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Global habitat suitability and invasion risk of melon thrips

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Abstract

1. Invasive species pose major threats to agriculture, biodiversity and livelihoods. However, risk assessments are often reactive rather than predictive. The melon thrip (*Thrips palmi* Karny) is a regulated quarantine pest native to Southeast Asia that has established in over 50 countries, but its global potential distribution under current and future environmental scenarios remains insufficiently characterized.
2. Using 86 georeferenced occurrence records and six WorldClim bioclimatic variables, we developed and validated a Maxent model to estimate current and future (2081–2100) global habitat suitability for *T. palmi*.
3. Model performance was strong (Area Under Curve = 0.81, True Skill Statistic = 0.53, Continuous Boyce Index = 0.63). The most influential predictors were precipitation of the wettest month (37.7%), precipitation of the driest month (36.7%) and annual mean temperature (9.7%).
4. Suitable habitat for *T. palmi* is projected to increase from 4.1% of current global land area to 7.82% by 2081–2100, a 92.8% expansion. The greatest increases are expected to occur in West and East Africa, South and Southeast Asia, and Central and South America, alongside poleward expansion into temperate regions of Europe and North America.
5. Our study supports proactive surveillance, phytosanitary regulation and integrated pest management for *T. palmi* in vulnerable agricultural regions.

KEYWORDS
environmental, invasive pest, Maxent, risk assessment, species distribution modelling, *Thrips palmi*

INTRODUCTION

Globalization has accelerated the spread of invasive species, with over 37,000 alien species now established worldwide (Seebens et al., 2017; Roy et al., 2023). Invasive insects spread via international human activity and substantially affect biodiversity, agriculture and public health (Roy et al., 2023). The global economic cost of invasions is substantial, with estimates ranging from $165 billion to $1.4 trillion annually (Bradshaw et al., 2016; Renault et al., 2022). Environmental change can exacerbate these risks by altering abiotic and biotic conditions (Beaury et al., 2020; Shabani et al., 2020). However, species responses to environmental change are not uniform, and some invaders are expanding their ranges while others are contracting (Bates & Bertelsmeier, 2021; Bradley et al., 2024; Liu et al., 2020). Yet, under most high-emissions scenarios, invasion frontiers are projected to shift poleward (Beaury et al., 2020).

[Correction added on 04 June 2026, after first online publication: The Ethics Statement and Consent sections have been deleted.]

The melon thrip, *Thrips palmi* Karny, is a highly invasive pest native to Southeast Asia that now occurs in over 50 countries. It is listed as an A1 quarantine pest by the European and Mediterranean Plant Protection Organization (EPPO, 2017a) and has undergone a comprehensive risk assessment by the European Food Safety Authority (EFSA et al., 2025). *Thrips palmi* feeds on over 200 plant species, including many crops (CABI, 2022; Cannon et al., 2007), and transmits viruses such as groundnut bud necrosis virus, melon yellow spot virus and watermelon silver mottle virus (Mandal et al., 2017; Rotenberg et al., 2015). It may produce up to 15 generations annually, with outbreaks often coinciding with dry periods, and economic consequences extend beyond yield losses (EFSA et al., 2025; Ghosh, 2020). In 2015, the European Union intercepted *T. palmi* on vegetables from Ghana and banned imports, reducing Ghana's gross domestic product by $5 million (Saavedra Gonzalez et al., 2016). In England, eradication of an outbreak exceeded £56,000, with projected long-term losses of £20 million (MacLeod et al., 2004).

Current management strategies for *T. palmi* include sanitation, biological control and chemical control. However, these strategies remain insufficient across landscape scales due to widespread resistance, rapid population growth, broad host range and continued trade-mediated dispersal (Cannon et al., 2007; Seal, 2004; Shen et al., 2023; Shi et al., 2020). Consequently, proactive surveillance informed by predictive modelling is essential. For example, correlative species distribution models that relate occurrence records to environmental variables to estimate climatic suitability are widely used in invasive pest risk assessment (Khwarahm, 2025; Waheed et al., 2025). For *T. palmi*, modelling studies have been conducted at regional scales, including CLIMEX-based projections for the Korean Peninsula (Park et al., 2014) and species distribution model approaches incorporating land-use change (Hong et al., 2019). However, a comprehensive global assessment of habitat suitability under current and future environmental scenarios is lacking, limiting the ability to anticipate invasion risks beyond well-studied regions.

Here, we used a Maxent modelling framework to: (i) predict the current and future global distribution of *T. palmi*; (ii) quantify changes in environmentally suitable areas between baseline conditions (1970–2000) and a high-emissions scenario for 2081–2100; (iii) identify key bioclimatic drivers of *T. palmi* geographic distribution; and (iv) quantify countries at greatest risk of invasion or range expansion, including those in Europe, Africa and the Americas. The Maxent modelling framework we used is effective for presence-only data and performs robustly across highly variable sample sizes (Aidoo et al., 2025; Lissovsky & Dudov, 2021). We hypothesized that environmentally suitable areas for *T. palmi* would increase in the future, but effects would vary worldwide. Our results provide actionable insights to support surveillance, phytosanitary policy and integrated pest management for this globally important quarantine pest.

MATERIALS AND METHODS

Species data

Georeferenced occurrence records of *T. palmi* were compiled from peer-reviewed literature (Web of Science, PubMed, Google Scholar), the CABI Agriculture and Bioscience (CABI: www.cabi.org/) and the Global Biodiversity Information Facility (GBIF; www.gbif.org). Records were filtered to remove erroneous and duplicate entries, such as those with implausible coordinates or identical latitude-longitude pairs, as well as those located in oceans or missing coordinate data. To reduce spatial clustering, one occurrence per grid cell was retained. Spatial thinning was applied using the *spThin* R package (Aiello-Lammens et al., 2015) with a minimum nearest-neighbour distance of 5 km, reducing spatial autocorrelation and potential inflation of model performance (Aiello-Lammens et al., 2015). Following filtering and thinning, 86 occurrence records (from an initial 124) were retained for model calibration (Figure 1; Aidoo et al., 2026).

Environmental data

Nineteen bioclimatic variables at 2.5 arc-min resolution were obtained from WorldClim v2.1 (Booth et al., 2014; Fick & Hijmans, 2017). Four variables (mean temperature of the wettest quarter, mean temperature of the driest quarter, precipitation of the warmest quarter, precipitation of the coldest quarter) were excluded because of known spatial artefacts (Booth, 2022; Escobar & Craft, 2016). The remaining variables were screened for multicollinearity using the *usdm* R package (Naimi & Araújo, 2016), applying variance inflation with correlation of $|r| > 0.7$, retaining six predictors: (i) annual mean temperature, (ii) mean diurnal range, (iii) isothermality, (iv) precipitation of the wettest month, (v) precipitation of the driest month and (vi) precipitation seasonality (Table S1). We also obtained future projections (2081–2100) from CMIP6 as the ensemble mean of six general circulation models (BCC-CSM2-MR, CNRM-CM6-1, EC-Earth3-Veg, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0) with a high-emissions scenario, Shared Socioeconomic Pathway (SSP) 585, to represent a precautionary upper-bound trajectory for invasion risk.

Modelling and evaluation approach

We used the Maxent algorithm (Phillips et al., 2017), implemented in R (Banta, 2024), to model habitat suitability of *T. palmi*. Model tuning was performed using the *ENMeval* package (Muscarella et al., 2014) to optimize feature classes (linear [L], quadratic [Q], product [P], hinge [H]) and the regularization multiplier (RM). RM values ranging from 1 to 5 were combined with FCs "L", "LQ", "H", "LQH" and "LQHP", yielding 25 candidate models (Table S2). Of the 86 records, 77 were used for training and 9 for testing. A total of 10,000 background points were sampled within a 6-degree buffered minimum convex polygon around the occurrence records, following Kass et al. (2018). Model tuning and evaluation were conducted using 10-fold cross-validation with 10 replicates, which provides a robust assessment of model performance (Kass et al., 2021; Muscarella et al., 2014). Model selection was based on the corrected Akaike Information Criterion (AICc), and the optimal model was identified as FC = LQH and RM = 3 (Table S2).

Response curves were enabled to show how each environmental variable influences habitat suitability. Jackknife tests were used

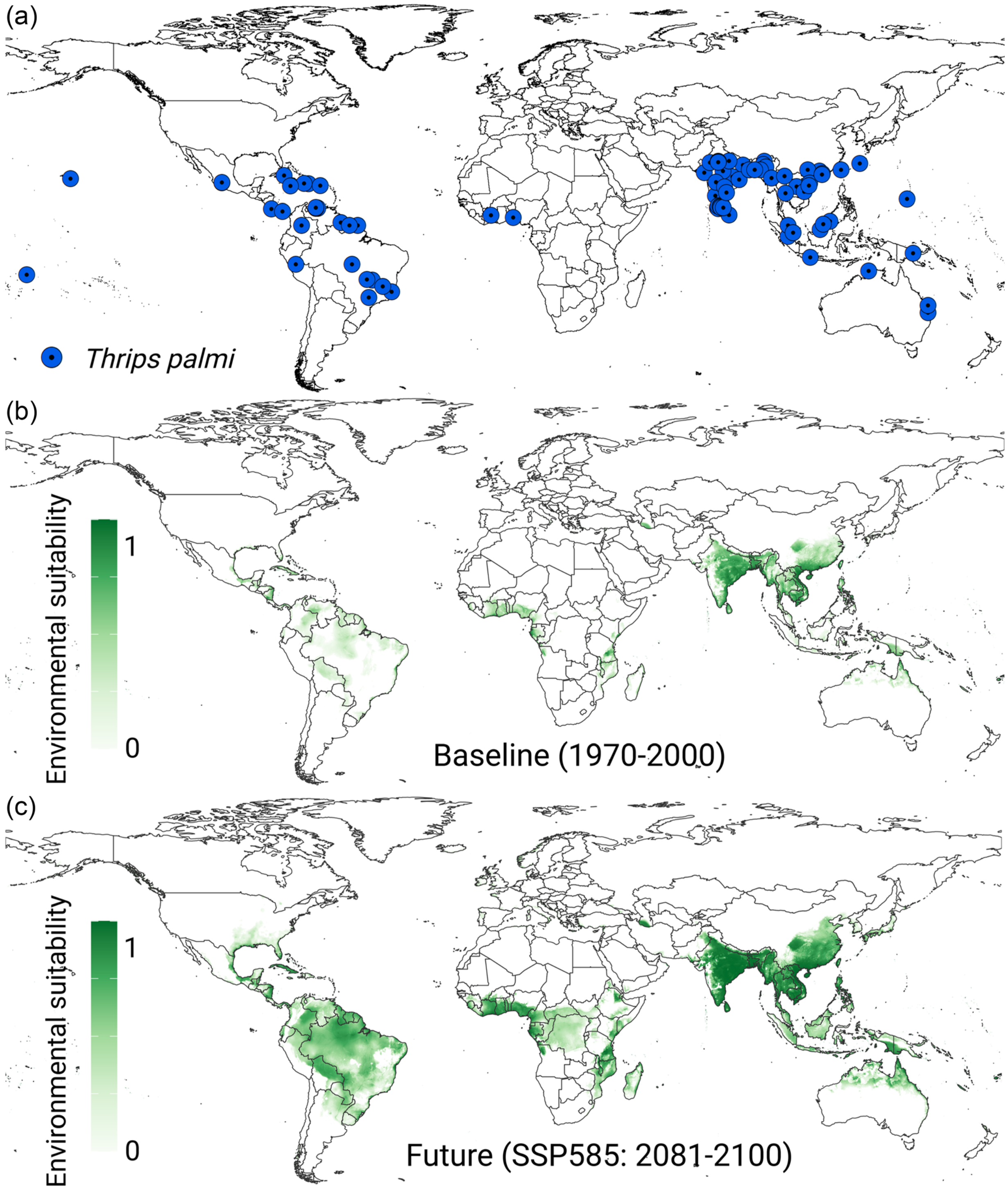

FIGURE 1 Global distribution and projected habitat suitability of *Thrips palmi*. (a) Occurrence records used for model calibration. (b) Baseline suitability (1970–2000). (c) Future suitability under SSP585 (2081–2100), based on the mean of six global circulation models. Suitability ranges from low (light green) to high (dark green).

to evaluate the importance of individual predictor variables and their contribution to model performance. The model output format was specified as *cloglog*, with both clamping and fade-by-clamping selected. Clamping and fade clamping were applied to limit extrapolation (Phillips et al., 2006). The continuous suitability outputs (0–1) were converted to binary habitat suitability maps using the maximum test sensitivity plus specificity (*maxSSS*) threshold, with values >0.518 classified as suitable (Liu et al., 2013). Changes in suitable area were quantified as the proportion of global land classified as suitable under current (baseline) and future (2081–2100) conditions, and the percentage change was calculated accordingly.

Model performance was evaluated using the area under the curve (AUC), the true skill statistic (TSS) and the Continuous Boyce Index (CBI), where AUC >0.8 indicates strong discriminatory ability, TSS >0.5 indicates good predictive accuracy and CBI >0.5 reflects reliable and consistent model predictions (Allouche et al., 2006; Bradley, 1997; Liu et al., 2025). All analyses were conducted in R v4.4.1 (R Core Team, 2024).

RESULTS

Model performance and contribution of environmental variables

We found low difference between training and test AUC (AUCdiff = 0.017; Table S3), indicating minimal overfitting of the model (feature class = LQH, regularization multiplier = 3; Table S2). The Maxent model demonstrated strong predictive performance (AUC = 0.813, TSS = 0.53, CBI = 0.63) (Table S3). Among six retained predictors, precipitation of the driest month contributed most to model performance (37.7%), followed by precipitation of the wettest month (36.7%). The remaining variables contributed less: annual mean temperature (9.7%), mean diurnal range (8.8%), isothermality (6.1%) and precipitation seasonality (0.9%) (Table S1). Permutation importance values were consistent with these rankings, with precipitation of the wettest month (33.3%) and precipitation of the driest month (26.4%) showing the greatest influence, followed by isothermality (16.3%), mean diurnal range (10.8%), annual mean temperature (9.6%) and precipitation seasonality (3.6%) (Table S1). Jackknife analysis of test gain, training gain and AUC confirmed that precipitation of the warmest month and precipitation of the driest month had the highest individual predictive power, producing the greatest gain when used in isolation and the largest decrease in model performance when omitted (Figure S1a–c). Annual mean temperature and mean diurnal range contributed moderately, whereas isothermality and precipitation seasonality had minor effects (Figure S1).

Response curves indicated clear climatic responses of *T. palmi* (Figure S2a–f). Suitability increased with annual mean temperatures within 25–32°C, but declined outside this range (Figure S2a). Suitability decreased with increasing mean diurnal range, with the highest values at low variability <6°C (Figure S2b). Habitat suitability also showed a positive relationship with isothermality up to 40–50 (Figure S2c). Suitability increased with precipitation of the wettest month up to 300–400 mm before stabilizing (Figure S2d), whereas suitability declined as precipitation of the driest month exceeded 100 mm (Figure S2e). The relationship between suitability and precipitation seasonality was weakly negative at higher values (Figure S2f).

Global habitat suitability of *T. palmi*

Under baseline abiotic conditions (1970–2000), extensive areas of high habitat suitability were predicted across all global continents (Figure 1b). In Asia, suitable habitats were concentrated in Southeast Asia, including India, Thailand, Vietnam, Malaysia, the Philippines and southern China, with additional areas in Japan and South Korea. In Africa, high suitability was predicted in West Africa (e.g., Nigeria, Côte d'Ivoire, Ghana), East Africa (e.g., Mozambique, Tanzania) and parts of Central and Southern Africa. In the Americas, suitable areas occurred across Central and South America (e.g., Brazil, Colombia, Venezuela, Mexico), the Caribbean and the southern United States. In Oceania, suitable regions included northern and eastern Australia, Papua New Guinea and parts of New Zealand. In Europe, areas of high habitat suitability were limited to Mediterranean and Atlantic coastal regions, including Spain, Portugal and Turkey.

When models were projected to 2081–2100 (the 2090s) under SSP585, highly suitable areas expanded substantially, with broadly consistent patterns across all of the global circulation models (Figure 1c; Figure S3). Poleward expansion was most evident in North America, Europe and East Asia. Areas of high suitability remained largely stable across tropical regions, including South America, sub-Saharan Africa, and South and Southeast Asia, with additional gains in parts of Central America and northern Australia (Figure 2a,b). However, localized range contractions were predicted to occur in some regions (e.g., parts of the Caribbean), but these areas were limited relative to the overall expansion, and high-latitude and arid regions were unsuitable into the future. The total area of suitable habitat increased from 20.1 million km^2 (4.1% of global land area) under current conditions to 38.8 million km^2 (7.8%) in the 2090s, representing an absolute increase of 18.7 million km^2 and a 92.8% expansion relative to the historical baseline.

Suitable area for *T. palmi* increased across all continents in future conditions (Figure 3). The largest proportional increases were observed in South America (34.6%–73.5%), followed by Africa (10.1%–27.9%) and Oceania (16.2%–31.3%). Asia showed a moderate increase (27.5%–36.1%), while North America (4.55%–12.3%) and Europe (7.30%–9.70%) exhibited comparatively smaller increases (Figure 3).

DISCUSSION

Invasive species continue to impose substantial ecological and economic costs (Cuthbert et al., 2022; Early et al., 2016), and anticipating invasion risk is essential to optimize surveillance and prevent invasions. Our Maxent model found that precipitation-related variables were the main determinants of suitable thrips habitat, consistent with earlier studies linking rainfall to thrips dynamics (Cooper, 1991; Etienne et al., 1990; Ho & Chen, 1992). Our findings suggest that *T. palmi* is favoured by warm, humid conditions but may be limited under excessive rainfall (CABI, 2022; EPPO, 2017b). Temperature played a secondary but important role in structuring *T. palmi* distribution. Laboratory and field studies found that its development and survival could increase with temperature up to 35°C, beyond which physiological stress limits persistence (Cao et al., 2025; Yadav & Chang, 2014). This thermal sensitivity partly explains current latitudinal limits, with

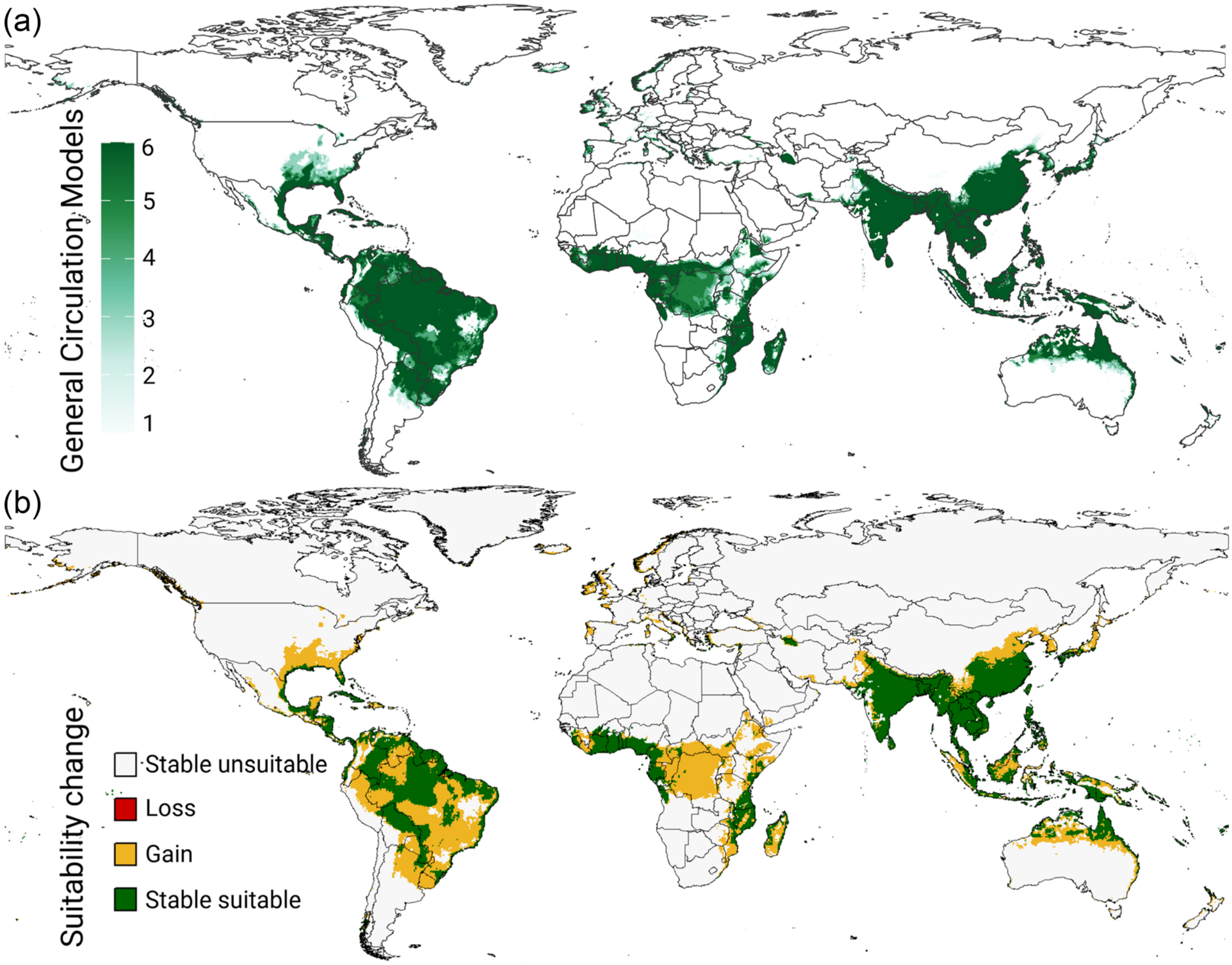

FIGURE 2 Ensemble agreement and projected suitability change for *Thrips palmi*. (a) Number of global circulation models ($n = 6$) predicting suitable habitat conditions. (b) Change in suitability from historical baseline (1970–2000) to 2081–2100 (2090s). Grey = stable unsuitable; red = loss; yellow = gain; green = stable suitable.

outdoor establishment restricted to tropical and subtropical regions (Sakimura et al., 1986). However, greenhouse cultivation can mitigate these constraints by providing buffered microclimates that enable persistence, as observed in northern China (Cao et al., 2019).

The predicted global distribution under current environmental conditions is consistent with known occurrence records and recent spread dynamics. Notably, the recent confirmation of *T. palmi* in Peru (EFSA et al., 2025) falls within areas identified as suitable in our baseline projections, providing empirical support for our habitat model predictions. Under future environmental conditions, substantial range expansion is projected, particularly into higher latitudes of North America, Europe and East Asia. This pattern is consistent with the historical spread of other invasive thrips, such as *Frankliniella occidentalis* (Kirk & Terry, 2003), which found that *T. palmi* may follow a comparable global expansion trajectory as environmental constraints relax. At regional scales, the implications are particularly pronounced. In Ghana, suitable areas are mainly concentrated in southern agricultural zones that underpin the horticultural export sector, where phytosanitary interceptions have already resulted in substantial economic losses (Saavedra Gonzalez et al., 2016). Projected northward expansion into currently less favourable regions suggests an increasing risk to inland production systems. Beyond direct feeding damage, the potential introduction of tospoviruses such as groundnut bud necrosis virus represents a major additional threat, particularly in West Africa where susceptible crops are widely cultivated.

Despite the general robustness of the modelling framework, several limitations should be acknowledged. Experimental evidence indicates that *T. palmi* populations exhibit variation in thermal tolerance linked to genomic structural variation (Ma et al., 2024), suggesting potential for rapid adaptation to novel environments. In addition, high genetic divergence among global populations points to a cryptic species complex, meaning that pooled occurrence data may obscure lineage-specific ecological niches (Rehsawla et al., 2025). Incorporating such genetic structure into future modelling efforts may improve predictive accuracy. Further, trade pathways, propagule pressure, host availability and natural enemy communities all influence establishment success (Bacon et al., 2012; EFSA et al., 2019; MacLeod et al., 2004; Prior et al., 2014; Vierbergen, 2001). Residual sampling bias in occurrence data may affect predictions, particularly in under-sampled tropical regions. Similarly, management strategies like biological control efficacy may vary across

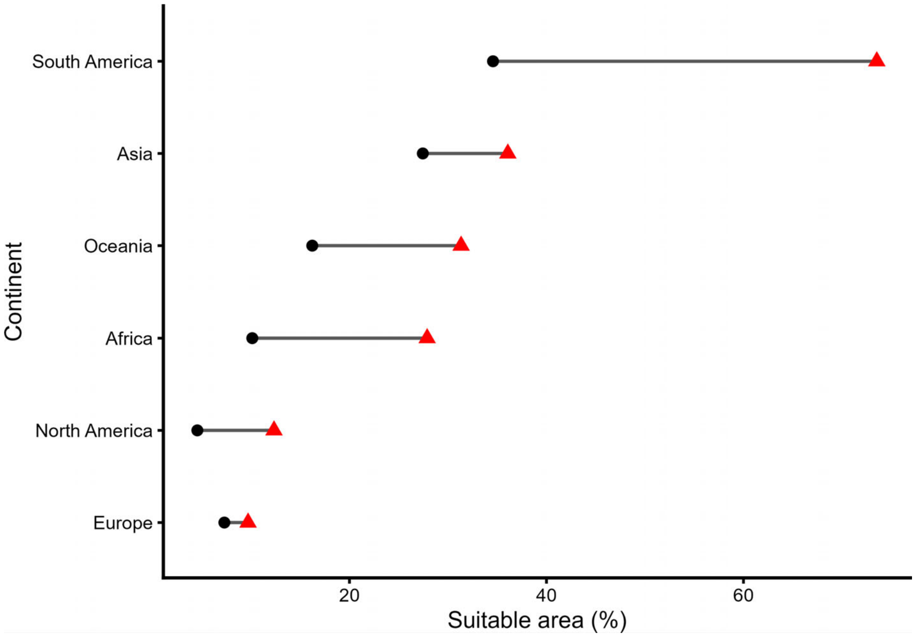

FIGURE 3 Continental comparison of *Thrips palmi* suitable area (%) between the historical baseline (1970–2000) and future (SSP585: 2081–2100) periods, based on the ensemble mean of six global circulation models. Black circles denote baseline suitability, red triangles denote future suitability and connecting lines indicate the magnitude of change.

regions (Seal, 2004). A further limitation is resistance to multiple insecticide classes which has been documented (Seal, 2004), and variation in resistance levels among populations indicates rapid, localized evolution under selection pressure (Cao et al., 2025). The potential spread of resistant populations via trade pathways highlights the need to integrate resistance monitoring programs into invasion management. Greenhouse cultivation can act as anthropogenic refugia, allowing *T. palmi* to persist beyond predicted environmental limits and potentially facilitating establishment in marginal regions (Gao et al., 2021). Additionally, the baseline period spans 1970–2000; therefore, some temporal mismatch between occurrence records and climate data may exist and should be considered when interpreting the results.

Nevertheless, our predictive maps provide a spatially explicit framework for prioritizing surveillance and phytosanitary intervention. Regions with high current and projected suitability, particularly in West Africa and parts of the Americas and Asia, should be prioritized for early detection and monitoring. Strengthening border inspections, especially for high-risk commodities such as live plants and fresh produce, will be essential. In Europe, even modest increases in suitability within intensive horticultural zones warrant targeted surveillance, particularly in protected cultivation systems. More broadly, coordinated international action under plant health frameworks, including the IPPC and EPPO, will be necessary to mitigate the continued spread of this economically important pest.

CONCLUSION

This study applied Maxent modelling to predict the potential distribution of *T. palmi* under current and future environmental scenarios. Precipitation of the driest month and precipitation of the wettest month were the most influential factors shaping habitat suitability, alongside temperature stability patterns. Projections suggest northward expansion of suitable areas by the 2090s, raising concerns for vegetable production in regions currently less affected. These findings highlight the need for proactive surveillance, early warning systems and adaptive management strategies to prevent establishment and limit impacts. By identifying high-risk areas, the findings provide a practical tool to support policymakers, plant protection agencies and stakeholders in developing targeted biosecurity and integrated pest management measures that safeguard crop productivity and farmer livelihoods in vulnerable regions.

AUTHOR CONTRIBUTIONS

Owusu Fordjour Aidoo: Conceptualization; formal analysis; writing – original draft. **Rosina Kyerematen:** Data curation; investigation; writing – review and editing. **Emmanuel Twum:** Data curation; investigation; methodology. **Frederick Leo Sossah:** Investigation; resources; writing – review and editing. **Gengping Zhu:** Investigation; methodology; validation. **David W. Crowder:** Investigation; project administration; resources; supervision; writing – review and editing.

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The authors declare that no external funding was received for this research.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The dataset supporting the findings of this study is available in the figshare repository: https://doi.org/10.6084/m9.figshare.32027067.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Percent contribution and permutation importance of the 19 bioclimatic variables considered in the MaxEnt modelling. Boldened (variables retained in the final model after spatial artefacts and discontinuities, as well as collinearity analysis are shown in bold).

Table S2. Evaluation of MaxEnt model parameter combinations using different feature classes (FC) and regularization multipliers (RM) of *Thrips palmi*.

Table S3. Performance metrics of the *Thrips palmi* distribution model across 10 cross-validation replicates. AUC (Area Under the Curve), TSS (True Skill Statistic) and CBI (Continuous Boyce Index) are presented. AUC Diff represents the difference between training and testing AUC values and indicates model overfitting.

Figure S1. Jackknife analysis of variable importance based on (a) test gain, (b) regularized training gain and (c) AUC for *Thrips palmi*. Bars represent model performance when each variable is used in isolation (blue), omitted (cyan) and included with all variables (red).

Figure S2. Response curves showing the relationship between selected climatic variables and the predicted suitability of *Thrips palmi* based on the MaxEnt model. Panels represent the effects of (a) annual mean temperature (bio1), (b) mean diurnal temperature range (bio2), (c) isothermality (bio3), (d) precipitation of the wettest month (bio13), (e) precipitation of the driest month (bio14) and (f) precipitation seasonality (bio15). The red line represents the mean predicted suitability across model replicates, while the blue shaded area indicates ±1 standard deviation. Suitability is expressed as cloglog output, which approximates the probability of species presence.

Figure S3. Projected global environmental suitability of *Thrips palmi* under future climate conditions based on six General Circulation Models (GCMs): (a) BCC-CSM2-MR, (b) CNRM-CM6-1, (c) EC-Earth3-Veg, (d) IPSL-CM6A-LR, (e) MIROC6 and (f) MRI-ESM2-0. Suitability values range from 0 (low suitability) to 1 (high suitability), with darker green indicating higher environmental suitability.

Figure S4. Global distribution of model uncertainty (standard deviation) for *Thrips palmi* under future climate scenarios. Higher values indicate greater variability among model predictions and lower agreement, with uncertainty concentrated in tropical and subtropical regions.

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