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Model-based prediction of the potential geographical distribution of the invasive coconut mite, *Aceria guerreronis* Keifer (Acari: Eriophyidae) based on MaxEnt

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[Correction added on 28 April 2022, after first online publication: SSP5-5.85 has been corrected to SSP5-8.5 in point 3 of the Abstract.]

Abstract

1. The coconut mite *Aceria guerreronis* Keifer (Acari: Eriophyidae), is a destructive mite pest of coconut, causing significant economic losses. However, an effective pest management strategy requires a clear understanding of the geographical areas at risk of the target pest.
2. Therefore, we predicted the potential global distribution *A. guerreronis* using a machine learning algorithm based on maximum entropy.
3. The potential future distribution for *A. guerreronis* covered the 2040 and 2060 periods under two climate change emission scenarios (SSP1-2.6 and SSP5-8.5) in the context of the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change.
4. The MaxEnt model predicts the habitat suitability for *A. guerreronis* outside its present distribution, with suitable habitats in Oceania, Asia, Africa, and the Americas. The habitat suitability for the pest will decrease from 2040 to 2060.
5. The areas with the highest risk of *A. guerreronis* are those with an annual average temperature of around 25°C, mean annual precipitation of about 1459 mm, mean precipitation seasonality close to 64%, an average variation of daytime temperature of about 8.6°C, and mean seasonality of temperature of about 149.7°C.
6. Our findings provide information for quarantine measures and policymaking, especially where *A. guerreronis* is presently still absent.

KEYWORDS
Aceria guerreronis, climate change, coconut mite, machine-learning algorithm, MaxEnt

INTRODUCTION

The coconut palm (*Cocos nucifera* L.), is one of the most important commercial palms produced in the tropical and sub-tropical regions, with coordinates ranging from 25° North to 25° South of the equator (Ahuja et al., 2014). Coconut is thought to originate in the region between Southwest Asia and Melanesia, where it shows the greatest genetic diversity based on modern molecular studies (Gunn et al., 2011). Coconut is a versatile crop that plays a significant role in the social and economic lives of many rural communities (Gurr et al., 2016). In Sri Lanka, coconut production accounts for 2.5% of the country's gross domestic product, 2.5% of export earnings, and 5% of jobs (L. C. P. Fernando et al., 2007). It also provides fuel, food, shelter, and beverages (Foale, 2005). The health benefits of coconuts are well documented, especially in providing calcium, magnesium, and potassium (Ahuja et al., 2014).

An invasive species, plant or animal that has been introduced outside its native range can pose a threat to the new area. Such species can be significant contributors to habitat loss, environmental depletion, and impairment, and their increasing spread is fueled both by global trade (Bradley et al., 2012; Westphal et al., 2008) as well as climate change (Pyšek & Richardson, 2010). In China, economic losses due to invasive species between 2001 and 2003, were US$ 14.45 billion (Xu et al., 2006), US$ 0.9–1.1 billion in Africa (Pratt et al., 2017), and in the USA and Australia, annual losses are around US$ 120 billion and 13.6, respectively (Hoffmann & Broadhurst, 2016; Pimentel et al., 2005). However, invasive species are not only a major threat to the economies of the affected countries, but also to agriculture, food security, and biodiversity conservation (Campbell et al., 2016; S. Kumar et al., 2014). Over the past 100 years, there has been a dramatic increase in the spread of invasive species due to increased trade, tourism, transportation, and travel (Hulme, 2009).

The coconut mite *Aceria guerreronis* Keifa (Acari: Eriophyidae), is an invasive pest that poses a serious threat to the coconut industry worldwide (Navia et al., 2013). The mite originated in the Americas but has been introduced into Asia and Africa (Návia et al., 2005). The mite usually starts feeding on the fruits as early as 3 months after fertilization, but generally, the highest infestations are seen in 3–7 months old coconut fruits (L. C. P. Fernando et al., 2003). Especially very young fruits, aged 1–4 months, are highly susceptible to mite infestation (Howard & Rodriguez, 1991). Mite infestation can affect the export acceptability of coconut fruits (Rezende et al., 2016). Coconut mite can be detected by a visible triangular white spot on the fertilized nuts (Mariau, 1969), found along the edge of the coconut's perianth. Mite infestations cause reductions in the yield of copra, a premature drop of coconut, reduced coconut fibre length and tensile strength, small deformed fruits, and result in a reduction in husk availability (Alam & Islam, 2014; Aratchige et al., 2016; P. P. Kumar & Ramaraju, 2010; Naseema Beevi et al., 2003; Wickramananda et al., 2007). Significant economic copra losses associated with mite infestations ranged from 10% to 16% in West Africa (Julia & Mariau, 1979), 0%–30% in Mexico (Hernandez, 1977), and 0%–31.5% in St. Lucia (Moore et al., 1989).

Climate change plays an important role in the distribution of species leading to either expansion or reduction of suitable habitats (Aidoo et al., 2019; Ajene et al., 2020; Sung et al., 2018; Thomson et al., 2010; Velásquez-Tibatá et al., 2013). Global warming is expected to change the distribution of species around the world, by changing their natural habitats (Velásquez-Tibatá et al., 2013). Greenhouse gas emissions due to anthropogenic activities are associated with global warming (Ge et al., 2015), which may force certain species to niche changes rather than dispersal to avoid extinction (Román-Palacios & Wiens, 2020). Increasing CO_2 levels can have a significant impact on plants and pathogens. For instance, it can lead to an increase in the production of fungal spores and thus the growth of pathogens, but can also increase plant resistance to pathogens (Coakey et al., 1999), affecting existing pest control strategies. Recent studies have focused on the effects of climate change on crops (Mall et al., 2017), pests, and diseases (Boland et al., 2004; Pautasso et al., 2012; Reddy, 2013), and the emergence of pest and disease outbreaks. Also, research has assessed the impact of climate change on abundance, distribution, ecological niche potential for arthropod pests, and the associated losses in crop production and their impact on food security (Gregory et al., 2005; Sharma & Prabhakar, 2014; Spathelf et al., 2014).

Species distribution models (SDMs) employ computer algorithms to predict the habitat suitability of a species across geographical space and time based on environmental data. Such models are important tools to evaluate the potential response of pests to climate change and have been useful at large spatial and temporal scales. For instance, SDMs have been successfully used to model the habitat suitability of the cassava green mite *Mononychellus tanajoa* (Bondar) and *Mononychellus mcgregori* (Flechtmann and Baker) (both Acari: Tetranychidae) (Parsa et al., 2015), tomato red spider mite *Tetranychus evansi* (Baker & Pritchard) (Acari: Tetranychidae) (Meynard et al., 2013), and palm mite *Raoiella indica* Hirst (Prostigmata: Tenuipalpidae) (Amaro & de Morais, 2013). Although there are several SDM algorithm methods, Maximum Entropy (MaxEnt) employs presence-only data to predict the distribution of species based on the theory of maximum entropy (Phillips et al., 2005, 2006, 2017). It is generally considered the most powerful tool when modelling pests with narrow ranges and where presence-only data exist (Baloch et al., 2020; Elith et al., 2006; S. Kumar et al., 2014; Y. Liu & Shi, 2020; Phillips et al., 2006).

Attempts to reduce the adverse effects of warming on insect pests must provide a deeper understanding of the response of individual species and the complex ecological processes underlying their response (Lehmann et al., 2020). Although the effect of climate change on pests of horticultural crops has considerably increased, information on its impact on the distribution of coconut mite, essential for mitigation measures, is generally lacking. Therefore, for the first time, we used MaxEnt to model and map regions suitable for coconut mites to provide information for the implementation of quarantine measures and highlight the need for policy formulation.

MATERIALS AND METHODS

Occurrence datasets

In the present study, we conducted a nationwide survey from April 2019 to February 2021 in Ghana to obtain *A. guerreronis* occurrence records. The locations where *A. guerreronis* was found were georeferenced using a handheld GPS device. The presence of the pest was based on the availability of any of the developmental stages and symptomatic fruits. These presence records were supplemented by an extensive scientific literature search (Aratchige et al., 2016; L. C. P. Fernando et al., 2003; Howard et al., 1990; Lawson-Balagbo et al., 2008; Navia et al., 2013), utilizing online databases, such as Web of Science, Science Direct, Google, Google Scholar, PubMed, and MEDLINE. We searched online using keywords, such as *A. guerreronis*, coconut mite, coconut eriophyid mites, first report, coconut pest, distribution of coconut mite, and the biology of coconut mite. In addition, we also consulted databases such as Global Biodiversity Information Facility (GBIF; http://www.gbif.org) and the Centre for Agriculture and Bioscience International (CABI; https://www.cabi.org/). In case only localities were provided, Google Earth Pro was used to extract the coordinates (i.e., latitudes and longitudes). Duplicate and fuzzy records were manually removed from the data.

Filtering of the *A. guerreronis* datasets

Occurrence records for running the Maxent model are often biased in the geographical space because of unequal sampling efforts across the study area (Botella et al., 2020; Stolar & Nielsen, 2015). Moreover, a distribution location is typically biased towards areas that are easily accessible to humans, such as nearby cities and other human habitation areas (Hijmans et al., 2005; Kadmon et al., 2004). This, however, suggests that distribution site data can significantly influence the outcome of a model due to spatial autocorrelation (Elith et al., 2011; Raghavan et al., 2019). To reduce this spatial autocorrelation, we used the R software package spThin to perform spatial filtering on the data (Aiello-Lammens et al., 2015). After this process, all remaining occurrence points were at least 5 km apart (Boria et al., 2014; Veloz, 2009). This distance was selected to restrict each cell to only one occurrence point since we used ~5-km spatial resolution climatic data in the model. Therefore, leaving 137 localities for the final model. The data were then converted into MaxEnt-compatible formats prior to analysis. In addition, we run the model using only the Ghana data and without it to check whether the adjustment will affect the habitat suitability predictions for *A. guerreronis* (Figure 1).

Environmental datasets

The climatic data used for this study were gathered from the WorldClim environmental database (http://www.worldclim.org/). These environmental variables have been widely used for species distribution modelling (Fick & Hijmans, 2017; Hijmans et al., 2005). The variables are mean climate values ranging from 1970 to 2000, with a high resolution of 2.5 arc-min (≈5 km at the equator) (Ramos et al., 2018). The datasets consisting of 19 bioclimatic variables are presented in Table 1.

SDMtools in ArcGIS software are proven to be effective in withdrawing highly correlated variables, maintaining only one variable per group with high correlation. Therefore, for the collection of variables, Pearson's correlation coefficients were calculated (Table S1), and those variables with values greater/or equal to 0.7 were considered as strong correlation (S. Kumar et al., 2014; Rank et al., 2020). Thus, the variables that were used in the final model as predictor variables are highlighted in bold in Table 1. The predictive contribution of environmental variables was estimated using the jackknife technique (Wei et al., 2018; Yang et al., 2013).

Model development and validation

The model for *A. guerreronis* was based on adjusting the default MaxEnt settings for certain combinations of resource types and the regularization multiplier (RM) (Jarnevich et al., 2015; Merow et al., 2013). We combined linear (L), quadratic (Q), product (P), threshold (T), and hinge (H) feature sets, using automatic feature selection plus RM = 1 to control the number of parameters and, therefore, the complexity of the model for the species (Elith et al., 2011). The area under the the curve (AUC) of the receiver operating characteristic curve (ROC) value was used to evaluate the model's performance (Peterson et al., 2008). The AUC value of 0.5, indicates that model predictions are no better than random (Peterson et al., 2011). The values below 0.5 are less than random, whereas those between 0.5 and 0.7 indicate poor performance. AUC values between 0.7 and 0.9 indicate moderate performance, while values greater than 0.9 indicate high performance. MaxEnt is a machine-learning method that predicts probability distribution based on the principle of maximum entropy. The model generates a suitability index ranging from 0 to 1, with 0 indicating inadequacy and 1 optimal suitability (Elith et al., 2011). We used ArcGIS version 10.8 to prepare the MaxEnt outputs and generate suitable and unsuitable areas for *A. guerreronis*. The Maximum Test Sensitivity Plus Specificity (MTSPS) threshold is considered simple and effective (C. Liu et al., 2005). Therefore, we used MTSPS to extract from the predictive models, the unsuitable and suitable areas for *A. guerrenoris*.

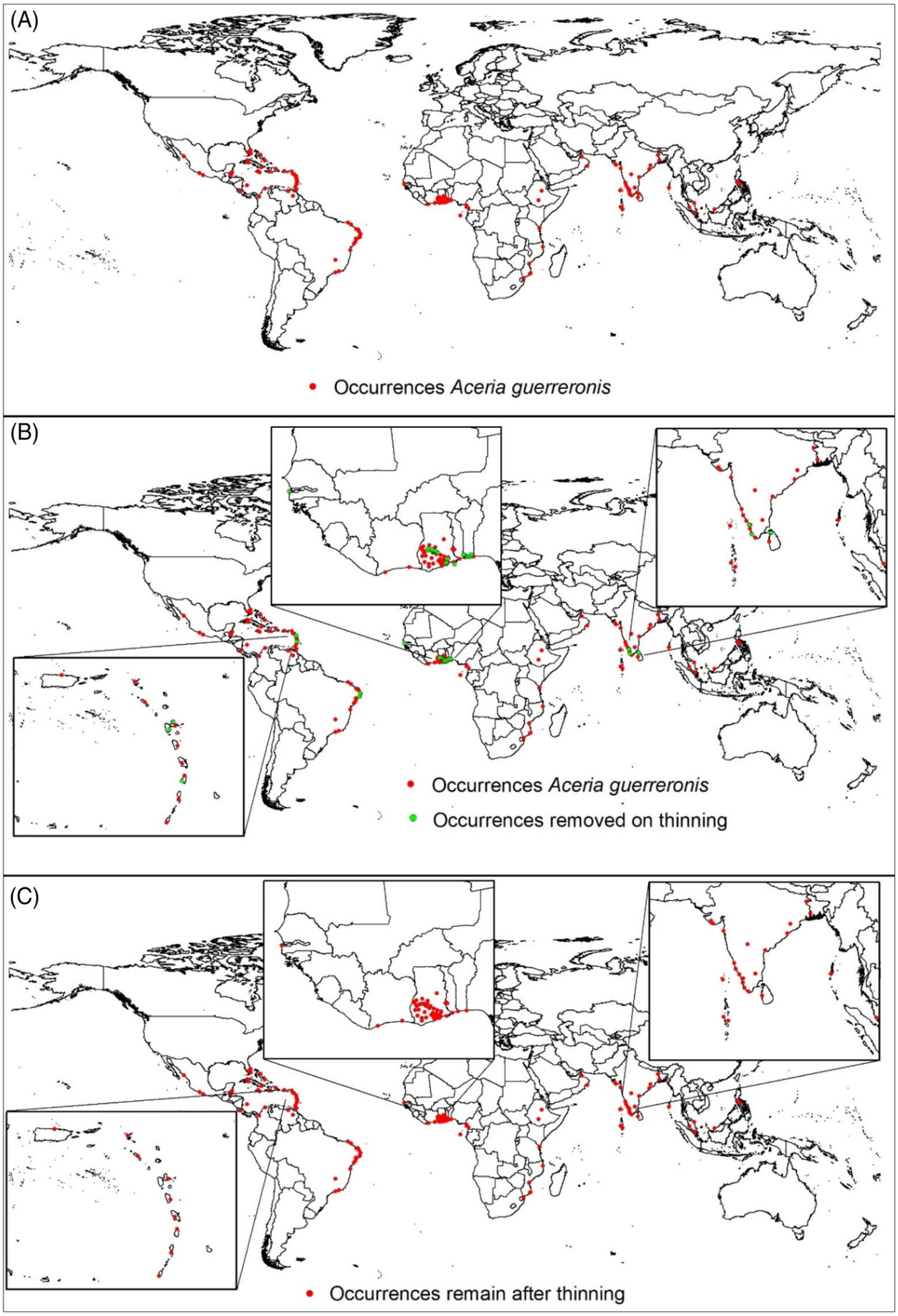

FIGURE 1 Current global distribution of *Aceria guerreronis* (a), the highlight of points removed after thinning (b); 137 remaining occurrence points used for the modelling (c)

RESULTS

Modelling performance

Based on the 19 bioclimatic datasets, the MaxEnt model provided satisfactory results with an AUC value of 0.975, thus, exceeding a random distribution. During modelling, 80% of the occurring sites were randomly selected as training data and the other 20% were used to test the resulting models. To predict future areas, we used four suitability classes (unsuitable: 0-MTSPS; low: MTSPS-0.5; medium: 0.5–0.7 and high: 0.7–1.0).

TABLE 1 Nineteen environmental variables used for the model with code and units

Code	Environmental variable	Unit
bio_1	**Annual average temperature**	**°C**
bio_2	**Average variation of day time temperature**	**°C**
bio_3	Isothermality	°C
bio_4	**Seasonality of temperature (SD × 100)**	**°C**
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**	**%**
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

Note: The environmental variables highlighted in bold were used for the final model.

Contribution of environmental variables

The relative importance of environmental variables based on the jackknife test indicated that seasonality of temperature (bio_4) and annual average temperature (bio_1) contributed most to the model when used in isolation (Table 2). The environmental variable with the highest gain, thus providing the most useful information by itself when used in isolation, was the seasonality of temperature (bio_4). The environmental variable that decreased the gain the most when omitted was the average variation of daytime temperature (bio_2), therefore, having the most information that is not present in the other variables (Figure 2a,b).

MaxEnt generates response curves and the variables that had such a small effect in the model make them unlikely to be biologically meaningful. The results of the individual response curves for the different bioclimatic variables showed that the predicted probability of occurrence of *A. guerreronis* positively correlated with temperature seasonality, annual precipitation and annual average temperature (Figure 3). The probability of *A. guerreronis* occurrence increased sharply up to a value of 200°C for temperature seasonality and started declining afterwards (bio_4; Figure 3a). The probability of *A. guerreronis* presence was consistently steady until −10°C when it started increasing with the annual average temperature (bio_12; Figure 3b). With increasing annual precipitation, the probability of *A. guerreronis* presence increased steadily up to a value of 800 mm before it started declining (bio_12; Figure 3c).

Globally, the results showed that the distribution of *A. guerreronis* occurs in areas with a mean seasonality of temperature of about 149.67°C, precipitation seasonality of about 64.62%, average variation of daytime temperature close to 8.62°C, annual precipitation close to 1459 mm, and an annual average temperature around 25°C (Table 2). The environmental variables that contributed most to the model were seasonality of temperature (43.28%), annual average temperature (22.35%), average variation of daytime temperature (18.98%), and annual precipitation (12.86%). The thermal conditions combined contributed 84.61% to the model, whereas rainfall conditions 15.38%.

Predicted current distribution for *A. guerreronis*

In the present study, *A. guerreronis* occurrence records were obtained from Africa, Asia, and the Americas (Figure 4). The model predicts that highly suitable areas for *A. guerreronis* are primarily centered on the west and east coasts of Africa, the south and east coasts of Asia, the north coast of Oceania, the east coast of South America, and the south coast of North America (Figure 5). Moreover, the prediction agrees with the present and proven records of *A. guerreronis* except for minor changes.

TABLE 2 Environmental variables considered in an *Aceria guerreronis* niche models and mean percentage contribution of environmental variables in an *A. guerreronis* distribution model; values were averaged over 10 repeated runs

Variable	Percentage contribution	Permutation importance	Min.	Max.	Avg.	SD
Annual average temperature (bio_1; °C)	22.35	70.12	14.18	27.89	25.09	1.76
Annual precipitation (bio_12; mm)	12.86	2.47	85	2522	1459.19	666.61
Precipitation seasonality (CV) (bio_15; %)	2.52	1.75	19.28	112.91	64.62	26.74
Average variation of daytime temperature (bio_2; °C)	18.98	16.09	4.60	12.62	8.62	1.67
Seasonality of temperature (SD × 100) (bio_4; °C)	43.28	9.57	22.60	375.73	149.67	92.58

Note: General statistics were calculated using all occurrences ($n = 166$).
Abbreviations: Avg., average; max., maximum; min., minimum; SD, standard deviation.

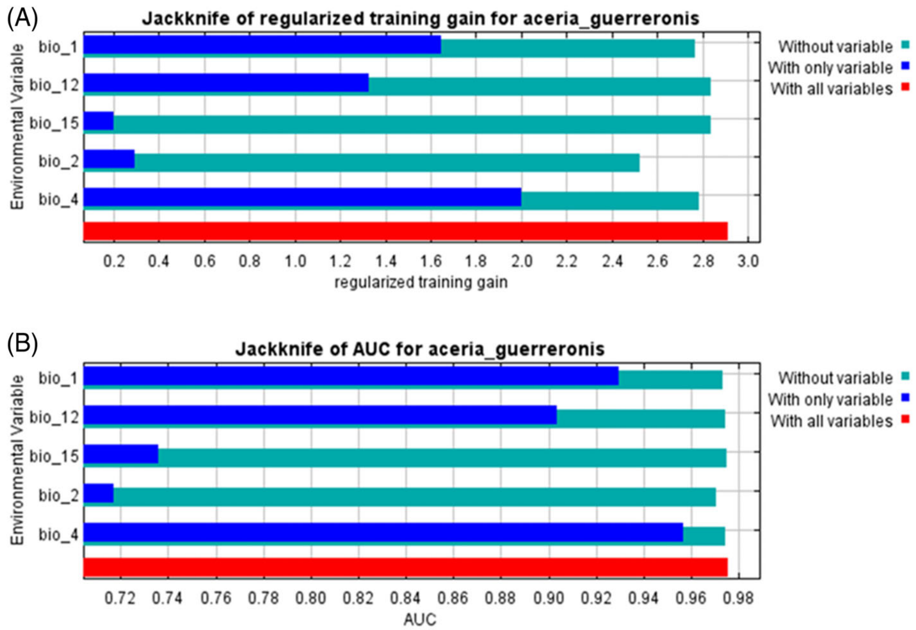

FIGURE 2 The relative importance of environmental variables based on (a) jackknife test of regularized training gain, and (b) jackknife of AUC for *Aceria guerreronis*

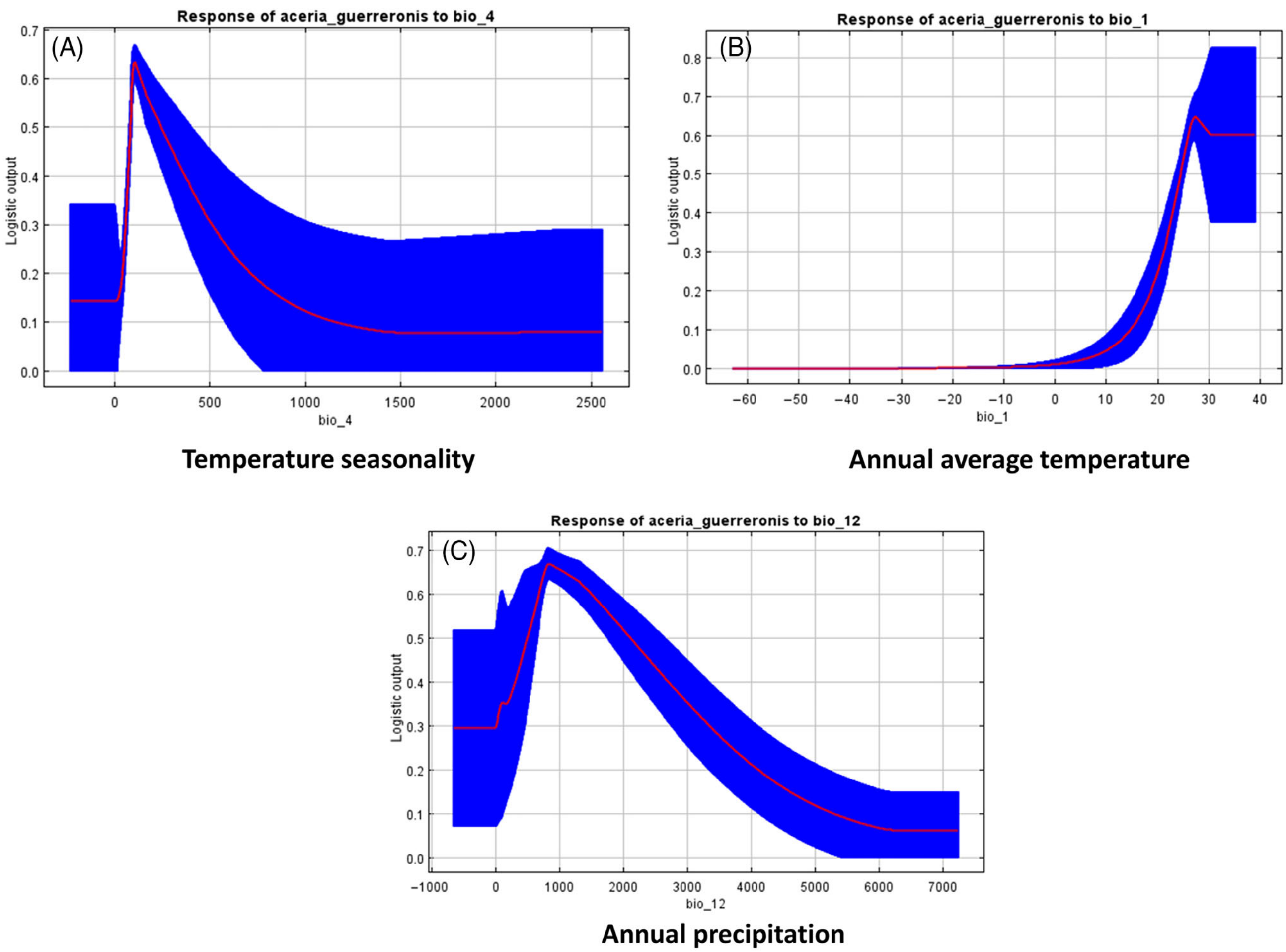

FIGURE 3 Response curves of the best predictors of *Aceria guerreronis occurrence*: (a) temperature seasonality (bio_4), (b) annual average temperature (bio_1) and (c) annual precipitation (bio_12). Red curves represent the average response and blue margins are ±1 SD computed over 10 replicates

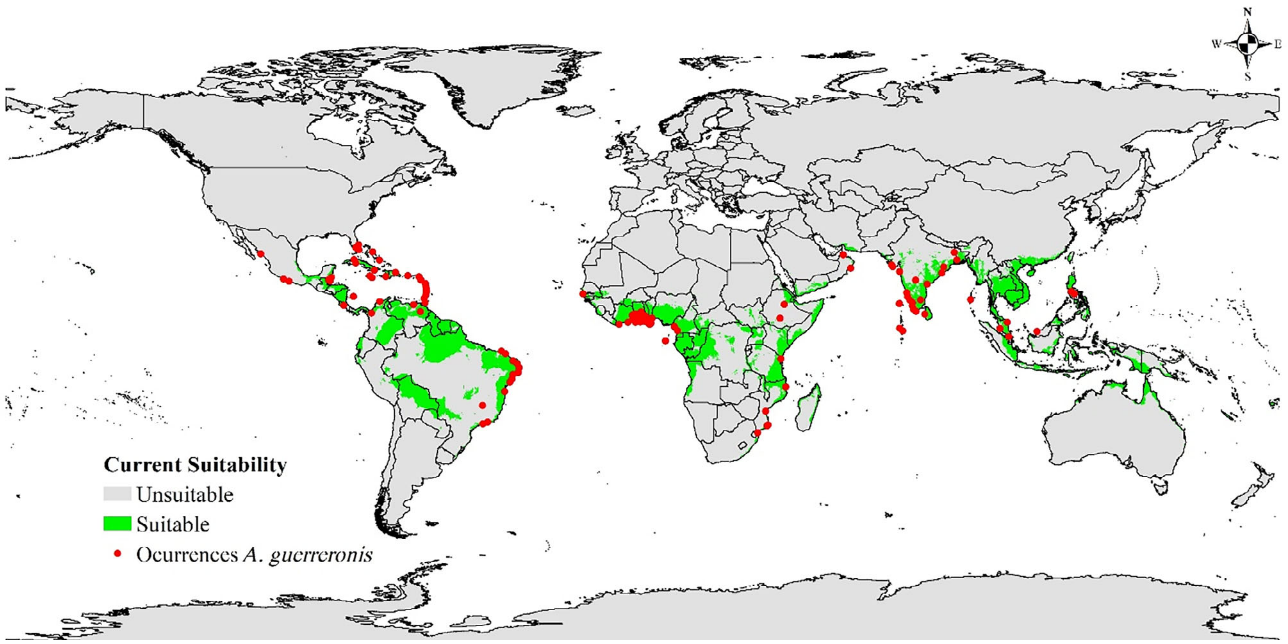

FIGURE 4 Present known distribution, and predicted suitable and unsuitable areas for *Aceria guerreronis*

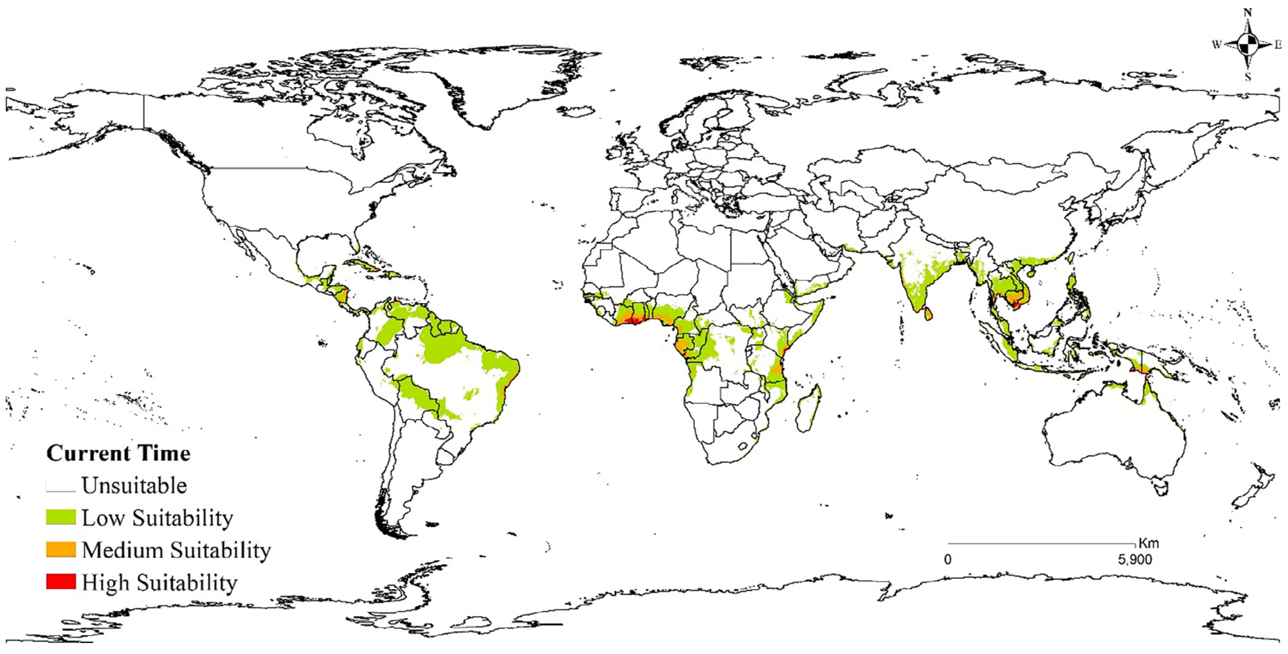

FIGURE 5 Current time global *Aceria guerreronis* suitability classes

Predicted future distribution for *A. guerreronis*

The future predictions showed an expansion of habitat suitability from the current time to the future. The model predicts that the major coconut-producing countries, such as Indonesia, India, Sri Lanka, Brazil, Vietnam, and the Philippines, will continue to remain suitable in the future. Under SSP2.6 (Figure 6), the model predicts a reduction in habitat suitability from 2040 to 2060. However, the areas that will remain medium to high suitability for *A. guerreronis* are mainly found on the west and east coasts of Africa, east coast of South America, south and east coasts of Asia, and north coast of Oceania. Under SSP8.5 (Figure 7), the model predicts that suitable areas for *A. guerreronis* will decrease from 2040 to 2060. However, habitat suitability for *A. guerreronis* will range from

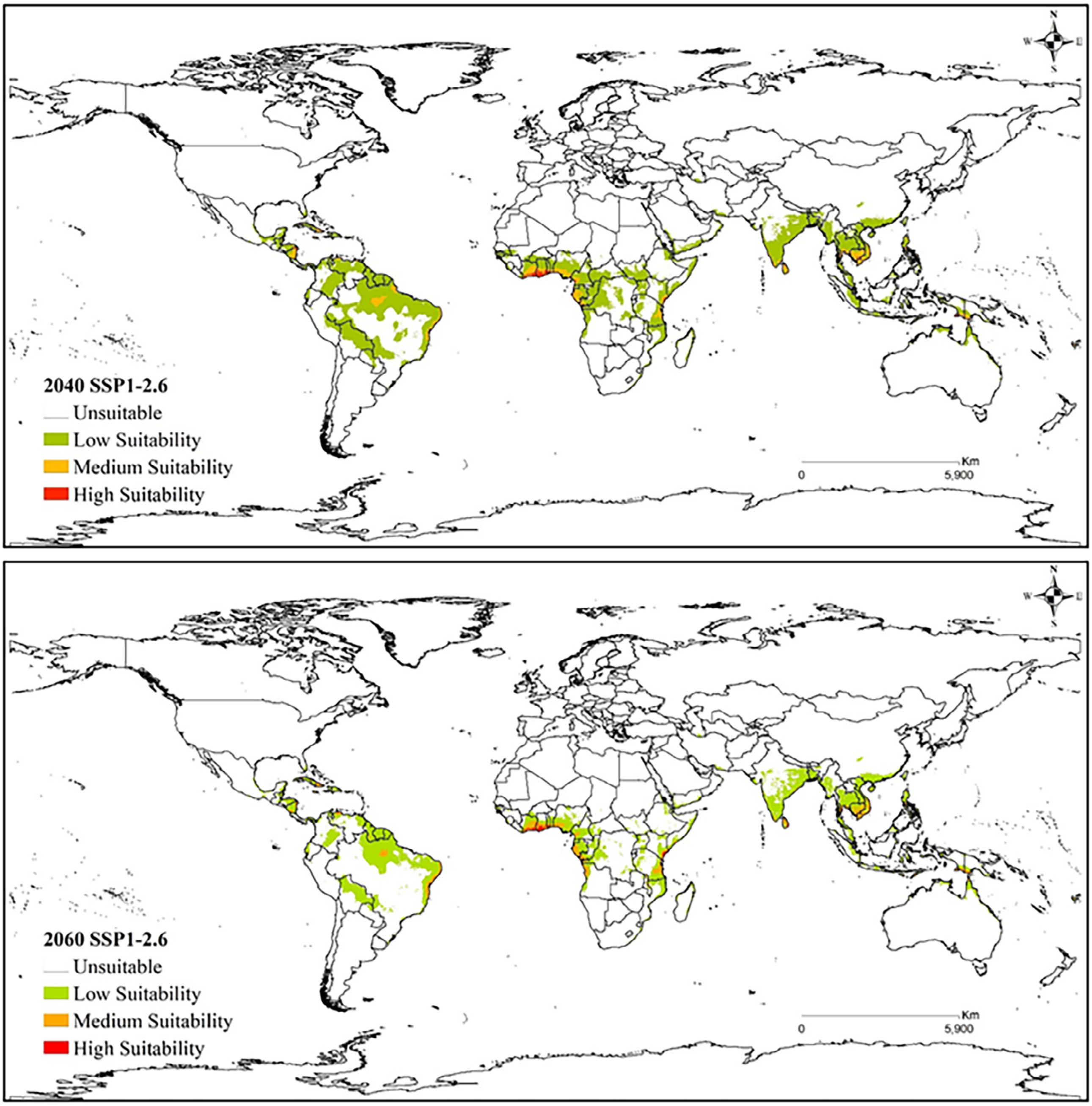

FIGURE 6 Predicted future distribution of *Aceria guerreronis* in the shared socio-economic pathway (SSP2.6) of climate conditions in 2040 and 2060

low to high. But, the areas with medium to high suitability are essentially centered on the east and west coasts of Africa, south and east coasts of Asia, east coast of South America, and north coast of Australia.

Predicted current distribution for *A. guerreronis* using only Ghana data and without it

The current time global habitat suitability predictions for *A. guerreronis* using all occurrences (Figure 8a), without Ghana occurrences (Figure 8b), and using only Ghana occurrences showed varying predictions (Figure 8c). The model's prediction shows a slight expansion of habitat suitability for the pest when Ghana occurrences were removed from the datasets (Figure 8b). However, the model predicted suitable areas where the pest was identified and sampled. But, when only Ghana records were used in the model, the model predicts suitable areas basically in Africa's west and east coasts, parts of the east and north coasts of South America, and the southeast coast of Asia (Figure 8c). The prediction with only Ghana data was also consistent with the known occurrence records of the pest in Ghana.

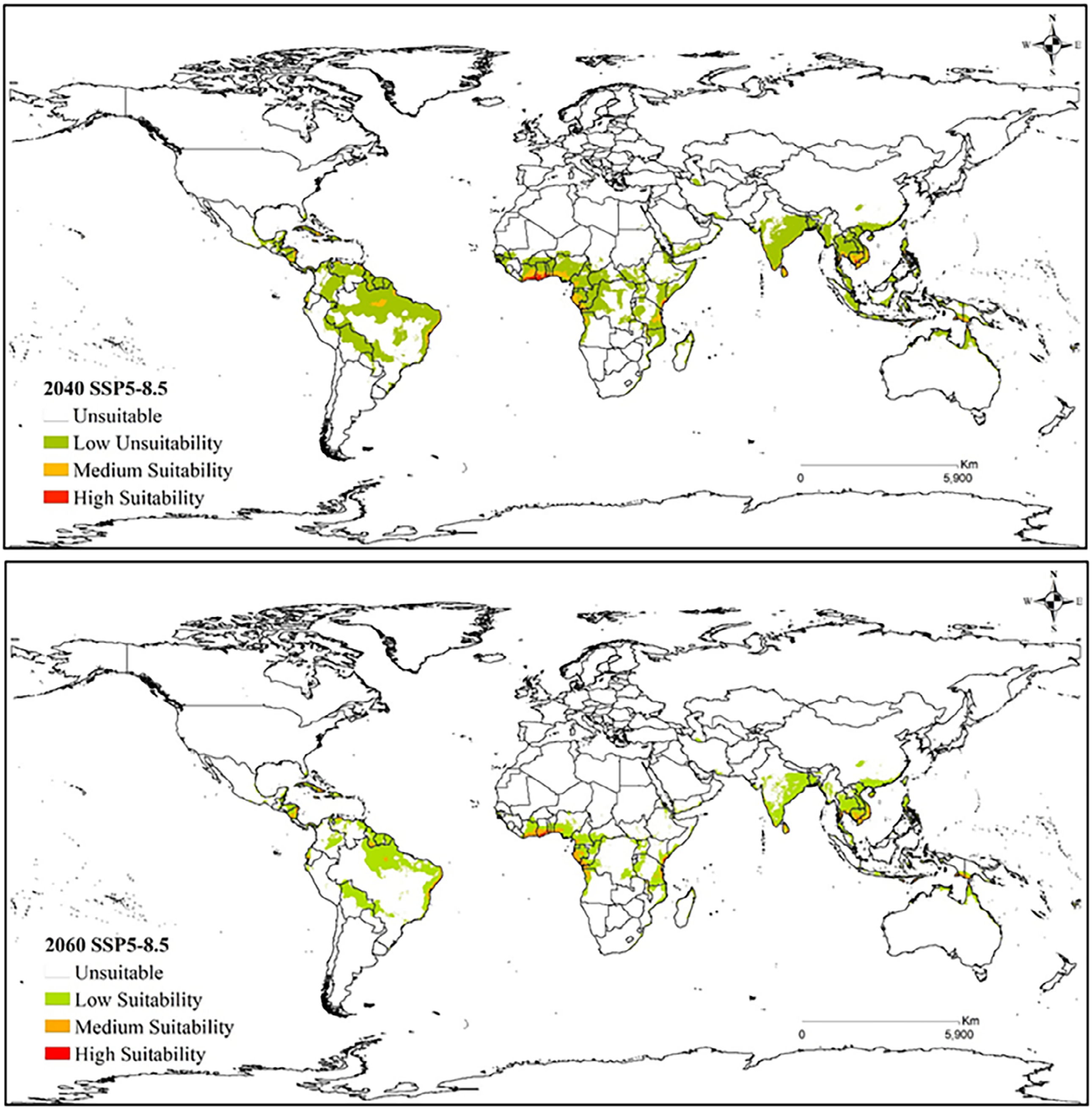

FIGURE 7 Predicted future distribution of *Aceria guerreronis* in the shared socio-economic pathway (SSP8.5) of climate conditions in 2040 and 2060

DISCUSSION

The invasive coconut mite is considered an economically important pest of coconut wherever it occurs. Although its exact origin is unknown, it is most likely a South American native travelled with the seeds to Africa and Asia (Návia et al., 2005). Therefore, the global potential distribution maps of its expansion are essential for economic and quarantine purposes worldwide, especially for areas where the pest has not been reported. In the present study, we used the MaxEnt model to predict the current and future distributions of *A. guerreronis*. MaxEnt theory has several advantages over other SDMs because of its high predictive power and, does not require absence records of the targeted species (Phillips et al., 2017). Previous studies have used the method to successfully predict climate suitable areas of several species on a local and global scale (S. Kumar et al., 2014; Ning et al., 2017; Santana Jr et al., 2019; Aidoo et al., 2022). Our model performance was high, with an AUC value of more than 0.9, suggesting that the model's predictions are reliable. Several studies have assessed MaxEnt model performance using AUC (Remya et al., 2015; Yang et al., 2013).

In our model, the environmental variables that had the strongest influence on coconut mite habitat suitability in descending order of

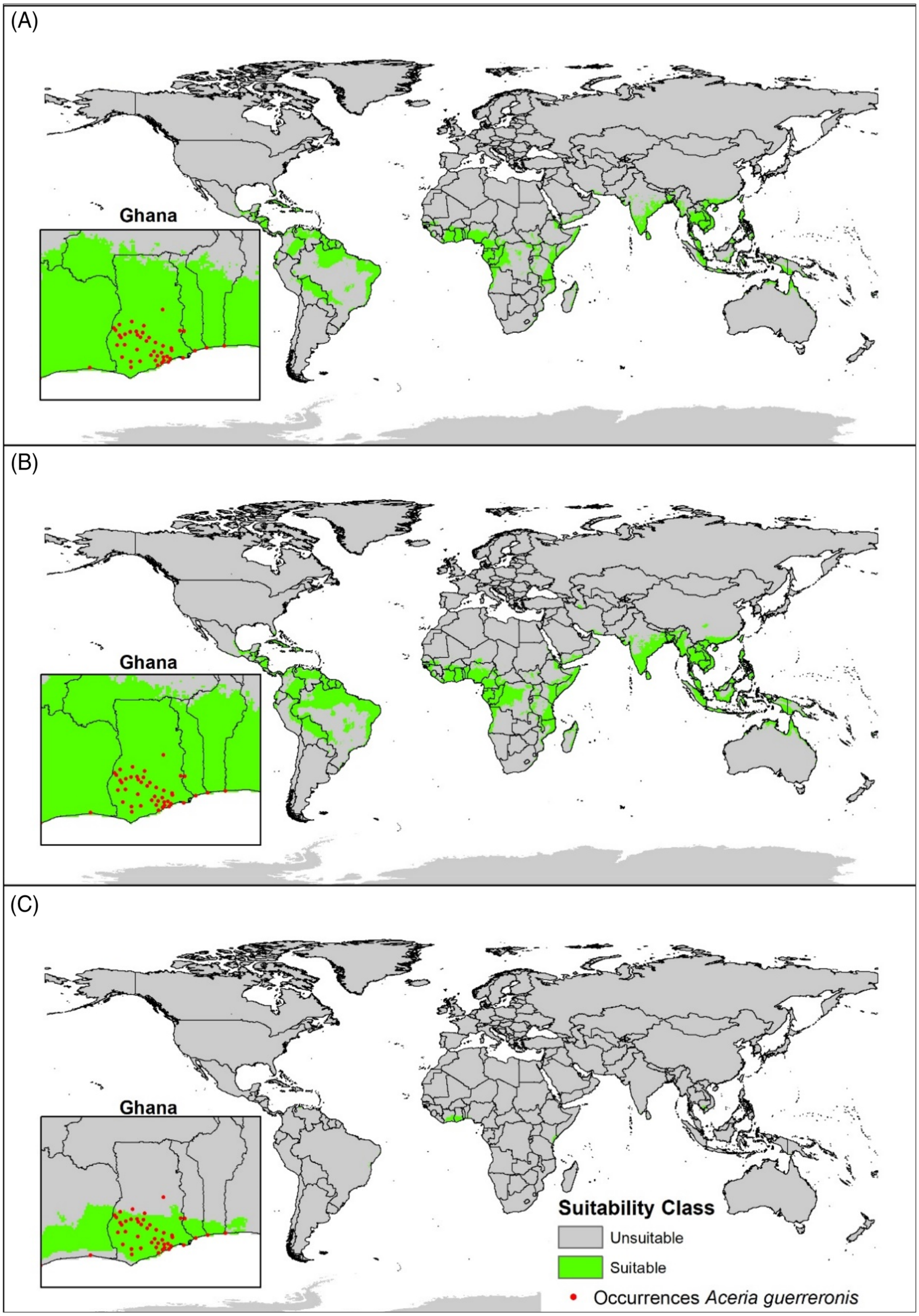

FIGURE 8 Exploring the effect of the data from Ghana

importance were seasonality of temperature, annual average temperature, average variation of daytime temperature, annual precipitation, and precipitation seasonality. This suggests that thermal parameters much more than rainfall are the main factors driving the potential distribution and spread of the coconut mite. These findings are consistent with previous studies which indicated that temperature influenced the seasonal abundance of *A. guerreronis* (Lawson-Balagbo et al., 2008). This, however, confirms that the main distribution zones are in the tropical and sub-tropical regions (Lawson-Balagbo et al., 2008). Earlier work has shown that the ideal temperature range for *A. guerreronis* development is between 9.3 and 33.6°C (Ansaloni & Perring, 2002), but it can live for at least 5 h of frost and for over a week below 5°C (Howard et al., 1990; Navia et al., 2013). However, high temperatures above 40 are detrimental to the development of the pest (Navia et al., 2013). Fernando and Aratchige (2010), reported that damage levels and rate of spread are higher in the dry- and intermediate than in wet climates. In addition, long periods of drought and high temperatures are significant climatic conditions influencing the distribution and establishment of *A. guerreronis* (Lawson-Balagbo et al., 2008).

Our model predicts that climate suitable areas for *A. guerreronis*, are primarily centered on the west and east coasts of Africa, south coasts of Asia, north and east coasts of South America, and coastal regions of Northern Oceania. Our findings show an expansion of habitat suitability outside the known distribution of the pest, particularly in Indonesia, Vietnam, Papua New Guinea, Mexico, Thailand, and Myanmar. In addition, the model's predictions are consistent with the historical records of the pest (Návia et al., 2005). These predictions are quite disturbing because the major coconut-producing countries where *A. guerreronis* has been reported will continue to be threatened by the pest. Given that prevention of biological invasion is more economical than post-entry management (Angulo et al., 2021; Cuthbert et al., 2021; Fantle-Lepczyk et al., 2022), global efforts are required to slow down the pest's invasion. Previous work has shown that the most efficient strategy to prevent biological invasion is implementing a comprehensive quarantine program, and ecological evaluation and monitoring programs (Xie et al., 2003). The presence of the pest in Brazil and Sri Lanka may require physical, biological, and chemical control measures to either eradicate or control the pest outbreaks. However, our predictions will serve as a guide in developing a more efficient management program for the pest.

In the present study, we used two socioeconomic pathways (SSPs 2.6 and 8.5). These pathways have been used to predict the impact of climate change on species (e.g., Kriegler et al., 2012). These are useful for determining the long-term consequences of human-induced climate change and provide useful information for preventing biological invasion. For the SSPs, the model predicts a contraction of suitable areas from SSPs 2.6 to 8.5. Rising global temperatures will mean that regions that are at present unsuitable to coconut mites, especially in Brazil, India, Australia, Nigeria, and Kenya, will become suitable habitats from now until 2040. Yet, global warming will also cause the ecological range of *A. guerreronis* to shift inwards, notably in parts of Kenya, Tanzania, Somalia, Cambodia, and Thailand. This will make areas that are presently highly suitable less until 2060. However, it is important to note that the exact impact of climate change on invasive species like *A. guerreronis* may vary depending on the geographical location, the country's wealth, and farm management practices (Nair et al., 2003; Navia et al., 2013; Pratt et al., 2017). Moreover, the presence of natural enemies, crop production practices, competition with native species, and lack of dispersal options, may prevent outbreaks in the invaded areas (Al-Shanfari et al., 2010). Notwithstanding, our findings will largely facilitate making informed decisions on mitigation measures for researchers, agriculturists, ecologists, and other stakeholders.

In the present study, we used bioclimatic variables and elevation datasets. But, there are several other biotic and/or abiotic factors, which were not considered in the present study. These factors may affect the biological invasion of *A. guerreronis* in the areas predicted to be suitable for the pest. For instance, host plants play a key role in the distribution and establishment of invasive species (Lu et al., 2013), but was not included in our model. Therefore, *A. guerreronis* host plants, such as coconut, *Lytocaryum weddellianum* (H. Wendl.), and *Syagrus romanzoffiana* (Cham.) (Návia et al., 2005), should be considered in future predictions. Anthropogenic activities, including the transport of coconut planting materials and international trade, may facilitate the spread of *A. guerreronis* to new areas (Sarkar, 2011). Finally, other factors, including geographic barriers, land-use changes, conflict and reconstruction, regulatory regimes, tourism, public health factors, and environmental concerns may also influence the outcome of our predictions (FAO, 2001; McNeely et al., 2001; Perrings et al., 2002; Pilcher, 2004; Zettler et al., 2004). These limitations should be considered in future investigations.

Using all occurrences, without Ghana occurrences, and using only Ghana occurrences data to run the models showed varying predictions. For instance, Ghana only data predicted habitat suitability for *A. guerreronis*, mainly Ghana, Côte d'Ivoire, Togo, Benin, and Nigeria. This also supports previous studies that sample size affects predictions of species habitat suitability (Støa et al., 2019; Syfert et al., 2013). It is worth mentioning that the results from the Ghana only data are expected, given that the data cover so little of the global range. This also shows how the model could lead to biases (Fourcade et al., 2014). A filtering method has been using in run models to reduce the spatial aggregation of records (Aiello-Lammens et al., 2015; Boria et al., 2014; Ramos et al., 2018; Santana Jr et al., 2019). However, all sample data are incomplete and potentially biased and may still have significant spatial autocorrelation when considering the global scale at which the models are run (Jarnevich et al., 2015). Thus, it is helpful to run a model considering uneven distribution occurrences group. Therefore, the interpretation of prediction considering the occurrences data should be taken into account to aim for precautionary measures to limit potential introductions of *A. guerreronis*. The model should continually run when *A. guerreronis* records are updated in the future.

CONCLUSION

Climate change will have a significant impact on the global distribution of *A. guerreronis*, based on the future model predictions from the current time to 2060, however, the specific effects will vary across different geographical locations. Our predictions will assist governments in making the most of their financial investments in pest control initiatives by determining areas that are or will become more or less suitable for current and potential future pest outbreaks. Therefore, we propose special precautionary measures to limit potential man-made introductions of *A. guerreronis* through improved regulations of importation of coconuts or coconut products into potentially suitable regions. Furthermore, research should focus on explorations and subsequent introductions and/or preservation of indigenous natural enemies as part of comprehensive integrated pest management (IPM) strategy against the coconut mite.

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CONFLICT OF 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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Conceptualization, formal analysis, methodology, writing - original draft, writing - review & editing, funding acquisition, project administration: Owusu Fordjour Aidoo. *Methodology, software, formal analysis, writing - review & editing*: Ricardo Siqueira da Silva. *Writing - review & editing, formal analysis, writing - original draft, writing - review & editing*: Paulo Antônio Santana Junior. *Writing - original draft, Software, formal analysis, writing - review & editing, funding acquisition*: Philipe Guilherme Corcino Souza. *Conceptualization, writing - original draft, writing - review & editing*: Rosina Kyerematen. *Conceptualization, methodology, formal analysis, writing - original draft, writing - review & editing, funding acquisition*: Felix Owusu Bremang. *Conceptualization, project administration, writing - review & editing*: Ndede Yankey. *Conceptualization, methodology, writing - original draft, writing - review & editing*: Christian Borgemeister.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

Table S1. Cross-correlation (Pearson correlation coefficient, r) between environmental variables

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