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Including climate change to predict the global suitable area of an invasive pest: *Bactrocera correcta* (Diptera: Tephritidae)

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ABSTRACT

Bactrocera correcta (Diptera: Tephritidae), as known as invasive pest guava fruit fly, can attack numerous host plants including many horticultural crops and cause huge destruction. Whilst its distribution is currently restricted in Southeast Asia, under the context of global trade and climate change, guava fruit fly can be transported with goods and spread with regional climate. Many countries have included the species on their quarantine pest lists, in order to offer the strategy for specific surveillance and early warnings, the research of predicting the suitable areas under climate change is essential. In this study, 56 environmental variables were initially tested, and six selected for final analysis using MaxEnt to predict suitable habitat, ENMeval package was used in R to avoid overfitting and run the models under two different greenhouse gas emission scenarios in 2030 and 2070 based on CMIP6. The total suitable area of the historical scenario is 3235.42×10^4 km^2, and it accounts for 24.06% of the world's total area and includes India and neighboring countries in Asia, pacific islands, and North Australia, Central and South America, central Africa. Water vapor pressure and solar radiation were the most influential variables for *B. correcta*, the rising temperature could lead increasing of suitable area slightly. The predictive results of the research can provide support for quarantine and management for the high-risk countries.

1. Introduction

Invasive species can have far-reaching ecological and economic impacts worldwide (Hulme, 2009; Mack et al., 2000; Diagne et al., 2020), invasive insects were estimated costing a minimum of US$70.0 billion per year globally (Bradshaw et al., 2016). Tropical fruit flies (Tephritidae) are among the largest family of Diptera, and are also considered among the most destructive invasive insects (Gutierrez et al., 2021; Lin et al., 2020; Papadopoulos et al., 2013), fruit flies are frequently introduced into new areas by human activity intentionally or unintentionally (Jiang et al., 2018; Qin et al., 2015). Fruit fly damage frequently leads to 80–100% crop loss (White and Elson-Harris, 1992), frugivorous Tephritid fruit flies in particular have been responsible for significant losses (Hendrichs et al., 2015).

Bactrocera correcta (Bezzi) is a polyphagous economic pest, has a wide range of commercial or edible host fruits, for example, *Citrus* spp., *Coffea canephora* Pierre ex Froehn. (As *Coffea robusta*), *Eugenia uniflora* L. (as *Eugenia mitchelli*), *Mangifera indica* L. (mango), *Prunus persica* (L.) Batsch (peach), *Psidium guajava* L. (guava), and a further 62 hosts in 30 families (Maynard et al., 2004; Sasaki, 2018).

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Adults lay eggs into fruit and can cause blemishes and discoloration; the maggots can act as secondary invaders by the time egg hatched and leads to the fruits not suited for human consumption. In 1995, *B. correcta* caused guava fruit damage ranging from 60% to 80% in Tamil Nadu, India (Jalaluddin, 1999). It is widely distributed in Asian countries including China, India, Myanmar, Nepal, Pakistan, Sri Lanka, Thailand, and Vietnam. A female individual of the pest was found in the Western Hemisphere in California in August 1986, since then, it has been detected several times in California, and has been found as well as in Florida since 1999, but no colonies were successfully established due to active eradication programs (Weems, 2004; Qin et al., 2015). It is demonstrated to be widely invasive in many countries, and has similar traits to successfully invasive relatives (White and Elson-Harris, 1992).

The average temperature of the future is projected to increase by 1.8–4 °C until the end of the 21st century (Skendzic et al., 2021). Climate change is causing species to shift their ranges, (Hulme, 2017; Schai-Braun et al., 2021; Taheri et al., 2021), yet many species may be poor at moving to new areas, particularly when they rely on other species for certain annual requirements (annual food, pollination, etc.) (Gaston, 1990; Wilson et al., 2007). Climate change can significantly alter the species distribution patterns (Barbet-Massin and Jetz, 2014). Insects are ectothermic organisms, local temperature and humidity may have a disproportionate impact on some species. However, invasive species may be less negatively impacted by climate change than native species. For example, invasive red fire ant had a good tolerance to extreme high temperatures (Wu et al., 2011), gipsy moths grew better under high CO_2 concentrations (Ge, 2012). Thus, understanding the potential invasive range of these species and how they may change can provide new insights to help preventative measures to be developed where necessary.

Species Distribution Models (SDMs), also known as bioclimatic models, climate envelopes, ecological niche models (ENMs), habitat models, resource selection functions (RSFs), they are models that relate species distribution data (the occurrence or abundance at known locations) with environmental status of those locations (Elith and Leathwick, 2009; Nasser et al., 2021) to predict the conditions that the species may be suitable for by extracting the environmental data of the existing sites (Hijmans, 2012). MaxEnt is a popular SDM, which relates species occurrences and known distributions using machine learning and the principle of maximum entropy (Phillips et al., 2006; H. Zhao et al., 2020; Z. Zhao et al., 2020). It also allows the exploration of the climate change effects on a species' future distribution (Elith et al., 2011; Zhan et al., 2022). It requires presence only data, has better prediction validity and performs better than other models (Elith et al., 2006; Phillips et al., 2006; Reddy et al., 2015; Gao et al., 2020).

This study aimed to identify the key environmental variables on a global scale and predict the historical and future suitable areas of invasive *B. correcta* under climate change scenarios using the MaxEnt model.

2. Materials and methods

2.1. Occurrence data

In this study, the open field occurrence data was derived from Global Biodiversity Information facility (GBIF), the Centre of Agriculture and Bioscience International (CABI, https://www.cabi.org/), and literature resources (Fig. 1) (Qin et al., 2015). 188 localities were confirmed to be distributed worldwide. Spurious points were removed, for example, Eradication records of California and Florida derived from GBIF were removed (Weems et al., 2004). To remove spatial autocorrelation in occurrence points we used rarefy (Brown, 2017; Veloz, 2009), SDMtoolbox (version 2.0) was used to thin the collected datasets to avoid spatial autocorrelation, finally 103 occurrence records were used for modeling.

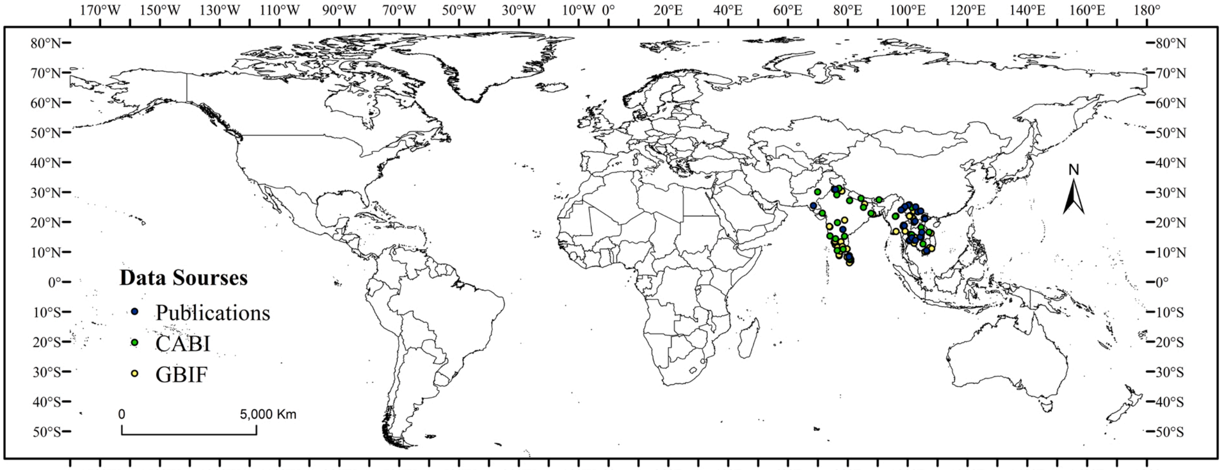

Fig. 1. Occurrence data of *Bactrocera correcta*. Green dots from published literature; Yellow dots from GBIF; Blue dots from CABI.

2.2. Environmental variables

We selected variables influencing a species ability to access resources and survive in physical space. Temperature, humidity, wind speed, barometric pressure and solar radiation can impact flight ability of insects (Goldshtein et al., 2021; Lessio and Alma, 2004; Pawson et al., 2017; Rousse et al., 2009; Chen and Seybold, 2014). Solar radiation is a key factor affecting the insects` development through light, heat and temperature. Exposure to UV radiation could increase *B. dorsalis* cohort mortality and the duration of pre-oviposition significantly (Cui et al., 2021). In addition, Paolo et al. (2021) stated that the abundance and diversity of fruit flies and its parasitoids varied with altitude. In this study, bioclimatic variables, elevation, monthly climate data for solar radiation, wind speed, water vapor pressure were downloaded from WorldClim Global Climate database version 2.1 (http://www.worldclim.org/), with the 5′ (9 km at equator) spatial resolution averaged for the years 1970–2000. Fifty-six variables in total were prepared for historical climatic conditions. Initially, zero-contribution rate variables were removed. To reduce the collinearity between highly correlated variables, correlation analysis and principal component analysis (PCA) were processed by SPSS. Six environmental variables were selected to run the final model (Table 1). This included one temperature bioclimatic variables bio7 (Temperature Annual Range), two precipitation bioclimatic variables bio16 (Precipitation of Wettest Quarter) and bio17 (Precipitation of Driest Quarter), solar radiation (March and July), and water vapor pressure variable in July. Topographic variables were not selected because we are primarily interested in the risk in agricultural areas, thus climatic factors are sufficient to explore potentially suitable area with similar conditions to native range. However, these models cannot compensate for niche shift, or climatic range truncation in native range, indicating the models will necessarily be conservative.

2.3. Modeling and evaluation

In order to simulate the suitable area of invasive species, MaxEnt model is developed to be one of the best models among the ENMs. (Elith et al., 2011; Helmstetter et al., 2021; Hijmans, 2012). However, MaxEnt is sensitive to sampling deviation and easy to overfit (Zhu et al., 2014). To avoid overfitting and improving transferability, parameters setting of MaxEnt was essential, R package “ENMeval” was chosen to mitigate model overfitting (Muscarella et al., 2014; Wei et al., 2020). MaxEnt parameter adjustment, including feature combinations (FCs, linear [L], quadratic [Q], product [P], threshold [T], and hinge [H]) and regularization multiplier (RM) value. In combination with the six feature types L, LQ, H, LQH, LQHP and LQHPT, the RM value ranges from 0.5 to 4 with an increment of 0.5 (Santana et al., 2019), “checkerboard2” was utilized to calculate the value of Akaike information criterion (AICc), the lowest delta AICc model (Warren et al., 2014) corresponding to RM value 4 and LQHPT were selected in the final model (Appendix S1). The other parameter settings were as follows: create response curves and jackknife analysis to measure variable importance, output format was Cloglog, output file type was *.asc. The random test percentage was set to 25%, the 10 percentile training presence was added, maximum iterations was set to 5000 (Swets, 1988), replicated run type was subsample with 10 replications. Many studies on the impact of environmental change have used thresholds determined by the species present distribution pattern to predict the change of future distribution, but the decline in habitat suitability does not mean species disappearance (Warren et al., 2014). Jenks Natural Breaks Classification (NBC) was used in this study, this method minimizes the variation within each range, so the areas within each range are as close as possible in value to each other. According to the result plots from MaxEnt, suitable area was classified into the following four levels referred to NBC (Arabameri et al., 2020), unsuitable area (0.00–0.08), low suitable area (0.08–0.30), moderately suitable area (0.30–0.60) and highly suitable area (0.60–1.00) (Gao and Shi, 2021). The model was evaluated by the area under receiver operating characteristic (ROC) curves with (AUC) values averaged over the replicated runs (Peterson et al., 2008), the models can be classified into these types, predictions worse than random ($AUC < 0.5$), predictions with poor performance ($0.5 \leq AUC < 0.7$), predictions with reasonable or moderate performance ($0.7 \leq AUC < 0.9$), and those with high performance ($AUC \geq 0.9$) (da Silva Galdino et al., 2017). This indicated that the model assumptions were met and the model output were reliable. We also used the partial ROC metric method (pROC) to evaluate model performance (Peterson et al., 2008) in case AUC calculated by MaxEnt can be overestimated. The pROC was calculated from NicheToolBox8, with 1000 replicates and $E = 0.05$.

2.4. Future projections

After 20 years’ development, Coupled Model Intercomparison Project (CMIP) has become a core component of national and international climate change assessment (Eyring et al., 2016). In this study, future climate conditions were downscaled version of global climate model (GCM) from CMIP6 based on Worldclim v2.1 dataset. To avoid the spatial heterogeneity caused by the climate variables

Table 1
Variables selected in final model with percent contribution and permutation importance.

Variable	Variable description	Percent Contribution	Permutation importance
vapr7	Water vapor pressure in July	44.2	14
srad3	Solar radiation in March	33.4	65.3
bio16	Precipitation of Wettest Quarter	15.2	6.3
bio17	Precipitation of Driest Quarter	4.9	9.9
Bio7	Temperature Annual Range	1.5	4.2
srad7	Solar radiation in July	0.9	0.3

that might lead to potential distribution changes at regional scale, three GCMs were selected: BCC-CSM2-MR (BCC), IPSL-CM6A-LR (IP), and MIROC-ES2L (MI), estimated for 2030 (average for 2021–2040) and 2070 (averaged for 2061–2080). These models were chosen to represent a range of possible, but highly supported scenarios. The data was converted by ArcGIS 10.2 (ESRI Inc., Redlands, CA, USA). URL http://www.esri.com/sofware/arcgis/arcgis-for-desktop. The combination of Socio-economic Paths (SSPs) and Representative Concentration Pathways (RCPs) in the new CMIP6 emphasis more on the consistency of future radiative forcing scenarios with shared socio-economic scenarios. Five different global features were depicted for the SSPs (SSP1–5) (O'Neill et al., 2013; Popp et al., 2017). SSP5 with very high greenhouse gas emissions (SSP5–8.5), and SSP1 with stringent mitigation scenario (SSP1–2.6) in this research to predict the suitable area under climate change. Finally, we averaged the projection across GCMs for each climate scenario to map suitable area globally. The invasion-suitable area under different scenarios in six continents separately were calculated in ArcGIS 10.2 for comparison.

3. Results

3.1. Model performance and variable contributions

The model performance of *B. correcta* showed an excellent predictive ability as AUC value averaged from 10 replicates was 0.976 (Appendix S2 A) and the mean value for AUC ratio at 0.05 over 1000 replicates was 0.953785 (Appendix S2 B), indicating a good performance of the Maxent models. According to the jackknife analysis (Appendix S3), vapor7 was the variable with highest gain when used in isolation, the environmental variable that decreased the gain the most when it is omitted was srad3. When sorted by contribution rate from the highest to lowest, six chosen environmental variables were vapor7 (July vapor, 44.2%), srad3 (solar radiation in March, 33.4%), bio16 (Precipitation of Wettest Quarter, 15.2%), bio17 (Precipitation of Driest Quarter, 4.9%) and bio7 (Temperature Annual Range, 1.5%), srad7 (solar radiation in July, 0.9%) (Table 1). The response curve created by Maxent (Appendix S4) indicated high probability of occurrence of *B. correcta* in regions with the water vapor pressure (vapor7) above 2 kPa in July, solar radiation in March (srad3) between 19,701 and 27,670 kJ m^{-2} day^{-1}.

3.2. Historical suitable area of *B. correcta*

The historical suitable area (averaged for the year of 1970–2000) was showed in Fig. 2, suitable habitat exists across Asia. The suitable area in Asia except for the current distribution, including part of Southern Yemen, Iran and Oman, small areas of southwest Saudi Arabia, southern Bhutan, the whole of Bangladesh, Laos, and Cambodia, and most of Philippines, Indonesia, and Malaysia. The suitable area in Africa was restricted between plus or minus ten degrees of latitude, but no *B. correcta* has yet been recorded there. As for North America, most suitable area was concentrated in most part of Florida and Central America. The most suitable area of South America was also restricted in the north regions, there were also low and moderately suitable area in the central part. The climatically suitable area in the historical scenario was 3235.42×10^4 km^2, and it accounted for 24.06% of the world's total area. The continent with the largest suitable area was Africa, occupied 43.06% of the total area, Europe has the least suitable area, with 0.392% of the whole continent, in between were the other 4 continents following by North America (9.64%), Oceania (26.43%), Asia (29.45%), and South America (31.89%) (Table 2).

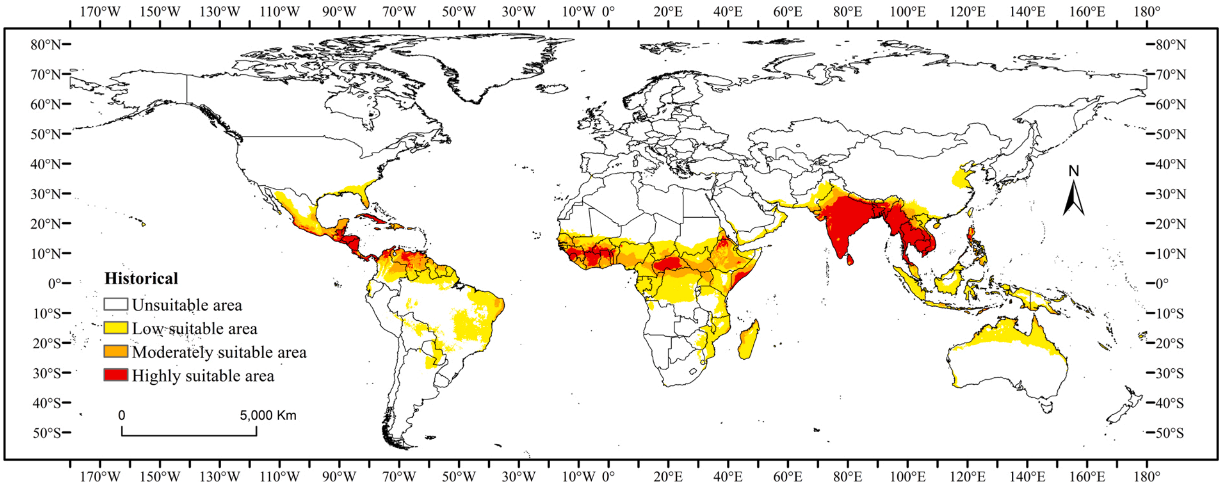

Fig. 2. Historical suitable area of *B. correcta* produced by MaxEnt (3.4.1), near-current environmental data were used in this part (averaged from 1970 to 2000). Blank space indicates unsuitable area (0.00–0.08); yellow space indicates low suitable area (0.08–0.30); orange space indicates moderately suitable area (0.30–0.60) and red space indicates highly suitable area (0.60–1.00).

Table 2
Projected suitable area globally for *B. correcta* under historical and future (2030 and 2070) climate scenarios expressed as an area (10^4 km^2), and as a percentage of the total area per continent, as predicted by MaxEnt modeling. SSP5–8.5 refers to a Shared Socio-economic Pathway (SSP) scenario with very high greenhouse gas emissions; SSP1–2.6 refers to a second SSP scenario with stringent mitigation of greenhouse gas emissions.

	Historical (1970–2000)		2030-ssp126		2030-ssp585		2070-ssp126		2070-ssp585	
	Suitable area /10^4 km^2	% total area	Suitable area /10^4 km^2	% total area	Suitable area /10^4 km^2	% total area	Suitable area /10^4 km^2	% total area	Suitable area /10^4 km^2	% total area
Asia	918.36	29.45%	966.75	31.00%	937.69	30.07%	957.89	30.72%	925.61	29.68%
Africa	1287.18	43.06%	1300.51	43.51%	1299.07	43.46%	1319.69	44.15%	1307.95	43.76%
North America	234.01	9.64%	265.83	10.95%	241.81	9.96%	260.29	10.73%	244.06	10.06%
Latin America	561.86	31.89%	625.23	35.49%	567.59	32.22%	612.55	34.77%	589.34	33.45%
Europe	9.01	0.39%	8.78	0.38%	8.76	0.38%	8.97	0.39%	8.76	0.38%
Oceania	225.00	26.43%	270.51	31.78%	260.82	30.64%	278.86	32.76%	245.33	28.82%
World[a]	3235.42	24.06%	3437.60	25.57%	3315.74	24.66%	3438.24	25.57%	3321.04	24.70%

[a] World area excludes the Antarctica.

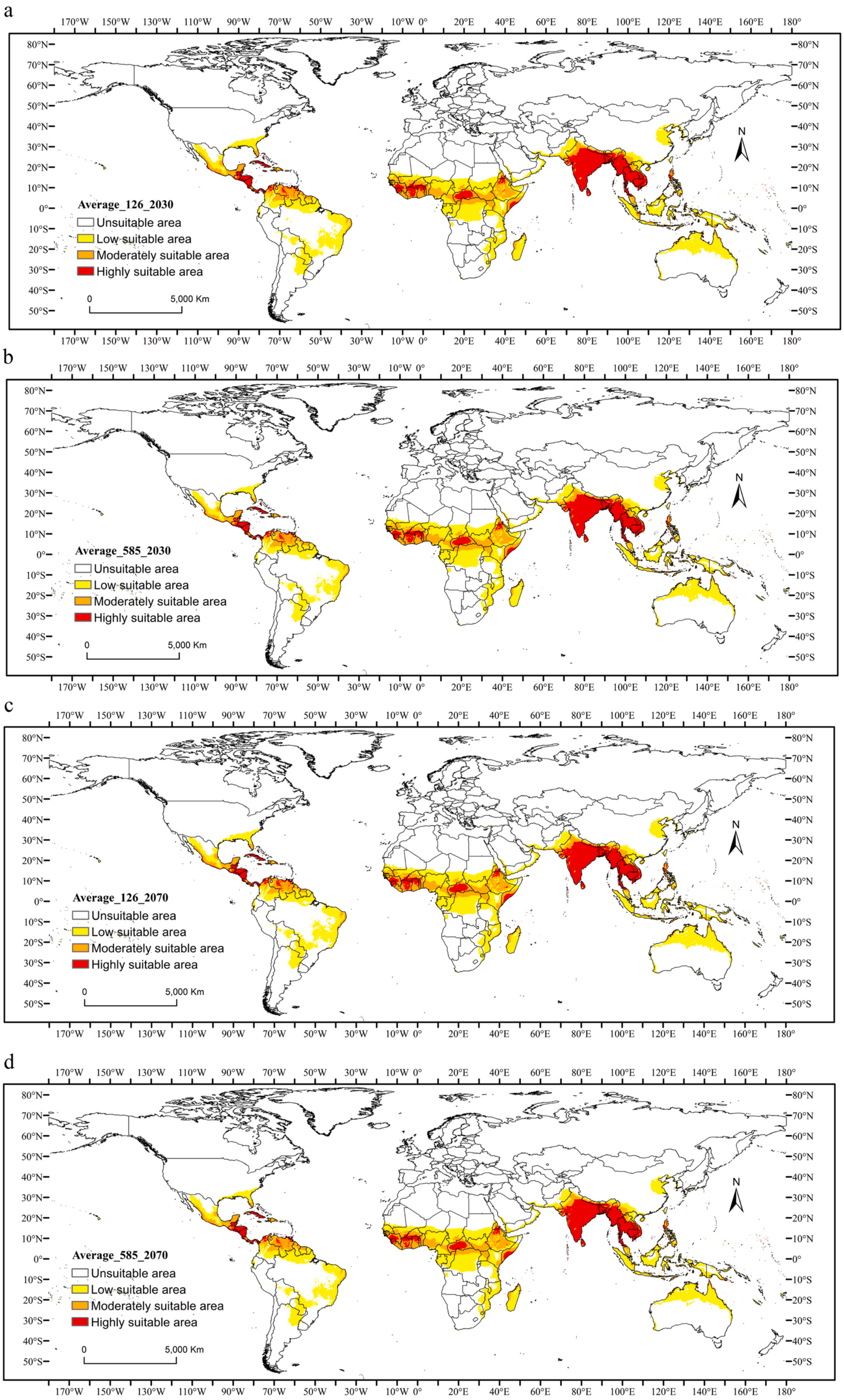

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Fig. 3. Suitable areas for *B. correcta* produced by MaxEnt predictions under 2030–2070 using three global climate models [BCC-CSM2-MR (BCC), IPSL-CM6A-LR (IP), MIROC-ES2L (MI)]. a. 2030-SSP126; b. 2030-SSP585; c. 2070-SSP126; d. 2070-SSP585. Shared the same method of classification with the historical scenario.

3.3. *Future suitable area of B. correcta*

Fig. 3(a–d) showed the suitable area of *B. correcta* under future climate change scenarios in 2030 and 2070. The results showed the greatest potential future expansion in South America and Oceania. The suitable area of South America increased marginally from 561.86 $km^2 \times 10^4 km^2$ to 589.34 $km^2 \times 10^4 km^2$, the overall area increased by 1.56% (SSP-585 in 2070). In the north Oceania, the suitable area and risk level has increased. Highly suitable area for *B. correcta* was are projected to be in South Asia and Southeast Asia, suitable area of Asia will also increase under future climate scenarios. In 2030, under a stringent management of greenhouse gas emission scenario (SSP126), the suitable area was 3437.60 $\times 10^4 km^2$, which was 1.06 times the historical suitable area, the total suitable area was up to 25.57% of the world. In 2070, the suitable area was projected to increase to 3438.24 $\times 10^4 km^2$ under scenario SSP126, it was 202.82 $\times 10^4 km^2$ more than under the historical conditions and similar as 2030 under same scenario. Under scenario SSP585, the total suitable area will increase to 24.70% of the world's land area in 2070 and 24.66% in 2030 (Table 2).

4. Discussion

Bactrocera correcta is currently restricted to South and Southeast Asia, and our MaxEnt models predicted that South America, Central Africa and Oceania are also suitable for this species, and like its sister species these areas may be vulnerable to invasion if the species were released there. In North America, *B. correcta* has been detected several times in Florida, which had been predicted to be suitable area, however, California was not predicted to be suitable.

Bactrocera correcta was first discovered in Yunnan Province, China in 1982 (Bezzi, 1916), and was introduced into Western Yunnan from Southeast Asia and gradually dispersed Eastward (Qin et al., 2016). After almost 40 years of development, the distribution of *B. correcta* was still restricted to Yunnan Province, recent expansion to Guangxi Province (X. Liu et al., 2019; Y.Y. Liu et al., 2019), which matches our model predictions. Additionally, Shandong, Anhui and Jiangsu Provinces in eastern China are also predicted to be suitable area, but there is nodirect natural pathway from the south to the east.

Over millennia, humans have transported plant and animal species outside their natural range (Meyerson and Mooney, 2007; Perrings et al., 2005), causing invasions and can facilitate biological invasions (Bertelsmeier, 2021). The invasion of fruit flies is mostly due to anthropogenic transport, often in fruit, plants or soil (White and Elson-Harris, 1992). Dipteran family Tephritidae, the fruit flies, comprises more than 5000 species classified into 500 genera distributed worldwide. Most of them have multiple hosts, and they can disperse with their hosts (Aketarawong et al., 2014; Scolari et al., 2021). The propagule pressure hypothesis emphasizes that the number of invaders released into non-native regions can determine invasion success (Sierocinski et al., 2021), Yamamichi et al. (2014). stated that propagule size and timing both affect the invasion success. With the development of globalization and the increasing demand for transport networks, the prediction accuracy of invasive species will improve by taking into account the propagule pressure and species dispersal (natural and artificial).

Similar to another notorious pest, *Bactrocera dorsalis* (oriental fruit fly), *B. correcta* shares similar biological characteristics, has a wide host range and can cause significant damage to crops, thus both economic threats worthy of detailed attention. *B. dorsalis* was not present in South Africa until 2006, monitoring data showed that small numbers of oriental fruit fly had been captured between 2007 and 2008 but has not been recorded since late 2008 suggesting that these insects are likely to be transported by infected fruit (Manrakhan et al., 2015). In Hawaii, annual losses in major fruit crops caused by the oriental fruit fly may exceed 13%, or US$ 3 million (Culliney, 2002). To eradicate the species, many countries have invested huge sums, for example it was estimated that it would cost from US$ 44–176 million in crop losses, additional pesticide use, and quarantine requirements if California did not eradicate the pest (Cantrell et al., 2002). Both of the species were originally from the Southeast Asia, and *B. dorsalis* has recently invaded parts of Africa, central China and Europe, highlighting the need for vigilance. The suitable area of *B. correcta* was also of concern. An eclosion rate model indicated that *B. correcta* was expected to be able to establish itself throughout China in warmer months (Qin et al., 2015).

Similarly, *Bactrocera zonata*, the peach fruit fly, a similar species to *B. correcta* is absent from China. However, if it invaded China, the peach industry alone could suffer from 0.82 to 3.07 billion dollars economic loss of (Qin et al., 2021). Although no studies have assessed the potential economic losses of guava fruit flies, the number of annual losses in the countries where its presence is staggering, for example, India is a main producing area of mango and guava, the yield of guava fruit in Tamil Nadu is reduced by the guava fruit fly by 60% (Jalaluddin, 1999). Given the wide range of host plants in tropical and subtropical areas, vigilance should be necessary to prevent the establishment of species such as guava fruit fly in regions which are vulnerable to them.

Understanding potentially suitable conditions, and the importance of climatic changes, the results showed vapor pressure and solar radiation were the most influential variables for *B. correcta*. Annual trends of water vapor pressure are like the annual temperature, the vapor pressure will be higher when temperature was higher, vapor corresponded to the higher temperatures in July affecting the distribution of *B. correcta*. This is consistent with records of *C. capitata* which increased in April to May, and peaked in July (Tiring and Satar, 2021); *B. dorsalis* has also been reported to peak in June and July (Li et al., 2010). Moreover, the temperature, solar radiation and vapor pressure could interact to each other, and should be considered simultaneously. But there are few monitoring experiments have been conducted on guava fruit flies, and it is recommended that early surveillance should be intensified in July to prevent outbreaks.

Some invasive species prefer warmer conditions (Cai et al., 2018; X. Liu et al., 2019; Y.Y. Liu et al., 2019; Wallace, 2014; H. Zhao et al., 2020; Z. Zhao et al., 2020). The results showed under climate change scenarios, the suitable area of *B. correcta* will increase slightly, and the suitable area under Shared Socio-economic Pathways 126 was larger than the higher greenhouse emission scenario SSP585. From a physiological perspective, some insects can enhance heat resistance by heat hardening, and the results are consistent with evidence that *B. correcta* hardens better at lower temperatures whereas *B. dorsalis* hardens better at higher temperatures (Gu et al., 2019).

An important limitation of the distribution expansion of *B. correcta* could be the species competition from *B. dorsalis* which is more competitive in host adaptation and reproduction (Liu et al., 2017). Other abiotic influencing factors, such as land use, human factors (Chen et al., 2020; Liu et al., 2020) were also not considered in current study. CLIMEX model showed a wider suitable range (Li, 2015), different results may be due to the different approaches, spatial resolutions, and variables. Ensemble modeling was suggested to be applied in future study in order to avoid the limitation from single models (Thuiller et al., 2009; Zhu et al., 2020).

This study predicted that the suitable regions for the guava fruit flies falls between latitudes between 30 degrees north and south latitude. In addition to its known range in Southeast Asia, suitable areas including North America, Latin America, Africa and Oceania, and imports of fruit from infected regions to these regions require special scrutiny given the potential for establishment. To manage the guava fruit fly, the most effective method is prevention its spread, monitoring the population dynamics was suggested to be adopted by quarantine departments.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2022.e02021.

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