environment and Sustainable Development (UESD) for access to instruments.

Author contribution statement

OFA, PGCS, MS, PASJ, SE, MCP, RSS and CB conceived and designed research. OFA, CB, RSS and RK. PGCS, MS, OFA and RK acquired data. PGCS, OFA analyzed the data. All authors read the final manuscript.

Availability of data and materials

Correlation analysis of environmental variables are deposited on Zenodo (https://zenodo.org/record/5366710#.YTAHJY77S02; 10.5281/zenodo.5366710).

Funding

This research was financially supported by GIZ through the project on “Strengthening Citrus Production Systems through the Introduction of Integrated Pest Management (IPM) Measures for Pests and Diseases in Kenya and Tanzania (SCIPM)” (Project no.: 14.1432.5-001.00/Contract no.: SCIPM 81180346) through the International Centre of Insect Physiology and Ecology (icipe). We also gratefully acknowledge the icipe core funding provided by UK Aid from the Government of the United Kingdom; Swedish International Development Cooperation Agency (Sida); the Swiss Agency for Development and Cooperation (SDC) and the Kenyan Government.

Code Availability

Please contact the corresponding author for code of decent request.

Declaration of Competing Interest

The authors declare that they have no known conflict of interests.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

Abreu EF, Lopes AC, Fernandes AM, Silva SX, Barbosa CJ, Nascimento AS, Laranjeira FF, Andrade EC (2020) First Report of HLB Causal Agent in Psyllid in State of Bahia, Brazil. Neotropical Entomology 49(5):780-2.

Aidoo OF, Tanga CM, Mohamed SA, Khamis FM, Opisa S, Rasowo BA, Kimemia JW, Ambajo J, Sétamou M, Ekesi S, Borgemeister C (2021) The African citrus triozid *Trioza erytreae* Del Guercio (Hemiptera: Triozidae): temporal dynamics and susceptibility to entomopathogenic fungi in East Africa. International Journal of Tropical Insect Science 41(1): 563-73.

Aidoo OF, Tanga CM, Mohamed SA, Khamis FM, Baleba SB, Rasowo BA, Ambajo J, Sétamou M, Ekesi S, Borgemeister C (2020). Detection and monitoring of 'Candidatus' Liberibacter spp. vectors: African citrus triozid *Trioza erytreae* Del Guercio (Hemiptera: Triozidae) and Asian citrus psyllid *Diaphorina citri* Kuwayama (Hemiptera: Liviidae) in citrus groves in East Africa. Agricultural and Forest Entomology 22(4):401-9.

Aiello-Lammens ME, Boria RA, Radosavljevic A, Vilela B, Anderson RP (2015) spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38(5): 541-5.

Ajene IJ, Khamis FM, van Asch B, Pietersen G, Rasowo BA, Ombura FL, Wairimu AW, Akutse KS, Sétamou M, Mohamed S, Ekesi S (2020) Microbiome diversity in *Diaphorina citri* populations from Kenya and Tanzania shows links to China. PloS one. 26:15(6):e0235348.

Boria RA, Olson LE, Goodman SM, Anderson RP (2014) Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecological modelling 10: 275:73-7.

Boykin LM, De Barro P, Hall DG, Hunter WB, McKenzie CL, Powell CA, Shatters RG S (2012). Overview of worldwide diversity of *Diaphorina citri* Kuwayama mitochondrial cytochrome oxidase 1 haplotypes: two Old World lineages and a New World invasion. Bulletin of Entomological Research 102(5):573-82.

Bové JM (2006) Huanglongbing: a destructive, newly-emerging, century-old disease of citrus. Journal of plant pathology 7-37.

Bradley AP (1997) The use of the area under the ROC curve in the evaluation of machine learning algorithms. Pattern recognition 30(7): 1145-1159.

Brown JL, Bennett JR, French CM (2017) SDMtoolbox 2.0: the next generation Python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. PeerJ 5:e4095.

Chen XD, Stelinski, LL (2017) Resistance management for Asian citrus psyllid, *Diaphorina citri* Kuwayama, in Florida. Insects 8(3):103.

Cocuzza GE, Alberto U, Hernández-Suárez E, Siverio F, Di Silvestro S, Tena A, Carmelo R (2017) A review on *Trioza erytreae* (African citrus psyllid), now in mainland Europe, and its potential risk as vector of huanglongbing (HLB) in citrus. Journal of pest science 90(1):1-7.

Cornejo JF, Chica EJ (2014) First record of *Diaphorina citri* (Hemiptera: Psyllidae) in Ecuador infesting urban citrus and orange jasmine trees. Journal of Insect Science, 14(1): 298.

Costa Lima AM (1942) Homopteros. Insetos do Brazil. Esc. Nac. Agron. Min. Agr, 3, 1-327.

Costa MG, Barbosa JC, Yamamoto PT, Leal RM (2010) Spatial distribution of *Diaphorina citri* Kuwayama (Hemiptera: Psyllidae) in citrus orchards. Scientia Agricola 67:546-54.

Couture JJ, Lindroth RL (2013) Impacts of atmospheric change on tree–arthropod interactions. In Developments in Environmental Science 13:227-248.

Das DK, Singh J, Vennila S (2011) Emerging crop pest scenario under the impact of climate change–a brief review. Journal of Agricultural Physics 11: 13-20.

Davis RI, Gunua TG, Kame MF, Tenakanai D, Ruabete TK (2005) Spread of citrus huanglongbing (greening disease) following incursion into Papua New Guinea. Australasian Plant Pathology 34(4): 517-524.

Djeddour D, Pratt C, Constantine K, Rwomushana I, Day R (2021) The Asian Citrus Greening Disease (Huanglongbing).

Durborow S (2012) An analysis of the potential economic impact of Huanglongbing on the California citrus industry. Texas A&M University-Commerce.

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. Diversity and distributions 17(1): 43-57.

Eschen R, Beale T, Bonnin JM, Constantine KL, Duah S, Finch EA, Makale F, Nunda W, Ogunmodede A, Pratt CF, Thompson E (2021) Towards estimating the economic cost of invasive alien species to African crop and livestock production. CABI Agriculture and Bioscience 2(1):1-8.

Farnsworth D, Grogan KA, van Bruggen AH, Moss CB (2014) The potential economic cost and response to greening in Florida citrus. Choices 29(316-2016-7737).

FAOSTAT (2019) FAO stat. http://www.fao.org/faostat/en/#data/QC.

Farr TG, Kobrick M (2000) Shuttle Radar Topography Mission produces a wealth of data. Eos, Transactions American Geophysical Union. 81(48): 583-585.

Finch DM, Butler JL, Runyon JB, Fettig CJ, Kilkenny FF, Jose S, Frankel SJ, Cushman SA, Cobb RC, Dukes JS, Hicke JA (2021) Effects of climate change on invasive species. InInvasive Species in Forests and Rangelands of the United States (pp. 57-83). Springer, Cham.

Fish and Wildlife Service U.S. 2012 The cost of invasive species (PDF | 831 KB).

Fick SE, Hijmans RJ (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International journal of climatology 37(12): 4302-4315.

Fitzpatrick MC, Gotelli NJ, Ellison AM (2013) MaxEnt versus MaxLike: empirical comparisons with ant species distributions. Ecosphere 4(5): 1-15.

Fuentes A, Braswell WE, Ruiz-Arce R, Racelis A (2018) Genetic variation and population structure of *Diaphorina citri* using cytochrome oxidase I sequencing. Plos one 13(6): e0198399.

García FC, Bestion E, Warfield R, Yvon-Durocher G (2018) Changes in temperature alter the relationship between biodiversity and ecosystem functioning. Proceedings of the National Academy of Sciences 115(43): 10989-10994.

GBIF.org (06 August 2021) GBIF Occurrence Download https://doi.org/10.15468/dl.dyna2a.

Gely C, Laurance SG, Stork NE (2020) How do herbivorous insects respond to drought stress in trees?. Biological Reviews 95(2): 434-448.

Halbert SE, Núñez CA (2004) Distribution of the Asian citrus psyllid, *Diaphorina citri* Kuwayama (Rhynchota: Psyllidae) in the Caribbean basin. Florida Entomologist 87(3): 401-402.

Hall DG, Richardson ML, Ammar ED, Halbert SE (2013) Asian citrus psyllid, *Diaphorina citri*, vector of citrus huanglongbing disease. Entomologia Experimentalis et Applicata 146(2): 207-223.

Heeb L, Jenner E, Cock MJ (2019) Climate-smart pest management: building resilience of farms and landscapes to changing pest threats. Journal of Pest Science 92(3): 951-969.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology: A Journal of the Royal Meteorological Society 25(15): 1965-1978.

Hijmans RJ, Elith J (2013) Species Distribution Modeling with R. R CRAN Project.

Hoffmann BD, Broadhurst LM (2016) The economic cost of managing invasive species in Australia. NeoBiota 31:1.

Kariyawasam CS, Kumar L, Ratnayake SS (2021) Potential distribution of aquatic invasive alien plants, *Eichhornia crassipes* and *Salvinia molesta* under climate change in Sri Lanka. Wetlands Ecology and Management 1-15.

Kumar S, Neven LG, Yee WL (2014) Evaluating correlative and mechanistic niche models for assessing the risk of pest establishment. Ecosphere 5(7): 1-23.

Kumar S, Spaulding SA, Stohlgren TJ, Hermann KA, Schmidt TS, Bahls LL (2009) Potential habitat distribution for the freshwater diatom *Didymosphenia geminata* in the continental US. Frontiers in Ecology and the Environment 7(8): 415-420.

Lawler JJ, Wiersma YF, Huettmann F (2011) Using species distribution models for conservation planning and ecological forecasting. In Predictive species and habitat modeling in landscape ecology (pp. 271-290). Springer, New York, NY.

Lehmann P, Ammunét T, Barton M, Battisti A, Eigenbrode SD, Jepsen JU, ... & Björkman C (2020) Complex responses of global insect pests to climate warming. Frontiers in Ecology and the Environment 18(3): 141-150.

Linders TE, Schaffner U, Eschen R, Abebe A, Choge SK, Nigatu L, Mbaabu PR, Shiferaw H, Allan E (2019) Direct and indirect effects of invasive species: Biodiversity loss is a major mechanism by which an invasive tree affects ecosystem functioning. Journal of Ecology 107(6):2660-72.

Mack RN, Simberloff D, Mark Lonsdale W, Evans H, Clout M, Bazzaz FA (2000) Biotic invasions: causes, epidemiology, global consequences, and control. Ecological applications 10(3):689-710.

Martini X, Pelz-Stelinski KS, Stelinski LL (2016) Factors affecting the overwintering abundance of the Asian citrus psyllid (Hemiptera: Liviidae) in Florida citrus (Sapindales: Rutaceae) orchards. Florida Entomologist 99(2):178-86.

Mead FW (1977) The Asiatic citrus psyllid, *Diaphorina citri* Kuwayama (Homoptera: Psyllidae). Florida Department of Agriculture Conservation Service, Division of Plant Industry Entomological Circular No. 180.

Merow C, Smith MJ, Silander Jr JA (2013) A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36(10):1058-69.

Naeem A, Freed S, Jin FL, Akmal M, Mehmood M (2016) Monitoring of insecticide resistance in *Diaphorina citri* Kuwayama (Hemiptera: Psyllidae) from citrus groves of Punjab, Pakistan. Crop Protection 86: 62-68.

Narouei-Khandan HA, Halbert SE, Worner SP, van Bruggen AH (2016) Global climate suitability of citrus huanglongbing and its vector, the Asian citrus psyllid, using two correlative species distribution modeling approaches, with emphasis on the USA. European Journal of Plant Pathology 144(3): 655-670.

Oke AO, Oladigbolu AA, Kunta M, Alabi OJ, Sétamou M (2020) First report of the occurrence of Asian citrus psyllid *Diaphorina citri* (Hemiptera: Liviidae), an invasive species in Nigeria, West Africa. Scientific reports 10(1): 1-8.

Owens HL, Campbell LP, Dornak LL, Saupe EE, Barve N, Soberón J, Ingenloff K, Lira-Noriega A, Hensz CM, Myers CE, Peterson AT (2013) Constraints on interpretation of ecological niche models by limited environmental ranges on calibration areas. Ecological modelling 10: 263:10-8.

Peterson AT, Papeş M, Soberón J (2008) Rethinking receiver operating characteristic analysis applications in ecological niche modeling. Ecological modelling 213(1): 63-72.

Peterson AT, Soberón J, Pearson RG, Anderson RP, Martínez-Meyer E, Nakamura M, Araújo MB (2011) Ecological niches and geographic distributions (MPB-49). Princeton University Press.

Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. Ecological modelling 190(3-4): 231-259.

Qureshi JA, Stansly PA (2010) Dormant season foliar sprays of broad-spectrum insecticides: An effective component of integrated management for *Diaphorina citri* (Hemiptera: Psyllidae) in citrus orchards. Crop Protection 29(8) 860-866.

Rank A, Ramos RS, da Silva RS, Soares JRS, Picanço MC, Fidelis EG (2020) Risk of the introduction of *Lobesia botrana* in suitable areas for *Vitis vinifera*. Journal of Pest Science 93(4): 1167-1179.

Ramos RS, Kumar L, Shabani F, Picanço MC (2019) Risk of spread of tomato yellow leaf curl virus (TYLCV) in tomato crops under various climate change scenarios. Agricultural Systems 173 524-535.

Rao CN, Shivankar VJ, Deole S, David KJ, Dhengre VN (2014) Insecticide resistance in field populations of Asian citrus psyllid, *Diaphorina citri* Kuwayama (Hemiptera: Psyllidae). Pesticide Research Journal 26(1): 42-47.

Riahi K, Van Vuuren DP, Kriegler E, Edmonds J, O'neill BC, Fujimori S, Bauer N, Calvin K, Dellink R, Fricko O, Lutz W (2017) The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global environmental change 42:153-68.

Rwomushana I, Khamis FM, Grout TG, Mohamed SA, Sétamou M, Borgemeister C, Heya HM, Tanga CM, Nderitu PW, Seguni ZS, Materu CL (2017) Detection of Diaphorina citri Kuwayama (Hemiptera: Liviidae) in Kenya and potential implication for the spread of Huanglongbing disease in East Africa. Biological Invasions 19(10):2777-87.

Sala OE, Chapin FS, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R (2000). Global biodiversity scenarios for the year 2100. Science 287(5459):1770-4.

Santana PA, Kumar L, Da Silva RS, Picanço MC (2019) Global geographic distribution of *Tuta absoluta* as affected by climate change. Journal of Pest Science 92(4): 1373-1385.

Saul WC, Roy HE, Booy O, Carnevali L, Chen HJ, Genovesi P, Harrower CA, Hulme PE, Pagad S, Pergl J, Jeschke JM (2017) Assessing patterns in introduction pathways of alien species by linking major invasion data bases. Journal of Applied Ecology 54(2):657-69.

Sétamou M, Bartels DW (2015) Living on the edges: spatial niche occupation of Asian citrus psyllid, *Diaphorina citri* Kuwayama (Hemiptera: Liviidae), in citrus groves. PloS one 10(7): e0131917.

Shimwela MM, Narouei-Khandan HA, Halbert SE, Keremane ML, Minsavage GV, Timilsina S, Massawe DP, Jones JB, van Bruggen AH (2016) First occurrence of *Diaphorina citri* in East Africa, characterization of the Ca. Liberibacter species causing huanglongbing (HLB) in Tanzania, and potential further spread of *D. citri* and HLB in Africa and Europe. European Journal of Plant Pathology 146(2):349-68.

Sillero N, Barbosa AM (2021) Common mistakes in ecological niche models. International Journal of Geographical Information Science 35(2): 213-226.

Srivastava V, Lafond, V, Griess VC (2019) Species distribution models (SDM): applications, benefits and challenges in invasive species management. CAB Review 14(10.1079).

Steven J. Philips, Miroslav Dudík, Robert E, Schapire (2021) [Internet] Maxent software for modeling species niches and distributions (Version 3.4.4). Available from url: http//biodiversityinformatics.amnh.org/open source/maxent/. Acessed on 2021-7-23.

Sule H, Muhamad R (2014) Dynamics and distribution of *Diaphorina citri* (Hemiptera: Psyllidae) in a citrus orchard in Terengganu, Malaysia. Scientific Papers-Series A, Agronomy 57: 461-465.

Tatebe H, Ogura T, Nitta T, Komuro Y, Ogochi K, Takemura T, Sudo K, Sekiguchi M, Abe M, Saito F, Chikira M (2019) Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. Geoscientific Model Development 12(7):2727-65.

Teck L, Abang F, Beattie A, Heng K, King W (2011) Seasonal population dynamics of the Asian citrus psyllid, Diaphorina citri Kuwayama in Sarawak. American Journal of Agricultural and Biological Sciences 6(4): 527-535.

Tian F, Mo X, Rizvi SAH, Li C, Zeng X (2018) Detection and biochemical characterization of insecticide resistance in field populations of Asian citrus psyllid in Guangdong of China. Scientific reports 8(1): 1-11.

Torres-Pacheco I, López-Arroyo JI, Aguirre-Gómez JA, Guevara-González RG, Yáñez-López R, Hernández-Zul MI, Quijano-Carranza JA (2013) Potential distribution in Mexico of *Diaphorina citri* (Hemiptera: Psyllidae) vector of Huanglongbing pathogen. Florida Entomologist 1:36-47.

Van Kleunen M, Dawson W, Essl F, Pergl J, Winter M, Weber E, Kreft H, Weigelt P, Kartesz J, Nishino M, Antonova LA (2015) Global exchange and accumulation of non-native plants. Nature 525(7567):100-3.

Wang R, Yang H, Luo W, Wang M, Lu X, Huang T, Zhao J, Li Q (2019) Predicting the potential distribution of the Asian citrus psyllid, *Diaphorina citri* (Kuwayama), in China using the MaxEnt model. PeerJ. 15:7:e7323.

Wang Y, Halbert S, Mohamed S, Delatte H, Reynaud B, Beattie GA, Holford P, Lu J, Cen Y (2021) Mitochondrial genomes reveal diverse lineages of *Diaphorina citri* Kuwayama (Hemiptera: Sternorrhyncha: Psyllidae) in Kenya and La Réunion. Biological Invasions 12:1-9.

Wang R, Yang H, Wang M, Zhang Z, Huang T, Wen G, Li Q (2020) Predictions of potential geographical distribution of *Diaphorina citri* (Kuwayama) in China under climate change scenarios. Scientific reports 8:10(1):1-9.

Wulff NA, Daniel B, Sassi RS, Moreira AS, Bassanezi RB, Sala I, Coletti DA, Rodrigues JC (2020) Incidence of *Diaphorina citri* Carrying Candidatus Liberibacter asiaticus in Brazil's Citrus Belt. Insects 11(10):672.

Xu H, Ding H, Li M, Qiang S, Guo J, Han Z, Huang Z, Sun H, He S, Wu H, Wan F (2020) The distribution and economic losses of alien species invasion to China. Biological Invasions 8(7):1495-500.

Figures

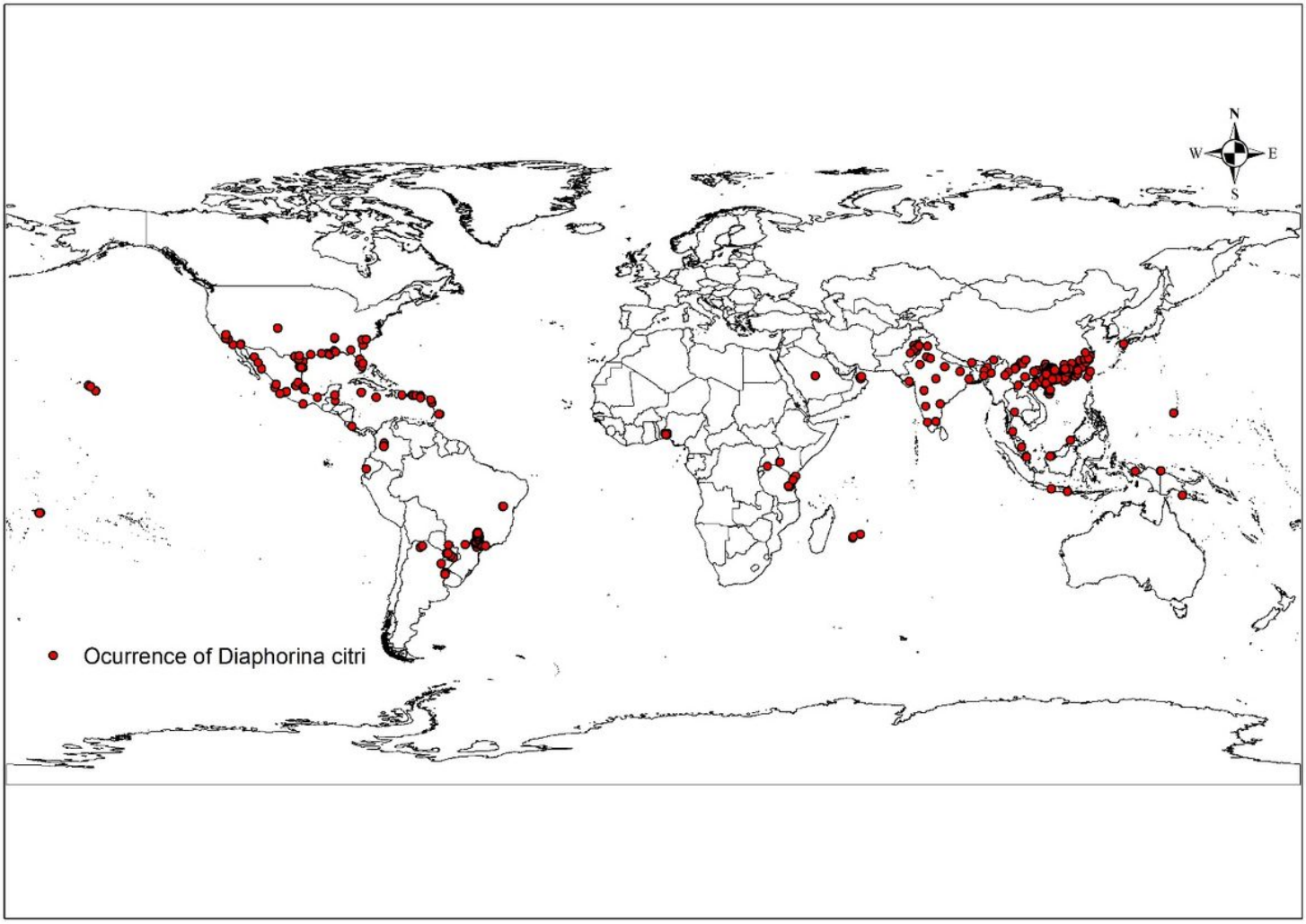

Figure 1

Current global Distribution of Diaphorina citri.

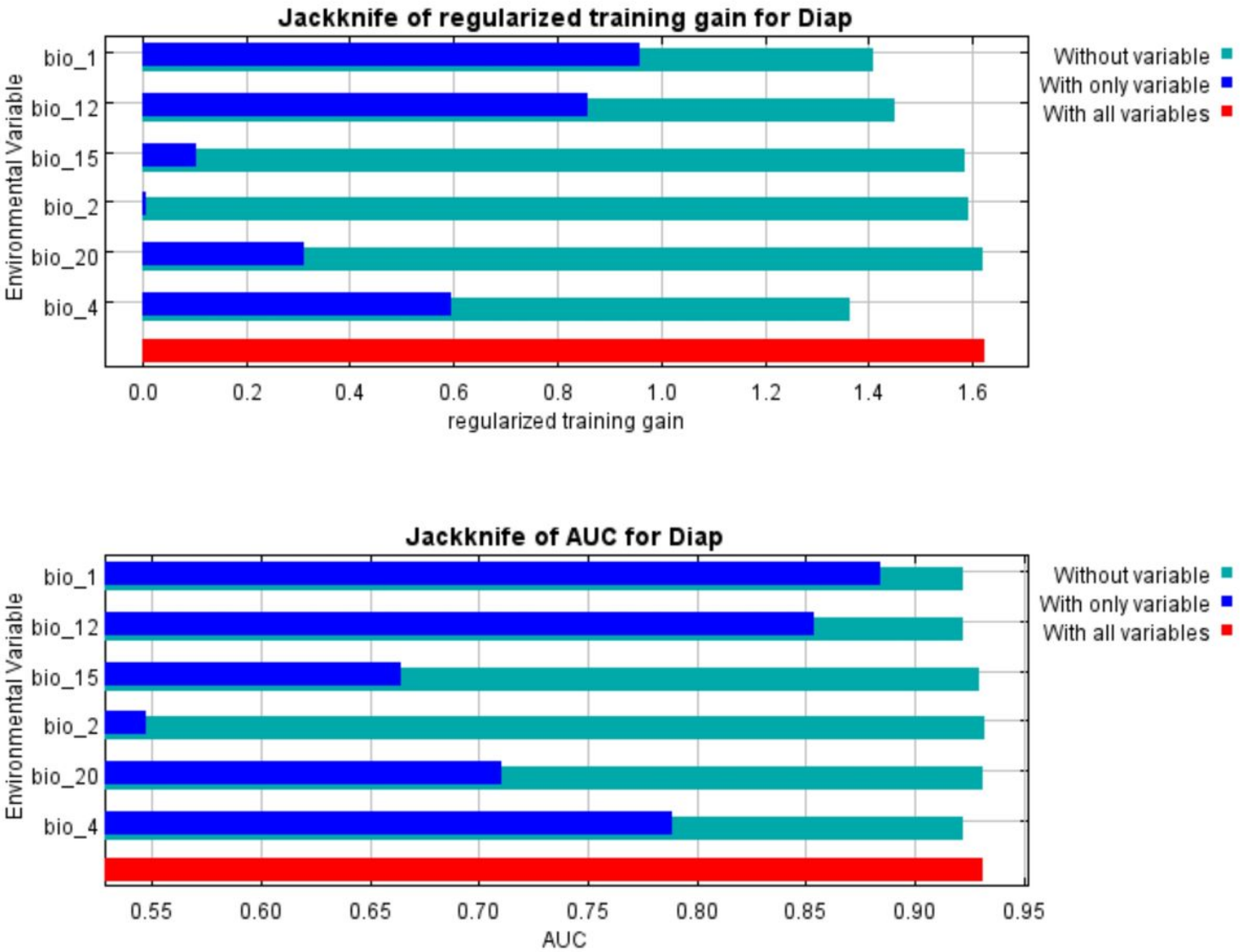

Figure 2

The relative importance of environmental variables based on the Jackknife test of regularized training gain (a) and AUCCV (b) in the Diaphorina citri model.

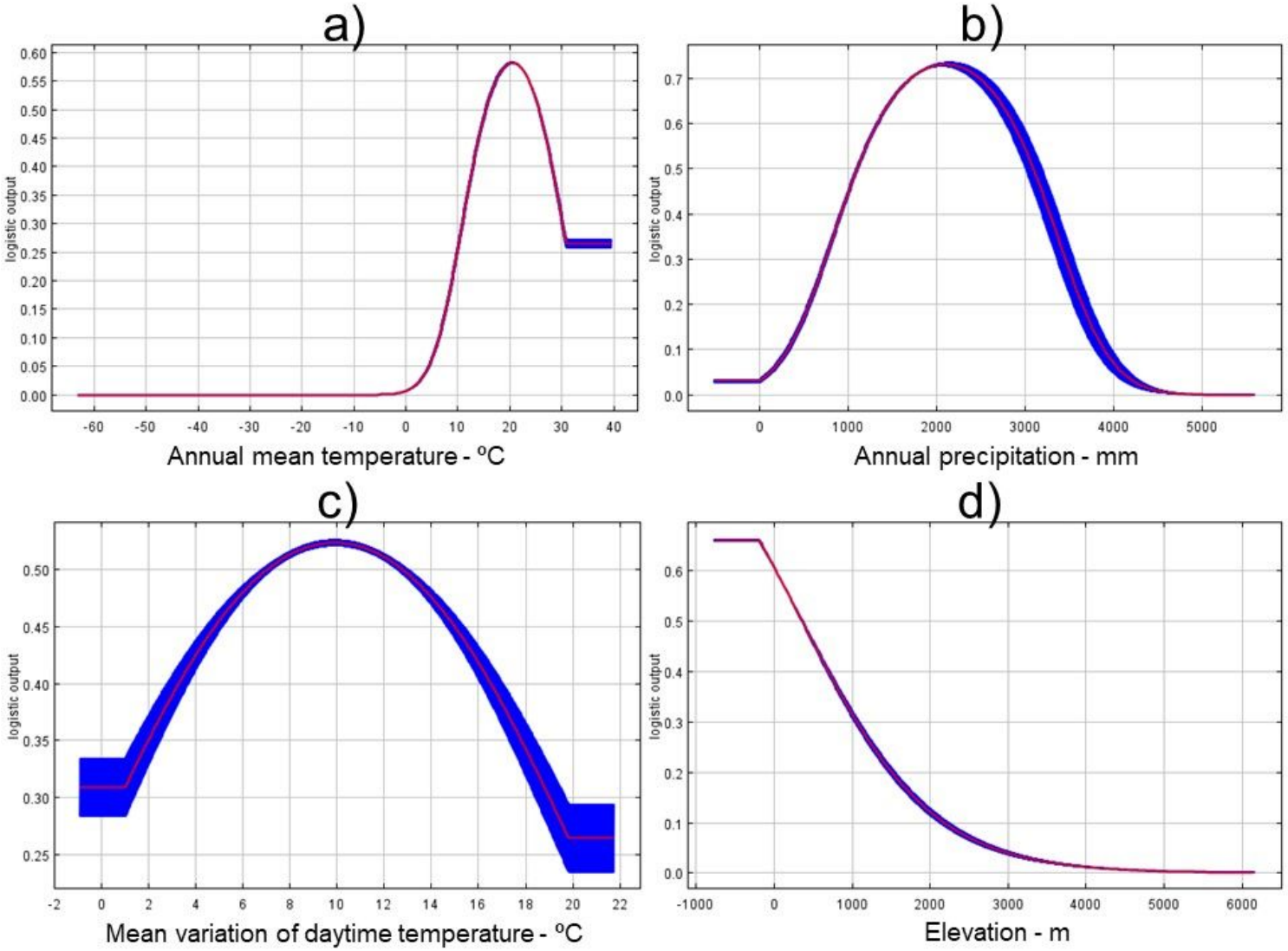

Figure 3

Response curves of the best predictors of Diaphorina citri occurrence: (a) Annual mean temperature (bio1), (b) annual precipitation (bio12), (c) mean variation of day time temperature (bio2) and (d) elevation. Red curves represent the average response and blue margins are ±1 SD computed over 10 replicates.

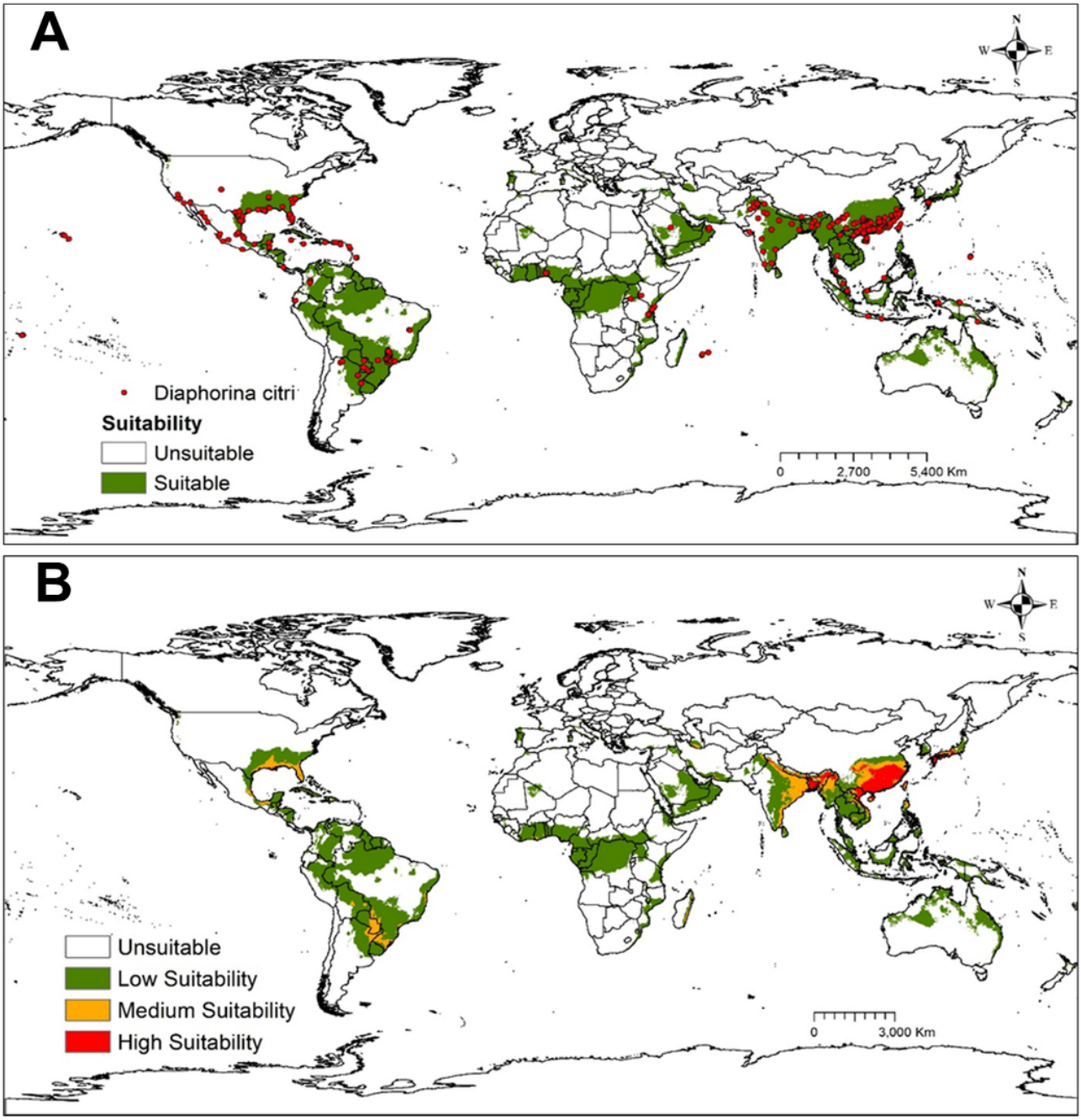

Figure 4

(A), Global Known Distribution and areas suitable to Diaphorina citri and (B) class of suitability under current climatic conditions using the MaxEnt model.

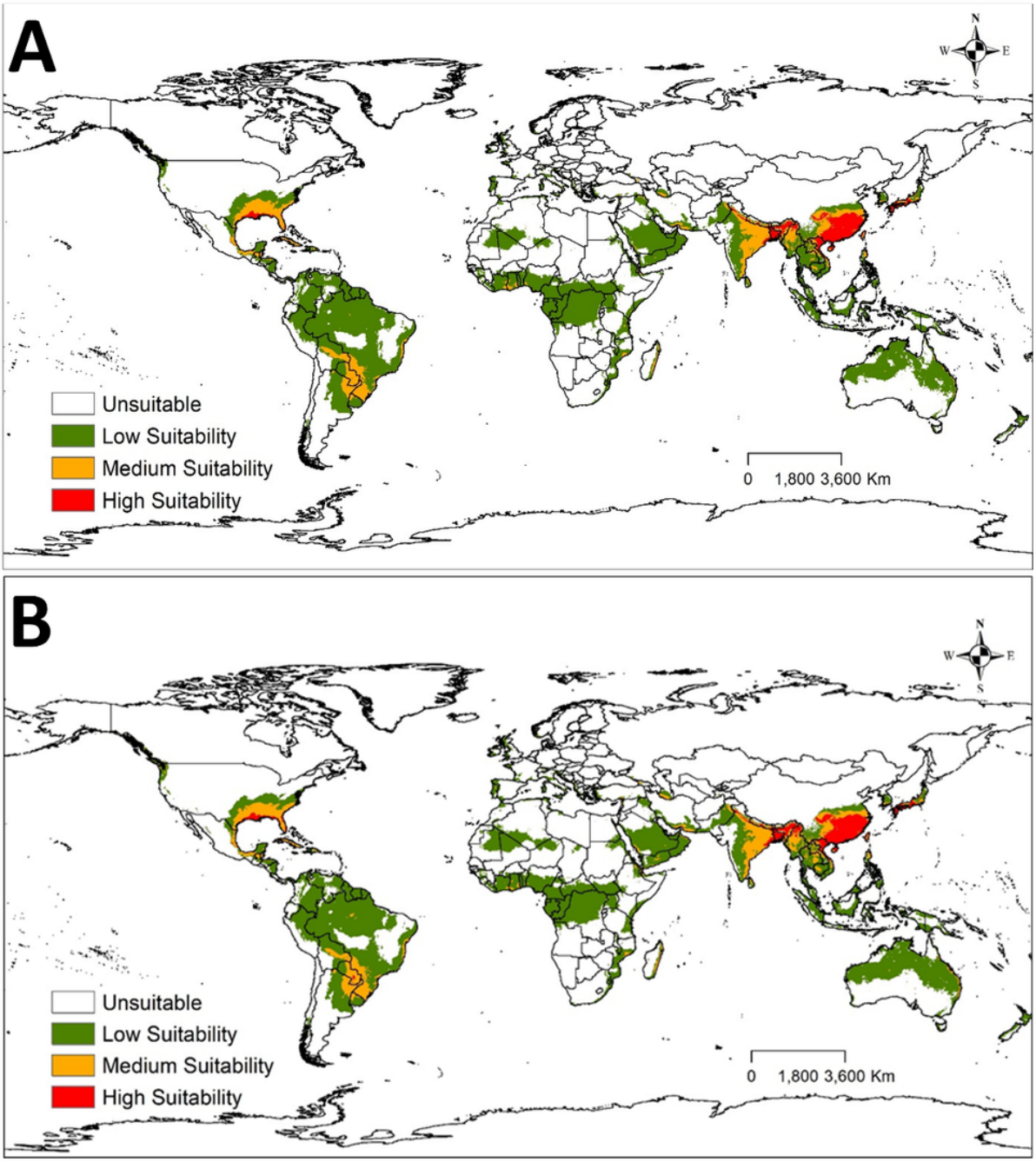

Figure 5

Class of suitability under scenario SSP1-2.6 on 2040 (A) and 2060 (B) using the MaxEnt model.

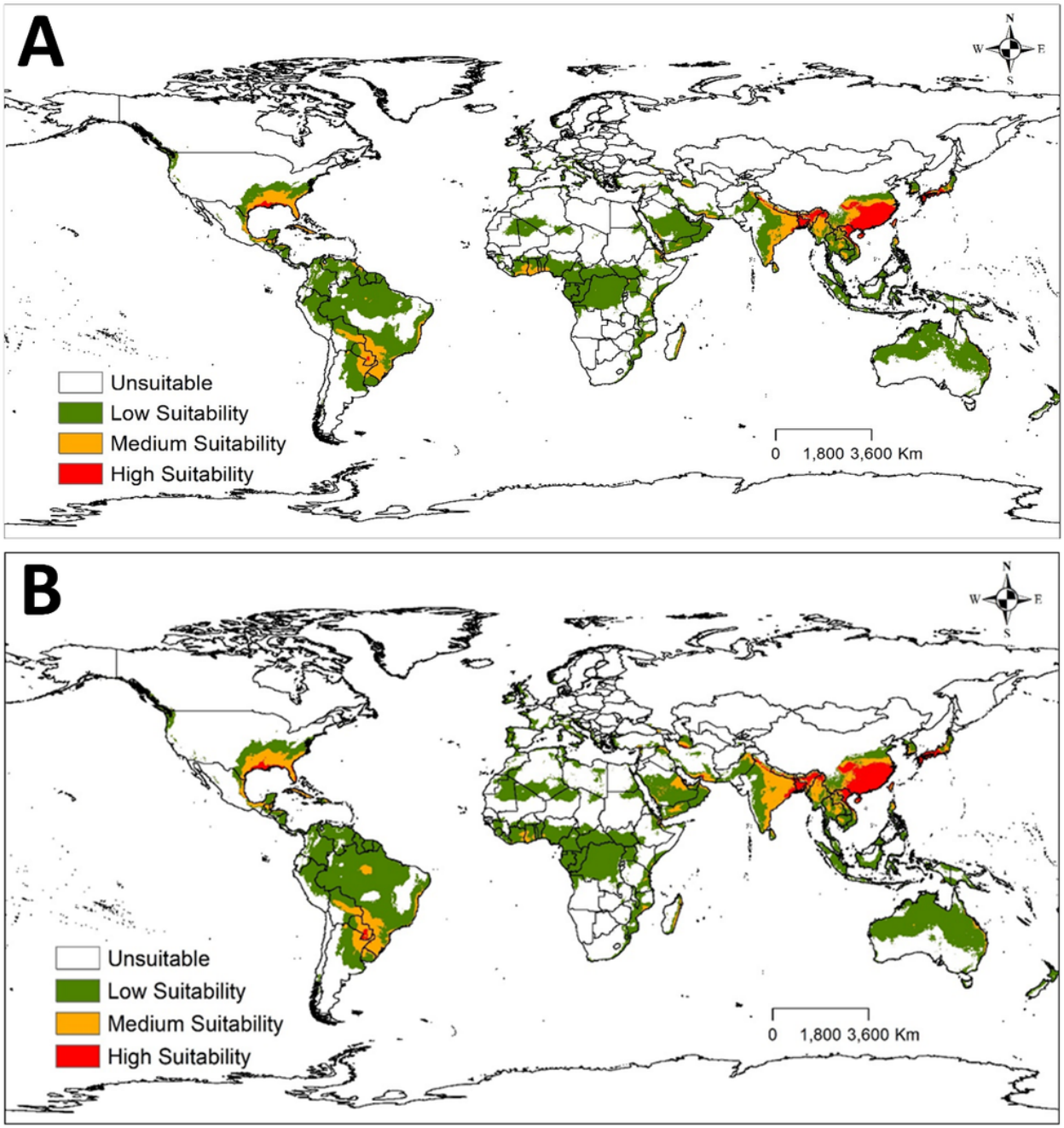

Figure 6

Class of suitability under scenario SSP5-8.5 on 2040 (A) and 2060 (B) using the MaxEnt model.

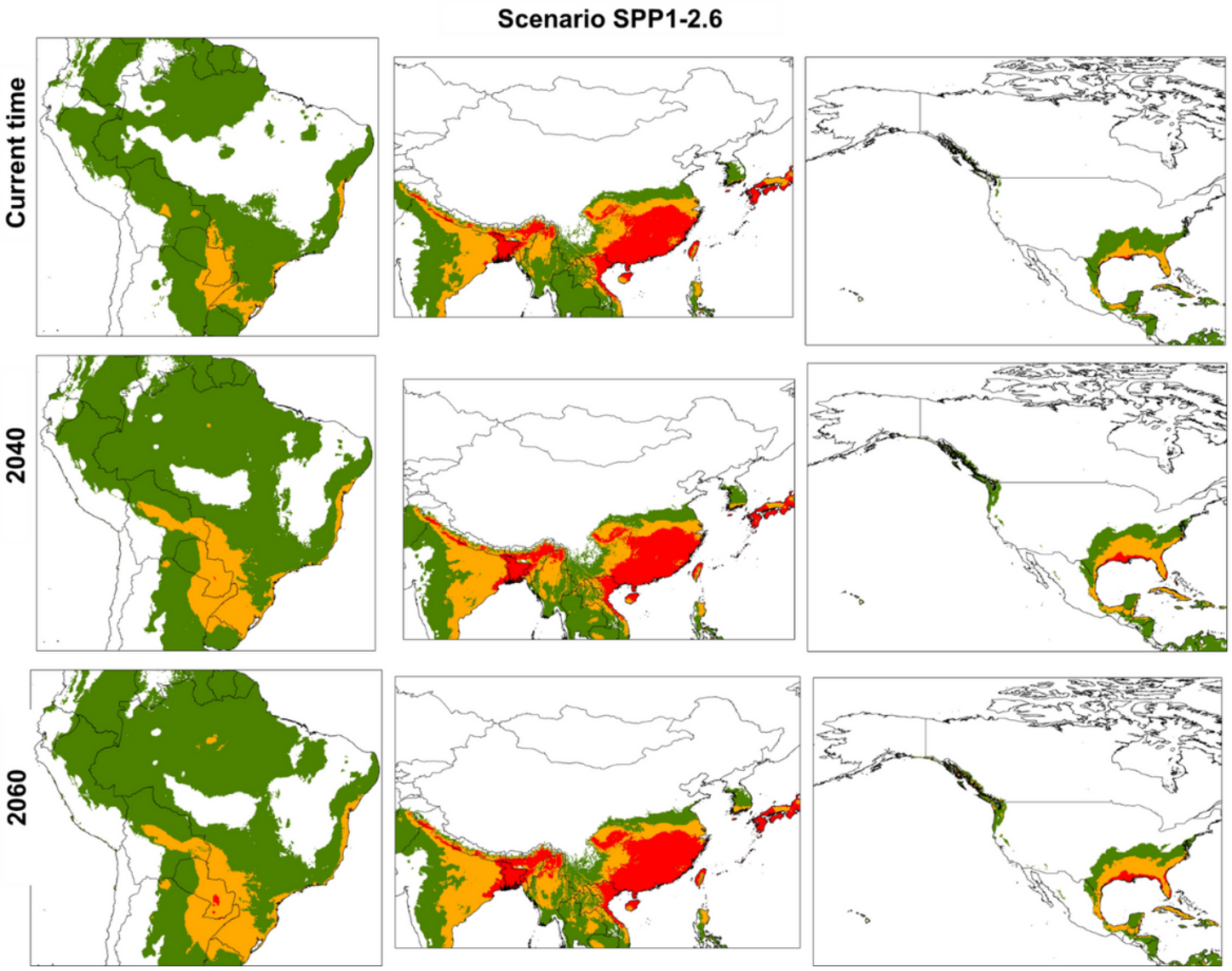

Figure 7

Suitability class for Diaphorina citri and its projections in the SSP1-2.6 scenario for the world's three largest citrus-producing regions. The areas presented are Brazil, China, and the USA. White are unsuitable areas, green low suitability, yellow medium suitability and red high suitability areas.

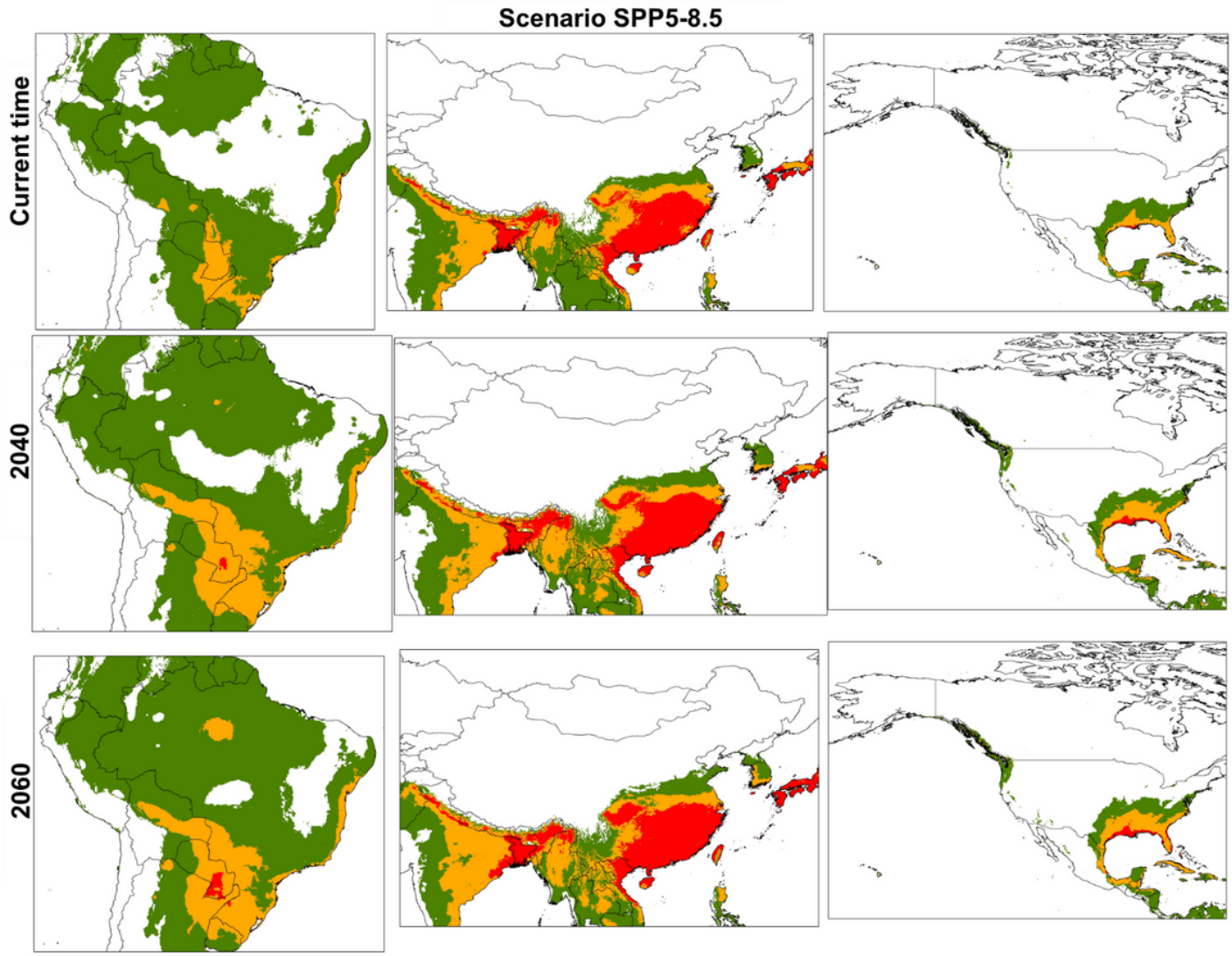

Figure 8

Suitability class for Diaphorina citri and its projections in the SSP5-8.5 scenario for the world's three largest citrus-producing regions. The areas presented are Brazil, China, and the USA. White are unsuitable areas, green low suitability, yellow medium suitability and red high suitability areas.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- GraphicalAbstractjps.png
- Supplementaryfile.xlsx