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Global Climate Suitability and Economic Risks of the Fall Armyworm *Spodoptera frugiperda* to Key Crops in Brazil

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ABSTRACT

Invasive species represent a growing threat to global food security and biodiversity. Integrating species distribution modeling with economic impact assessment enables the development of targeted, evidence-based strategies to mitigate these threats. In this study, we estimate global habitat suitability and associated economic risks posed by the invasive fall armyworm (*Spodoptera frugiperda*) to key crops in Brazil. Habitat suitability was modeled under Shared Socioeconomic Pathways (SSPs 245, 370, and 585) across three future timeframes (2030s, 2050s, and 2070s). The results indicate a consistent expansion of climatically suitable areas for *S. frugiperda* through the 2070s under all scenarios. The most important environmental variables shaping its distribution were the precipitation of the wettest quarter, mean temperature of the warmest quarter, elevation, and isothermality. Our economic risk mapping in Brazil identified soybean and corn production areas as the most vulnerable to *S. frugiperda* infestation, reflecting their extensive cultivation in regions with high climate suitability for *S. frugiperda*. These findings provide critical insights for developing adaptive strategies to reduce the future impact of *S. frugiperda* on agricultural productivity and food security.

1 | Introduction

Insect pests pose a significant threat to global food security, biodiversity, and human well-being (Pyšek et al. 2020). Many have expanded beyond their native ranges by overcoming natural geographic barriers, largely due to human-mediated activities such as trade and land-use change (Pyke et al. 2008; Lehan et al. 2013; Seebens et al. 2015; Finch et al. 2021; Bonnamour et al. 2023). Climate change has further compounded these threats. By the year 2100, global average surface temperatures are projected to increase by 1.1°C–6.4°C relative to 1980–1999 levels (Masters and Norgrove 2010), with major implications for pest population dynamics, geographic distribution, incidence, and severity (Harvey et al. 2023). Climate shifts may also reduce the effectiveness of traditional pest management strategies, particularly for invasive species (Skendžić et al. 2021). Therefore, understanding the habitat suitability of invasive pests under current and projected climate scenarios is critical for informing long-term management and policy interventions.

The fall armyworm (*Spodoptera frugiperda* (J.E. Smith); Lepidoptera: Noctuidae) is a highly invasive pest with a broad host range, feeding on more than 350 plant species (FAO 2017; Montezano et al. 2018). Native to the tropical and subtropical regions of the Americas, *S. frugiperda* has rapidly spread to over 100 countries, including those across sub-Saharan Africa, Asia, and Oceania (Brévault et al. 2018). The pest's life cycle duration varies with geography; in warmer climates, it can complete a generation in about 30 days, while in cooler regions, such as parts of the United States, the cycle can extend to 60–90 days (Pogue 2002; Kumar et al. 2022). The number of generations per year depends on local climate and adult behavior (Pogue 2002; Baudron et al. 2019). Adult moths are nocturnal and typically emerge on warm, humid evenings (Cock et al. 2017). In Africa alone, annual corn yield losses due to *S. frugiperda* are estimated at 8.3–20.6 million tonnes, translating to economic losses of $2.5 billion to $6.2 billion (Shylesha et al. 2018; Day et al. 2017). Across sub-Saharan Africa, combined losses in corn, sorghum, and sugarcane have been estimated at $13 billion, posing serious threats to food security and rural livelihoods (Abrahams et al. 2017; Bannor et al. 2022).

Species distribution models (SDMs) have emerged as powerful tools to estimate the potential geographic range of invasive species by correlating known occurrences with environmental variables (Booth et al. 2014; Aidoo et al. 2022; Amaro et al. 2023). The maximum entropy model (MaxEnt) has been applied to assess the global and regional habitat suitability of *S. frugiperda*, including studies in Africa (Abdel-Rahman et al. 2023), China (Jiang et al. 2022), and at the global scale (Ramasamy et al. 2022). The CLIMEX model has also been used to evaluate climate suitability projections for *S. frugiperda* under various scenarios (Paudel Timilsena et al. 2022). However, significant knowledge gaps remain, particularly concerning distributional models and the corresponding economic impacts in vulnerable agricultural regions.

In this study, we modeled global climate suitability and assessed the potential economic impacts of *S. frugiperda* in Brazil's major host crops. Specifically, we addressed the following questions: (i) Which global regions currently offer suitable habitat for *S. frugiperda*? (ii) How does the ecological niche differ between the pest's native and invasive regions? (iii) Which regions require intensified monitoring to track future spread? (iv) What are the projected economic impacts of *S. frugiperda* on major crops in Brazil? and (v) How is habitat suitability expected to shift under future climate change scenarios? The results of this study provide critical insights for early warning systems, guiding phytosanitary policies, and prioritizing intervention strategies. Moreover, they highlight Brazilian crop production areas that are most vulnerable to future *S. frugiperda* establishment, showing the importance of climate-informed pest risk assessments.

2 | Materials and Methods

2.1 | Species Data

Occurrence records for *S. frugiperda* were obtained from the Global Biodiversity Information Facility (GBIF) database using the *rgbif* R package (Chamberlain et al. 2023) and supplemented with additional records from peer-reviewed literature (Figure S1). The initial search retrieved 8884 occurrence points. To ensure data quality, we followed established data-cleaning protocols (Hijmans and Elith 2013; Zizka et al. 2019). Specifically, we retained only records with a spatial resolution of ≤1 km and excluded those located near capital city centers, country centroids, and GBIF headquarters. Duplicate entries, erroneous records (e.g., zero coordinates), and records lacking associated environmental variables were also removed. After filtering, 7110 georeferenced occurrences remained. To further reduce sampling bias and spatial autocorrelation, we applied environmental filtering following Velazco et al. (2022). The final dataset comprised 6793 unique records, including 3092 from the pest's native range and 3701 from its invasive range.

2.2 | Environmental Data

To characterize the environmental conditions influencing *S. frugiperda* distribution, we obtained global climate data for the period 2000–2023 from WorldClim version 2.1 (https://worldclim.org/data/monthlywth.html), at a spatial resolution of 2.5 arc-minutes. These data included monthly average maximum and minimum temperatures, as well as total monthly precipitation. From this dataset, we derived 19 bioclimatic variables using the biovars function from the *dismo* package (Hijmans et al. 2017), following the methodology outlined by Hijmans et al. (2017). These variables are commonly used to represent long-term climatic conditions, as they reflect interannual variability and key environmental constraints known to influence species' geographic distributions (O'Donnel and Ignizio 2012).

To complement the climate data, an elevation variable was added to the dataset, based on data from the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) (https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation) for variables with 2.5-arc-min resolution, and from the Shuttle Radar Topography Mission (SRTM) for variables with 30-s resolution (https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm). For model projections specific to Brazil under current climate conditions, a corresponding set of 19 bioclimatic variables was generated from the Brazilian Daily Weather Gridded Data (BR-DWGD) for the period 1994–2023 (Xavier et al. 2022). These data were resampled to a finer spatial resolution of 30 arc-seconds and integrated with the other environmental layers used in modeling.

Variable selection for model input was performed through an iterative process during Maxent model calibration, guided by both statistical contribution and biological relevance (Vignali et al. 2020). The final model retained eight ecologically meaningful predictors: Bio02—Mean diurnal range; Bio03—Isothermality; Bio10—Mean temperature of the warmest quarter; Bio14—Precipitation of driest month; Bio15—Precipitation seasonality; Bio16—Precipitation of wettest quarter; Bio19—Precipitation of coldest quarter, and elevation.

2.3 | Calibration Area, Background Selection and Validation

The calibration area (CA) was defined following the Biotic–Abiotic–Movement (BAM) framework, which considers regions accessible to a species based on its dispersal capacity, biotic interactions, and environmental conditions (Elith et al. 2011; Owens et al. 2013; Phillips et al. 2009). The CA was delineated using Köppen–Geiger climate classifications (Kottek et al. 2006; Brunel et al. 2010; Beck et al. 2018), encompassing both native and invaded regions to capture the full environmental niche of *S. frugiperda*. This area covered approximately 130,769,872.885 km^2.

To evaluate model performance, occurrence data were partitioned using a spatial block cross-validation approach. This method helps control spatial autocorrelation between training and test datasets and is widely recommended for assessing model transferability across space and time (Roberts et al. 2017; Valavi et al. 2018, 2019; Santini et al. 2021). A total of 30 spatial grids were generated with resolutions ranging from 0.5° (~56 km) to 5° (~557 km), divided into five spatial blocks, each containing a minimum of 20 occurrence records.

Sixty percent of the occurrence records were used to test for spatial autocorrelation and optimize grid selection. The final grid size was chosen based on the following criteria: (i) lowest spatial autocorrelation, as measured by Moran's I; (ii) highest environmental similarity, based on Euclidean distance; and (iii) smallest standard deviation in the number of records between training and test sets (Velazco et al. 2019). These analyses were conducted using the part_sblock function in the *flexsdm* R package (Velazco et al. 2022).

2.4 | Model Development

We developed SDMs for *S. frugiperda* using MaxEnt under a non-homogeneous Poisson point framework (Phillips et al. 2017) in R (R Core Team 2023). Model calibration involved testing 171 combinations of feature classes (FC) (linear, quadratic, hinge, and product) and regularization multipliers (RM) to optimize the trade-off between model performance and complexity (Merow et al. 2013; Moreno-Amat et al. 2015). The best-performing configuration, based on Akaike Information Criterion corrected (AICc), was RM = 0.5 with linear, quadratic, and hinge features only. We generated 10,000 background points randomly within the calibration area (CA). Spatial partitioning was performed using an environmental grid with a cell size of 522.05 km^2, Moran's I value of 0.672, and an environmental similarity index of 1356.436. We assessed the niche of *S. frugiperda* using the ecospat package (Broennimann et al. 2012, 2015; Di Cola et al. 2017). Habitat suitability was classified using the following thresholds, adapted from Pearson et al. (2007), Neven et al. (2018), and Suárez-Seoane et al. (2020): 0—MTP (MTP = Minimum Training Presence threshold): unsuitable, MTP—10MTP/2: marginal, 10MTP/2–10MTP: moderate, 10MTP–50%: optimal > 50%: highly suitable.

2.5 | Model Performance Assessment

Model performance was evaluated using multiple metrics, including the Area under the curve of the Receiver Operating Characteristic Curve (AUC-ROC)—(AUC), True Skill Statistic (TSS), and permutation importance. Validation was conducted through spatial block cross-validation to ensure robustness and avoid spatial autocorrelation biases (Roberts et al. 2017).

2.6 | Future Projections

To assess potential changes in habitat suitability under climate change, we generated projections using three Global Climate Models (GCMs) from CMIP6: MRI-ESM2-0, MIROC6, and MPI-ESM1-2-HR (Yukimoto et al. 2019; Shiogama et al. 2019; Von Storch et al. 2017). These models were run under three Shared Socioeconomic Pathways (SSPs: 245, 370, and 585) across three timeframes: 2030s (2021–2040), 2050s (2041–2060), and 2070s (2061–2080). Model outputs were presented in both continuous (probabilistic) and binary formats. Binary maps were generated using a threshold that maximized sensitivity and specificity, enabling more reliable interpretation for environmental management and policy decision-making (Liu et al. 2016).

2.7 | Economic Risk Zoning for Brazil

To estimate the economic vulnerability of Brazilian municipalities to *S. frugiperda*, we conducted economic risk zoning using the Municipal Agricultural Production (PAM) dataset from the Brazilian Institute of Geography and Statistics (IBGE). The following steps were performed: (a) total production values calculation for Brazil and all municipalities based on major host crops (herbaceous cotton (seed), rice (paddy), sugarcane, corn (grain), soybeans, sorghum); (b) computation of specialization indices, including the Location Quotient (QL), Relative Participation Index (PR), and Hirschman–Herfindahl Index (IHH) (Crocco et al. 2006); (c) Z-Score Standardization of all indicators (mean = 0 and standard deviation = 1); (d) Principal Component Analysis (PCA) to derive weights (θ_1, θ_2, θ_3) for indicators; and (e) calculation of the Normalized Concentration Index (ICn).

The Location Quotient (QL) measures the spatial concentration or dispersion of production across regions (municipalities) by comparing the proportion of a specific sector of the product's production in a municipality to the national share of that product:

$$QL_{ij} = \left(\frac{V\,P_{ij}}{V\,P_j}\right) / \left(\frac{V\,P_{iBR}}{V\,P_{BR}}\right)$$

Where:

VP_{ij} is the production value of product *i* in municipality *j*,

VP_j is the total agricultural production value of municipality *j*,

VP_{iBR} VP_{iBR} is the total production value of product *i* in Brazil, and

VP_{BR} is the total agricultural production value in Brazil.

The IHH measures the weight of a specific product's production within a municipality's agricultural structure:

$$\mathrm{IHH}_{ij} = \left(\frac{VP_{ij}}{VP_{iBR}}\right) - \left(\frac{VP_j}{VP_{BR}}\right)$$

The PR captures the relative importance of a product's production in a municipality compared to the national production:

$$PR_{ij} = \frac{VP_{ij}}{VP_{iBR}}$$

A normalized Concentration Index (ICn) is derived as a linear combination of the previous indicators, accounting for their different capacities to represent agglomeration forces:

$$\mathrm{ICn}_{ij} = \theta_1 QL_{ij} + \theta_2 PR_{ij} + \theta_3 \mathrm{IHH}_{ij}$$

Where θ_i represents the weight of each indicator.

To classify economic vulnerability, ICn values were grouped into five classes using the Fisher-Jenks natural breaks algorithm (Fisher 1958; Slocum et al. 2022), which optimizes class homogeneity. Higher ICn values indicate greater economic dependence on crops susceptible to *S. frugiperda*, and therefore, greater risk. Finally, economic risk was estimated using the formula:

$$\text{Risk} = \text{ICn} \times \text{Probability of Occurrence}$$

Where the probability of pest occurrence was derived from the Maxent habitat suitability model.

3 | Results

3.1 | Evaluation of Model Performance

The MaxEnt model demonstrated strong predictive accuracy for the potential distribution of *S. frugiperda*, with an Area Under the Curve (AUC) of 0.904 and a True Skill Statistic (TSS) of 0.655. The model also achieved an Omission or False Negative or Underprediction Rate (10%) and a Continuous Boyce Index (CBI) of 0.967, indicating reliable performance in suitability ranking. Full evaluation metrics are presented in Table 1.

TABLE 1 | Performance evaluation metrics for the MaxEnt model predicting the potential distribution of *Spodoptera frugiperda*.

Metric names	Values
True positive rate, sensitivity or recall (TPR)	0.89634
True negative rate or specificity (TNR)	0.75851
True skill statistic (TSS)	0.65484
Sorensen index	0.79730
Jaccard index	0.66344
F-measure on presence-background (FPB)	1.32687
Omission or false negative or underprediction rate (OR/UPR)	0.10366
Continuous Boyce Index (CBI)	0.96765
Area under ROC curve (AUC)	0.90478
Fractional predicted area (FPA)	0.19045
Area under precision/recall curve (AUCPR)	0.83669
Inverse mean absolute error (IMAE)	0.71673
False positive rate (FPR)	0.24149
Positive predictive value or precision (PPV)	0.78776
Negative predictive value (NPV)	0.45836
Accuracy	0.82742
F1 Score	0.83855
Balanced accuracy	0.82742
Matthews correlation coefficient (MCC)	0.66115
Minimum training presence (MTP)	0.02039
10% Minimum training presence (10MTP)	0.43083
Symmetric extremal dependence index (SEDI)	0.81055

3.2 | Contribution of Environmental Variables

The distribution of *S. frugiperda* was most strongly influenced by the precipitation of the wettest quarter, mean temperature of the warmest quarter, elevation, and isothermality (Figure 1A,B). Partial dependence plots illustrating the response curves of the most influential predictors are shown in Figure 2. Additionally, a histogram depicting the distribution density of *S. frugiperda* occurrences across environmental gradients is presented in Figure S2.

3.3 | Current Prediction

Model projections under current climatic conditions indicate a substantial expansion of suitable habitat for *S. frugiperda* beyond its known occurrence range (Figure 3A; Figure S3). The newly identified area at risk includes Poland, France, Hungary, Romania, Greece, North Macedonia, Norway, Serbia, Switzerland, Spain, and the United Kingdom, countries that cultivate economically important crops vulnerable to *S. frugiperda* infestations. Globally, the current suitable habitat was estimated at approximately 1.10×10^8 km^2 (Figure 3B). Suitability levels were classified into five categories: unsuitable, marginal, moderate, optimal, and high. The spatial distribution of these suitability classes is presented in Figure 3B.

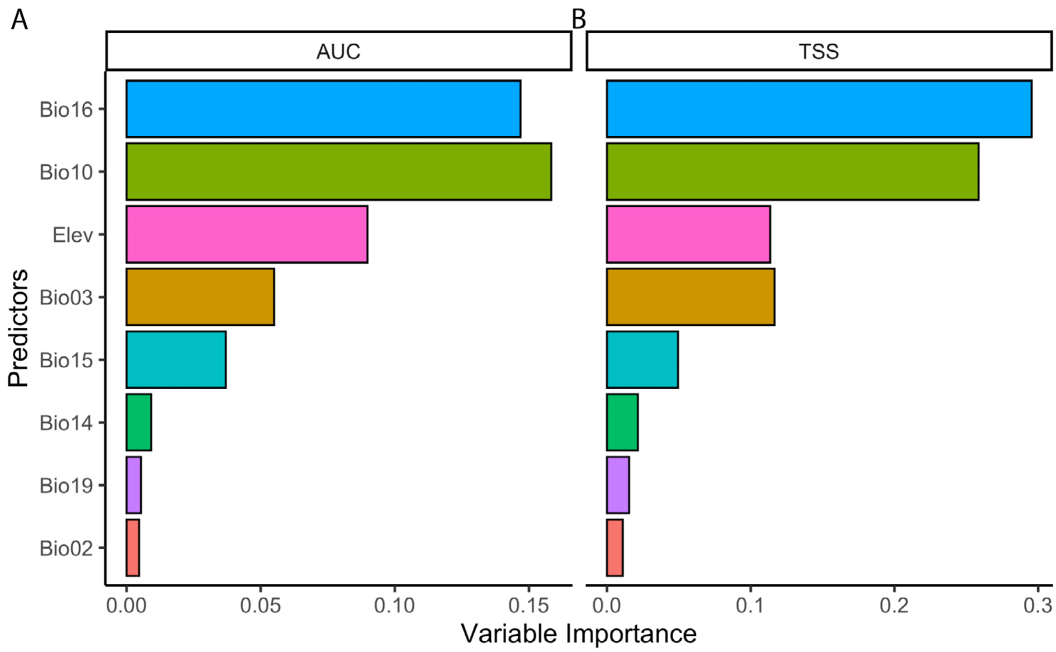

FIGURE 1 | Contribution of environmental variables to the MaxEnt model in predicting the distribution of *Spodoptera frugiperda*. Bio02—Mean diurnal range; Bio03—Isothermality; Bio10—Mean temperature of the warmest quarter; Bio14—Precipitation of Driest Month; Bio15—Precipitation Seasonality; Bio16—Precipitation of Wettest Quarter; Bio19- Precipitation of Coldest Quarter, Elevation. Each purple dot represents a predicted habitat suitability value for a given environmental variable, with all other variables held at their mean values. (A) AUC, Area under the curve, and (B) TSS, true skilled statistics.

In Brazil, suitable habitats for *S. frugiperda* are predominantly concentrated in the southern, southeastern, and central-western regions (Figure 4A). Detailed predictions at the national scale, including suitability estimates by state and municipality, threshold-based binary maps, extrapolation zones, and habitat suitability classes, are shown in Figure 4B–F. The total area identified as suitable for the pest in Brazil is approximately 8.49×10^6 km^2.

3.4 | Future Predictions

Future predictions suggest a continued expansion of habitat suitability for *S. frugiperda* under all three SSPs: 245, 245, and 585 (Figures 5 and 6). Key maize-producing countries, including Argentina, Brazil, China, India, Ukraine, and the United States, are expected to remain suitable habitats for *S. frugiperda* through the 2070s. Under SSP245, globally suitable habitat is projected to increase progressively from the 2030s (1.14×10^8 km^2) to the 2050s (1.17×10^8 km^2), and further by the 2070s (1.18×10^8 km^2). A similar trend is observed for SSP370, suitable habitat expanding from 1.14×10^8 km^2 in the 2030s to 1.17×10^8 km^2 in the 2050s and 1.19×10^8 km^2 by the 2070s. Under SSP585, projections indicate an even greater increase, from 1.15×10^8 km^2 in the 2030s to 1.18×10^8 km^2 in the 2050s, and 1.21×10^8 km^2 by the 2070s (Figure 6).

In Brazil, regions with very high habitat suitability are also expected to increase. Under SSP245, these areas expand from 1.02×10^6 km^2 in the 2030s to 1.43×10^6 km^2 by the 2070s (Figures 7 and 8). Similarly, under SSP370, areas with very high suitability are projected to expand, reaching 1.86×10^6 km^2 by the 2070s (Figures 7 and 8). Under SSP585, a comparable increase is projected with very high suitability areas expanding to 2.39×10^6 km^2 by the 2070s. These changes are predominantly concentrated in southern Brazil municipalities depicted, as detailed in Supplementary Figure S4.

3.5 | Niche Analysis

The first two axes of the principal component analysis (PCA) explained approximately 55% of the total variance across the eight environmental variables (Figure 9A). Among these, precipitation of the coldest quarter, precipitation of the driest month, and precipitation seasonality were the main contributors to PC1 (Figure 9B). In contrast, isothermality, precipitation seasonality, and precipitation of the wettest quarter were more influential to PC2 (Figure 9C). The niche equivalency test revealed significant differences between native and invaded ranges ($p = 0.009$ Figure 9D), indicating that the ecological niches occupied in these two regions are not identical. Moreover, the niche similarity test comparing the native to the invaded range (N—I) showed significant differences ($p < 0.05$; Figure 9E). Similarly, the reverse comparison (I—N) also showed significant differences ($p < 0.05$; Figure 9F).

Niche overlap between native and invaded regions (Figure 9G) was moderate, with a Schöener's D and Hellinger's *I* values of 0.49 and 0.67, respectively (Table S1), indicating overlap in environmental space. Niche expansion was estimated at 0.01, suggesting that *S. frugiperda* has colonized new areas with environmental conditions in the invaded range. The stability score of 0.99 indicates that a large portion of the niche remains conserved (Table S1). Notably, 8% of the climatic niche occupied in

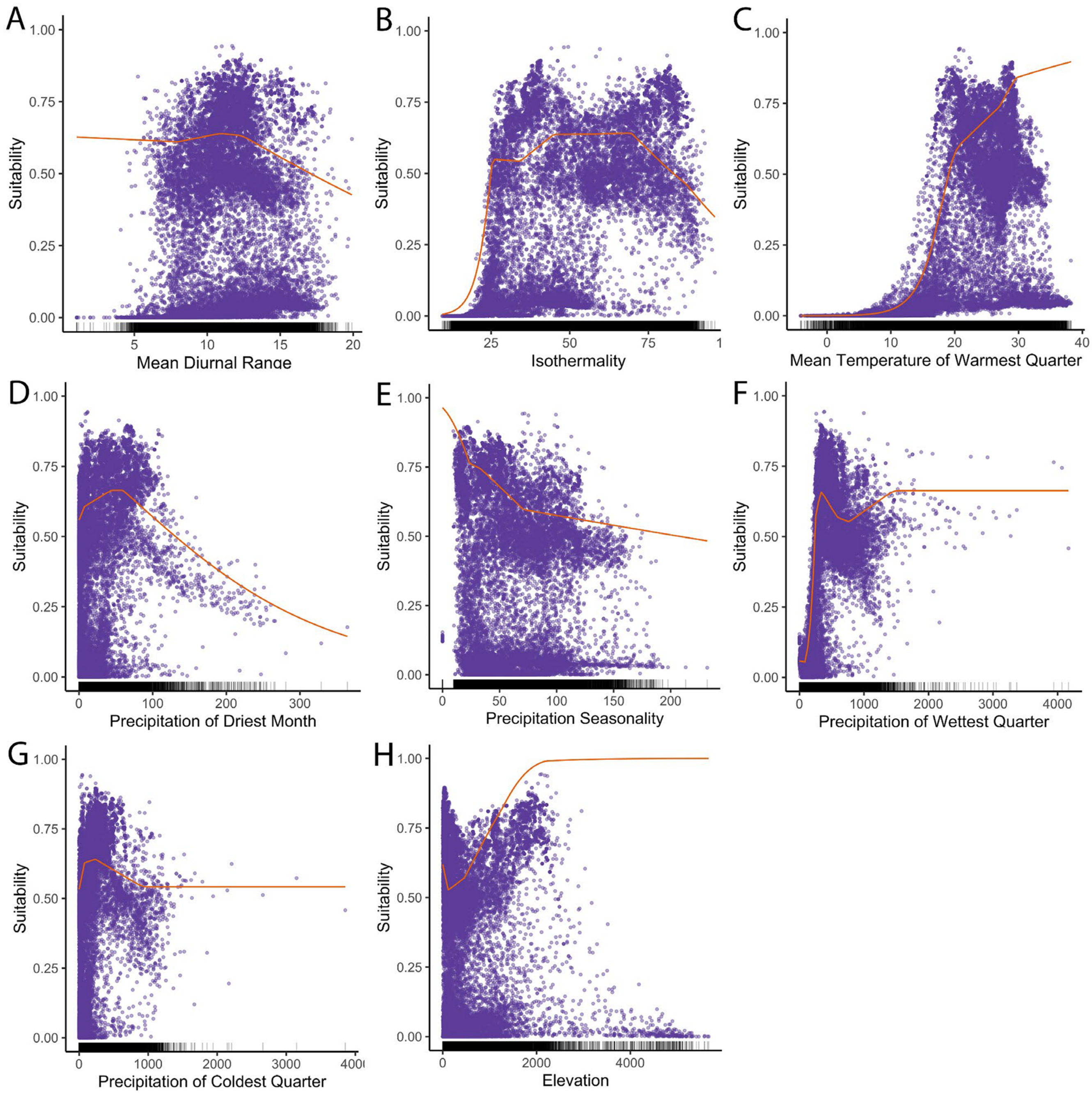

FIGURE 2 | Partial dependence plots of environmental variables used in the MaxEnt model for *Spodoptera frugiperda*. (A) Bio02—Mean diurnal range; (B) Bio03—Isothermality; (C) Bio10—Mean temperature of the warmest quarter; (D) Bio14—Precipitation of Driest Month; (E) Bio15—Precipitation Seasonality; (F) Bio16—Precipitation of Wettest Quarter; (G) Bio19—Precipitation of Coldest Quarter, (H) Elevation. Each purple dot represents a predicted habitat suitability value for a given environmental variable, with all other variables held at their mean values.

the native range was not occupied in the invaded range, despite the presence of similar environmental conditions (Table S1). In Figure S5, we show the niche occupancy profiles of the main bioclimatic variables in the native and invasive range.

3.6 | Potential Impacts on Key Crop Production in Brazil

In Brazil, sugarcane, soybeans, and corn are the most extensively cultivated crops for economic purposes, particularly in the central-western region. In contrast, herbaceous cotton, rice, and sorghum are produced in more localized areas, although these crops remain economically significant (Figure 10A–E). Risk assessments indicate that soybeans and corn production areas are highly vulnerable to *S. frugiperda*, with extensive zones of high to very high risk concentrated in the central and south-eastern regions of the country (Figure 11A–E). While sorghum and herbaceous cotton exhibit more spatially restricted production, they are nonetheless exposed to considerable pest-related threats in specific municipalities. Quantitative risk zoning further emphasizes that corn and soybeans are the most severely threatened

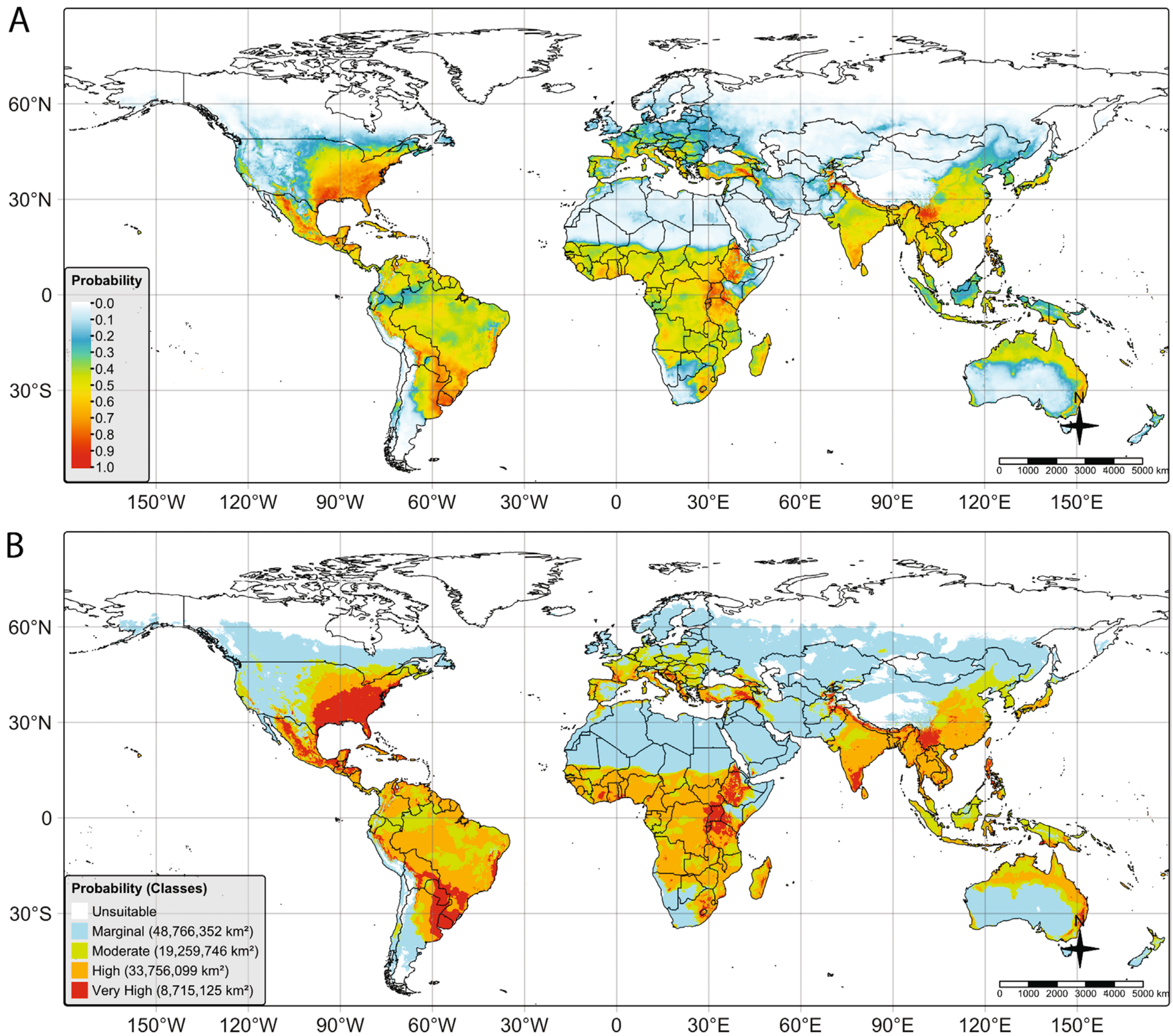

FIGURE 3 | Global potential habitat suitability of *Spodoptera frugiperda* under current conditions. (A) Continuous probability of occurrence. (B) Habitat suitability classified into five categories: unsuitable, marginal, moderate, optimal, and high.

crops, highlighting the need for geographically targeted and crop-specific pest management strategies. This information provides critical guidance for prioritizing intervention efforts and optimizing resource allocation to reduce the economic impact of *S. frugiperda* infestations in Brazil (Figure 12A–E).

4 | Discussion

Species distribution models are increasingly used to assess suitability for invasive species across spatial and temporal scales (Araújo et al. 2019; Ninsin et al. 2024). However, their predictive reliability can be compromised by sampling bias in species occurrence data, which may reduce model accuracy and generalizability (Dubos et al. 2022; Lamboley and Fourcade 2024). To address this challenge, we incorporated recent, high-quality occurrence records of *S. frugiperda* from validated sources and field surveys, applying stringent data filtering prior to modeling. Evaluation across a suite of performance metrics confirmed that the model exhibited strong predictive ability, supporting its application in pest risk assessment and spatial planning (Hosmer Jr. et al. 2013; Allouche et al. 2006).

Our predictions reveal that suitable habitats for *S. frugiperda* extend far beyond its currently reported distribution, including high-risk zones across several major maize-producing countries in Europe such as Romania, the United Kingdom, France, and Poland. Although *S. frugiperda* is highly polyphagous, feeding on more than 350 plant species (Montezano et al. 2018), maize remains its primary host. Its establishment in these regions could cause significant yield losses and economic disruption, posing a direct threat to food security and rural incomes.

The model also indicates sustained or emerging suitability for *S. frugiperda* in eight major maize-producing countries globally, including the United States, Brazil, Mexico, and Argentina

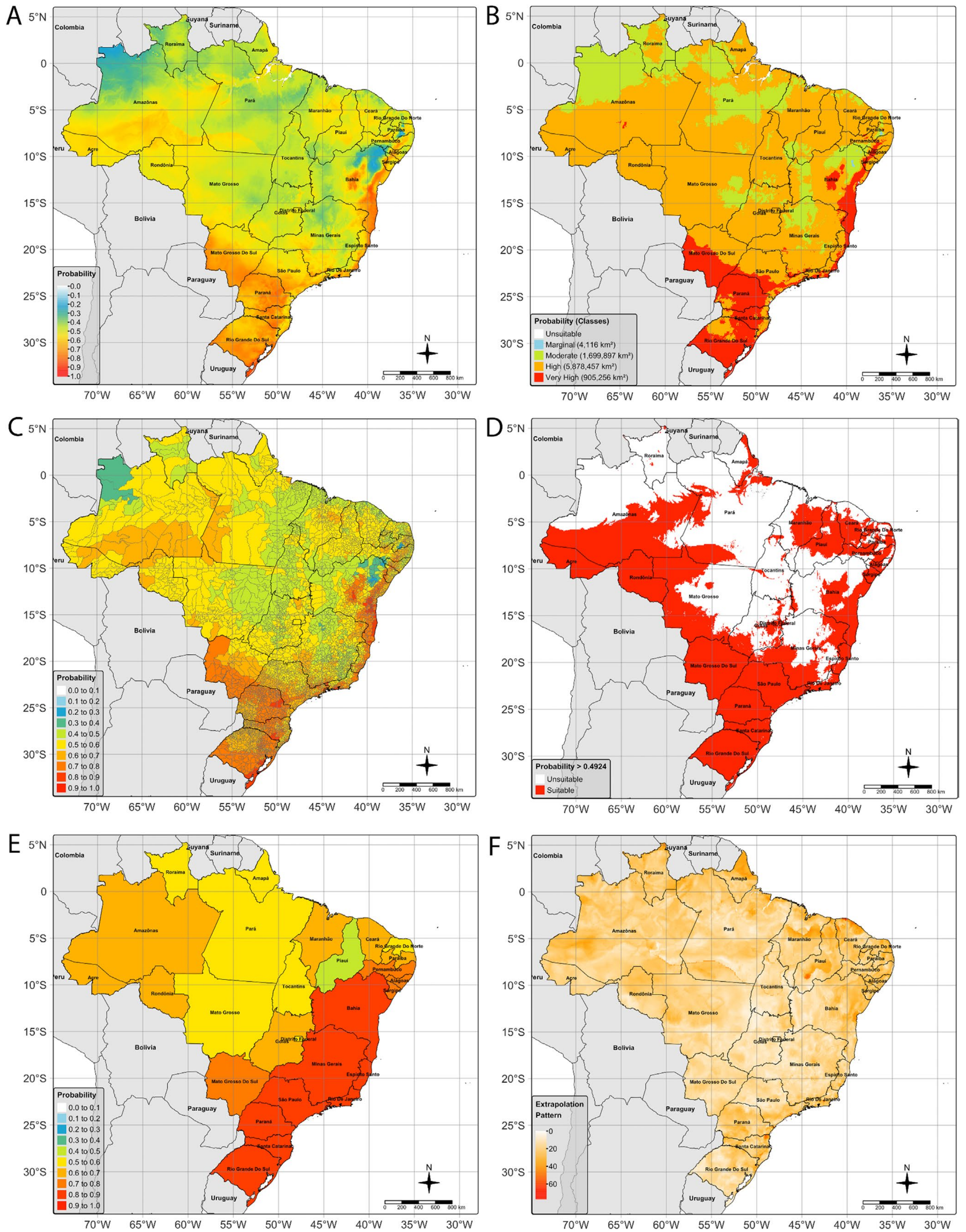

FIGURE 4 | Current habitat suitability of *Spodoptera frugiperda* in Brazil. (A) Suitability by state; (B) Habitat classified by suitability thresholds; (C) Probability of occurrence by municipality; (D) Binary threshold map; (E) Suitability range by state; (F) Areas of extrapolation.

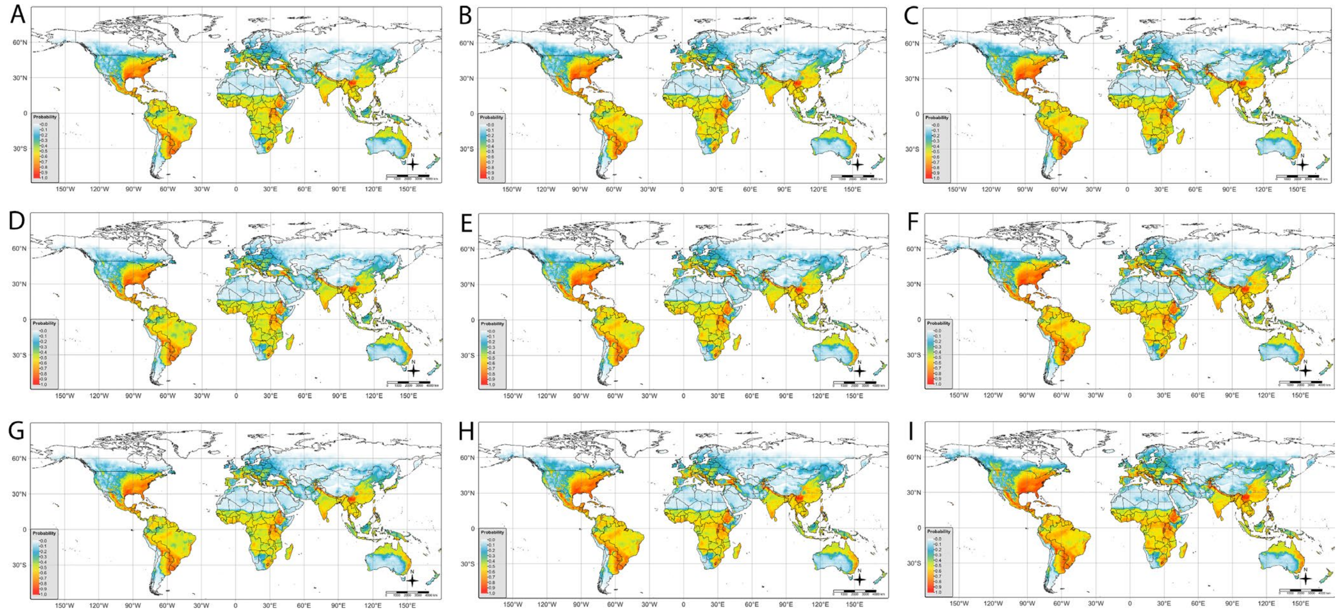

FIGURE 5 | Global projected habitat suitability for *Spodoptera frugiperda* under future climate scenarios: (A–C) SSP245 for the 2030s, 2050s, and 2070s; (D–F) SSP370 for the 2030s, 2050s, and 2070s; (G–I) SSP585 for the 2030s, 2050s, and 2070s.

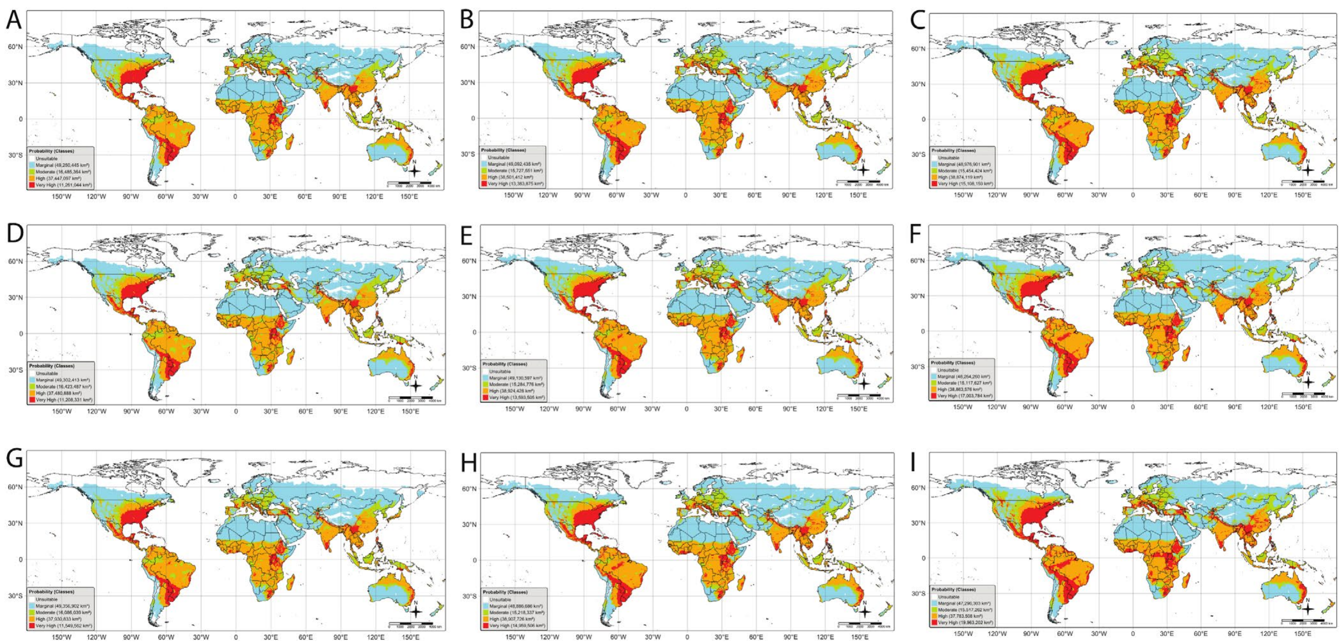

FIGURE 6 | Classified global habitat suitability for *Spodoptera frugiperda* under future scenarios: (A–C) SSP245 (2030s–2070s); (D–F) SSP370 (2030s–2070s); (G–I) SSP585 (2030s–2070s).

in the Americas; Ukraine in Europe; and China, India, and Indonesia in Asia (Erenstein et al. 2022). Ukraine has not yet reported infestations, highlighting the importance of proactive surveillance, early detection, and preemptive policy measures. Within Brazil, several municipalities cultivating economically vital crops such as rice, sugarcane, corn, soybeans, and sorghum were identified as highly vulnerable. These spatial risk maps provide actionable insights for targeted monitoring and management strategies.

Future projections under Shared Socioeconomic Pathways (SSP245, SSP370, and SSP585) indicate a steady expansion of suitable habitats from the present through the 2030s, 2050s, and 2070s. These results align with previous projections (Ramasamy et al. 2022), which indicated heightened establishment potential under SSP585 in the 2050s and 2070s. Our findings support the view that tropical and subtropical regions, including large parts of Africa, Southeast Asia, Oceania, and the Americas, will continue to support the persistence and spread of *S. frugiperda* under future climate scenarios (Paudel Timilsena et al. 2022).

The most important predictors of global habitat suitability in our model were precipitation of the wettest quarter, mean temperature of the warmest quarter, elevation, and isothermality.

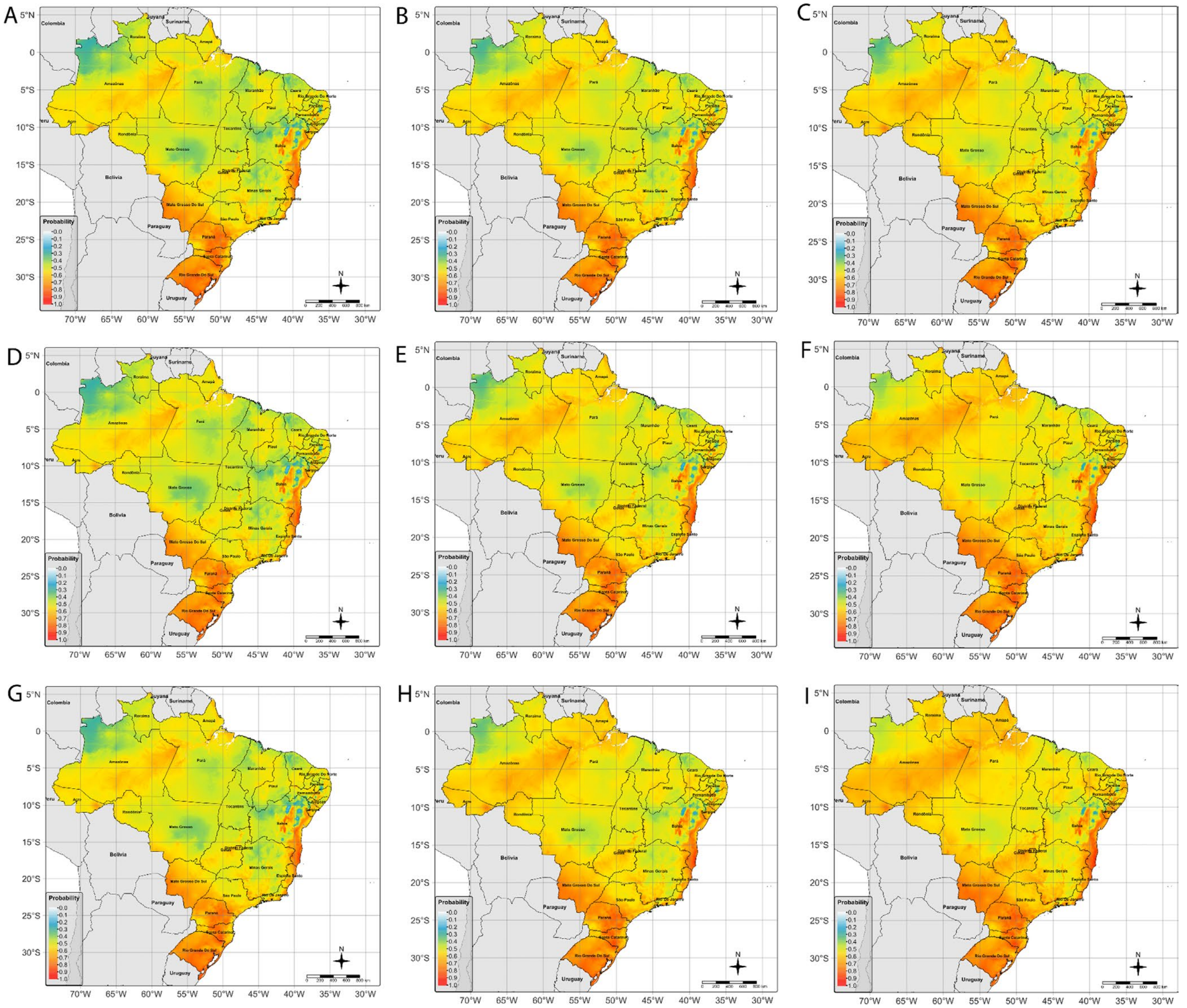

FIGURE 7 | Projected habitat suitability for *Spodoptera frugiperda* in Brazil under future climate scenarios: (A–C) SSP245 for the 2030s, 2050s, and 2070s; (D–F) SSP370 for the 2030s, 2050s, and 2070s; (G–I) SSP585 for the 2030s, 2050s, and 2070s.

These environmental variables are essential for regulating *S. frugiperda* development, survival, and migration. Our findings are consistent with prior studies that emphasized the importance of temperature and precipitation in determining invasion potential (Ramasamy et al. 2022). The broader range of predicted suitability in our study, relative to earlier models (Byeon et al. 2018; Wolmarans et al. 2010), is likely attributable to more comprehensive occurrence records and updated modeling techniques. Field studies further support these patterns: *S. frugiperda* is known to thrive under high temperatures and evapotranspiration (Cokola et al. 2021), and pupation and emergence are favored when soil moisture ranges between 6.8% and 47.6% (He et al. 2021). Although CLIMEX-based models by Paudel Timilsena et al. (2022) suggested that northern Africa may be unsuitable due to cold and arid conditions, our results also indicate that these areas could still support *S. frugiperda* establishment, possibly facilitated by irrigation and intensive cultivation.

In this study, we present two key contributions: 1) it is the first global quantification of the ecological niche of *S. frugiperda* in native and invaded ranges. The analysis revealed moderate niche overlaps and clear evidence of expansion into new climatic spaces. Given the species' widespread impact on crop productivity and food security (Bannor et al. 2022), these insights are essential for forecasting invasion trajectories and guiding early warning systems; and 2) the use of species distribution and ecological niche models in combination with productive concentration indicators to define the economic risk related to *S. frugiperda*. Although other zoning methods are widely used (Amaral et al. 2023; Gonçalves and Wrege 2018; Wollmann and Galvani 2013), the use of models that estimate the probability of a pest occurring, through the analysis of environments suitable for the species, together with the identification of productive clusters of crops susceptible to this pest, offers a robust methodological approach to define economic risk zoning.

Previous research has demonstrated the utility of SDMs in enhancing early detection, informing containment strategies, and identifying introduction hotspots (Peterson 2006). The spatial predictions and niche metrics presented here can

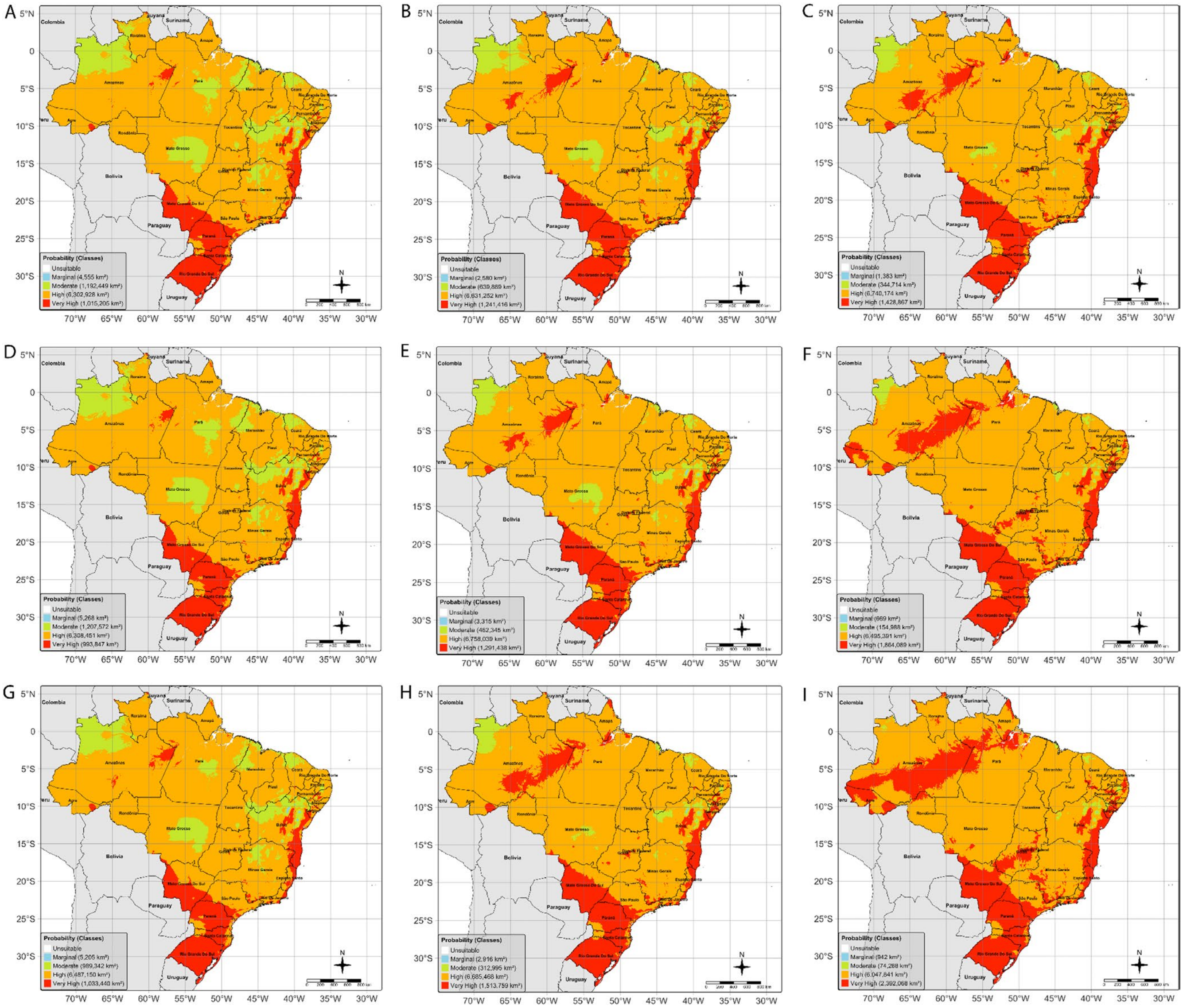

FIGURE 8 | Classified potential habitat suitability *Spodoptera frugiperda* in Brazil under future climate scenarios: (A–C) SSP245 (2030s–2070s); (D–F) SSP370 (2030s–2070s); (G–I) SSP585 (2030s–2070s).

support the development of robust surveillance frameworks in regions currently free from infestation. To strengthen preparedness, we recommend prioritizing research on strain-specific ecology, expanding farmer extension services, and supporting evidence-informed policy frameworks that promote integrated pest management at both national and international levels.

Despite the utility of SDMs, it is important to recognize their limitations. While our model incorporated key abiotic variables, including climate parameters and elevation, it did not account for biotic interactions or anthropogenic factors such as pest control practices, landscape configuration, or trade flows. These can profoundly influence establishment success and should be considered in future assessments. Additionally, the model does not factor in behavioral plasticity, emergency response capacity, or policy dynamics that could alter future distribution outcomes.

Another critical consideration is the genetic complexity of *S. frugiperda*, which comprises at least two strains, the rice strain (R) and the corn strain (C), that may differ in host preference, ecological adaptability, and migratory behavior (Miller et al. 2024; Nagoshi et al. 2023; Tessnow et al. 2022). Hypotheses such as allochronic activity, where strains differ in phenological timing, may also shape spatial distributions. However, in the absence of spatially resolved strain data, we modeled the species as a single ecological unit. While this approach provides a conservative estimate of invasion risk, future work should integrate molecular, behavioral, and ecological data to improve strain-specific predictions and enhance model precision.

5 | Conclusions

This study quantifies the current and projected habitat suitability of *S. frugiperda*, delineating climate risk zones that extend beyond its known distribution. The ecological niche analysis offers critical insights into regions at elevated risk of invasion, providing a valuable framework for proactive pest surveillance and risk assessment. With rising global temperatures, our

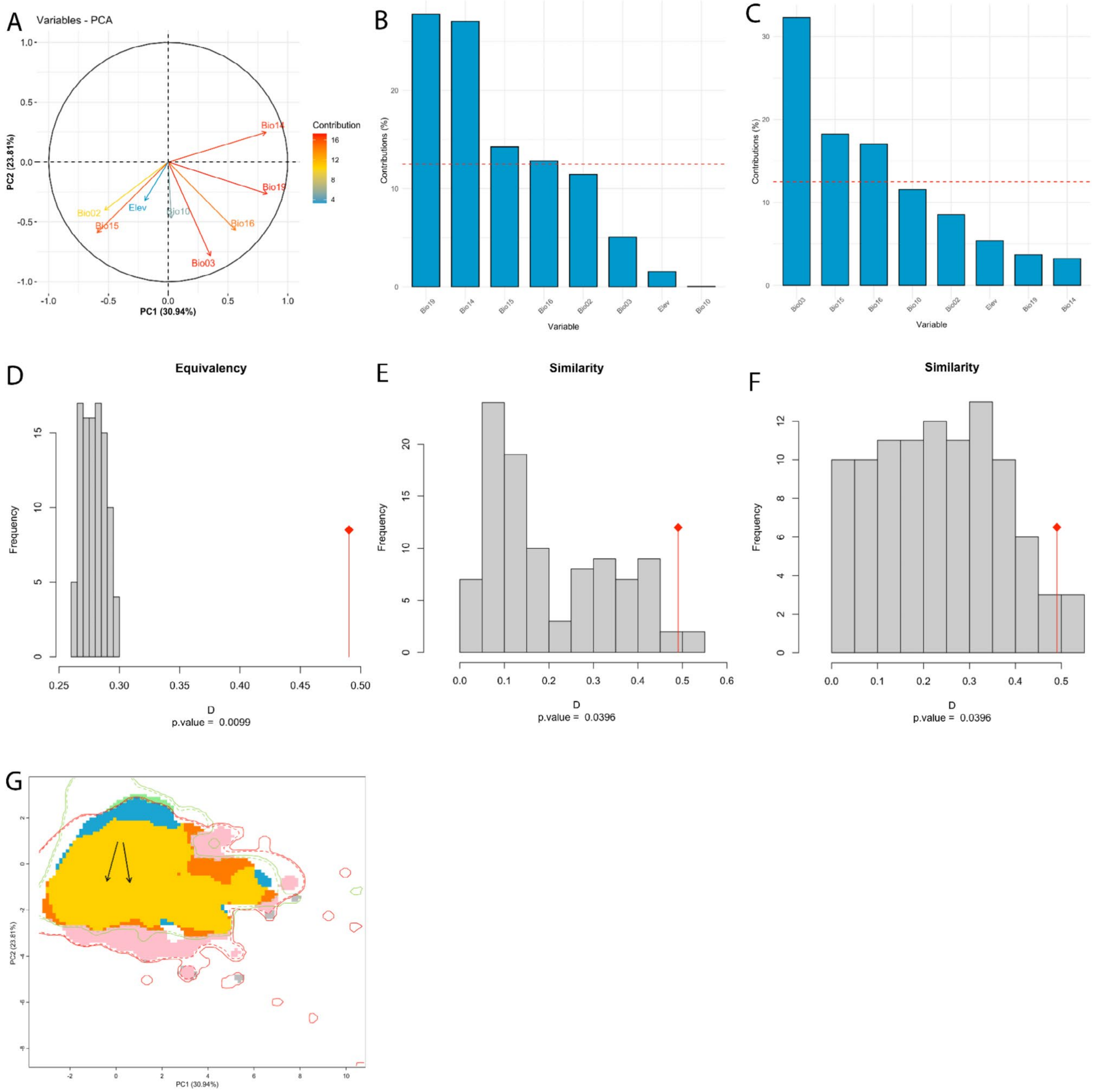

FIGURE 9 | Niche analysis of *Spodoptera frugiperda* in native and invaded regions. (A) PCA, the first two principal components derived from the environmental variables used for modeling. (B) Contribution of variables to PC1; (C) contribution to PC2. (D) Histogram of the niche equivalency test results. (E) Similarity test from native to invaded range (N—1). (F) Similarity test from invaded to native range (1—N). (G) Visualization of climatic niche overlap. Blue indicates unfilled native niche space, orange shows areas of niche expansion in the invaded range, and yellow indicates niche stability. Solid contour lines represent the environmental space of native (light green) and invaded (red) areas; dotted lines represent 90% of the available background environment. Shading indicates occurrence density, with darker areas representing higher density. Solid and dotted arrows indicate shifts in environmental centroids between native and invaded niches.

model predicts a consistent expansion of suitable habitats for *S. frugiperda*, particularly across major maize-producing regions. Several European countries are projected to remain highly suitable for the establishment of the pest, highlighting the pressing need for early detection and coordinated management strategies. We found soybean and corn as the most vulnerable crops at risk of *S. frugiperda* presence in Brazil. These findings serve as a resource for researchers, policymakers, agricultural stakeholders, environmental agencies, and non-governmental organizations in developing targeted and spatially informed interventions to mitigate the agricultural and economic impacts of this invasive pest.

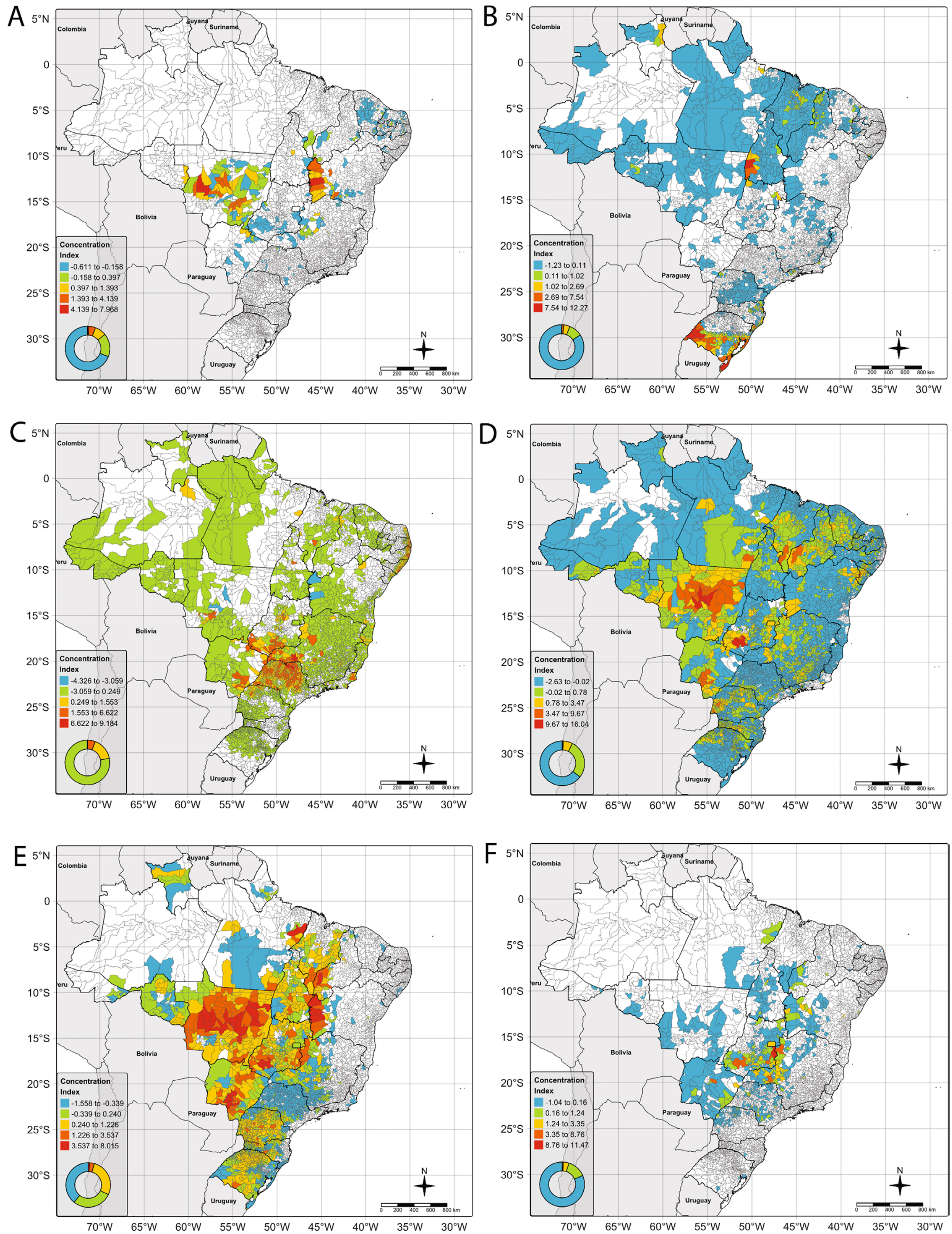

FIGURE 10 | Spatial distribution of the economic importance (ICn) of major crops across Brazilian municipalities: (A) Herbaceous cotton (seed), (B) Rice (paddy), (C) Sugarcane, (D) Corn (grain), (E) Soybeans, (F) Sorghum (in husk). Color gradients range from red/orange (high crop concentration) to green/blue (lower crop concentration or absence of production).

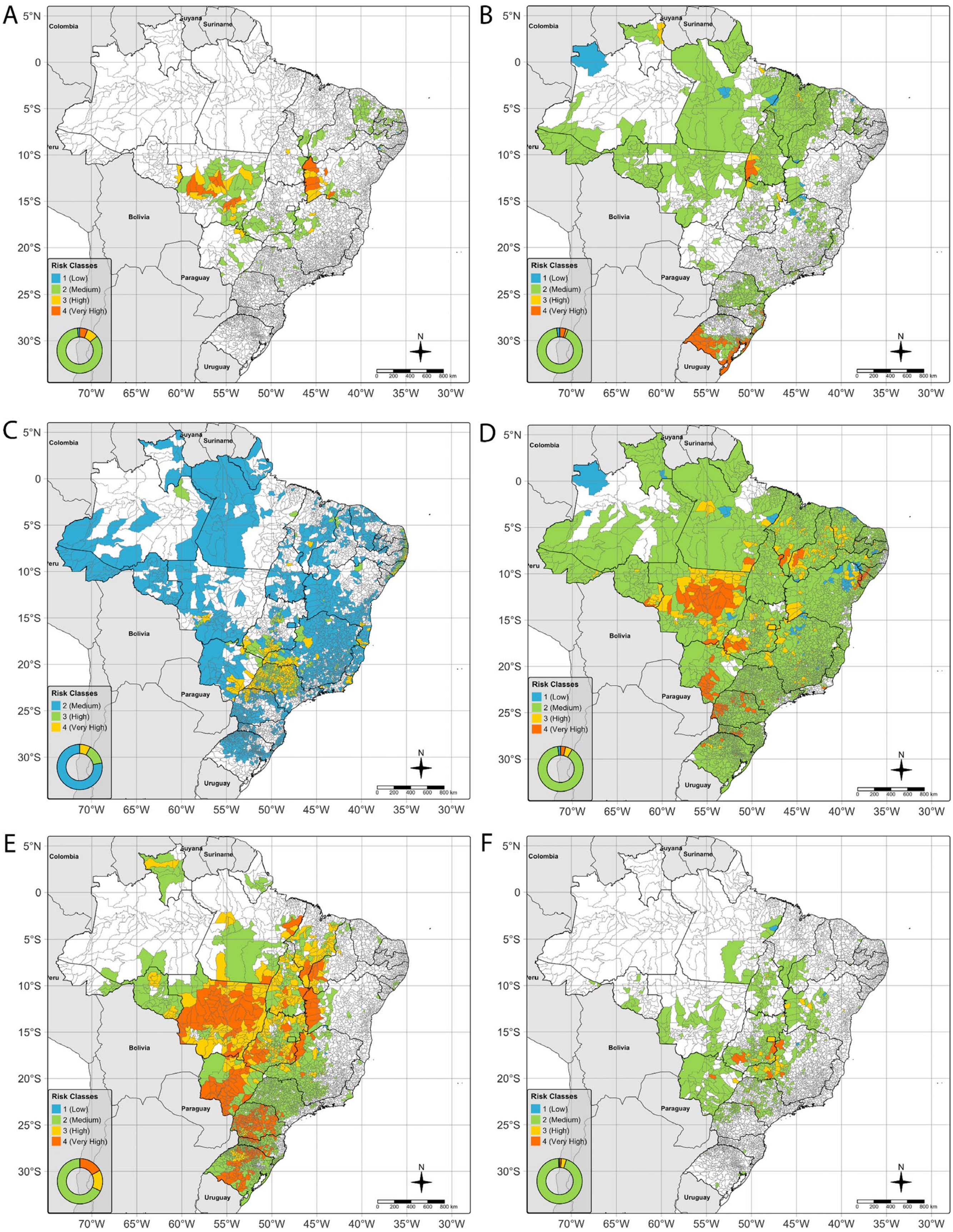

FIGURE 11 | *Spodoptera frugiperda* potential impacts on crop production in Brazilian municipalities for (A) Herbaceous cotton (seed), (B) Rice (paddy), (C) Sugarcane, (D) Corn (grain), (E) Soybeans, (F) Sorghum (in husk). Risk classes range from low (blue) to very high (red), reflecting regional vulnerability to fall armyworm infestation.

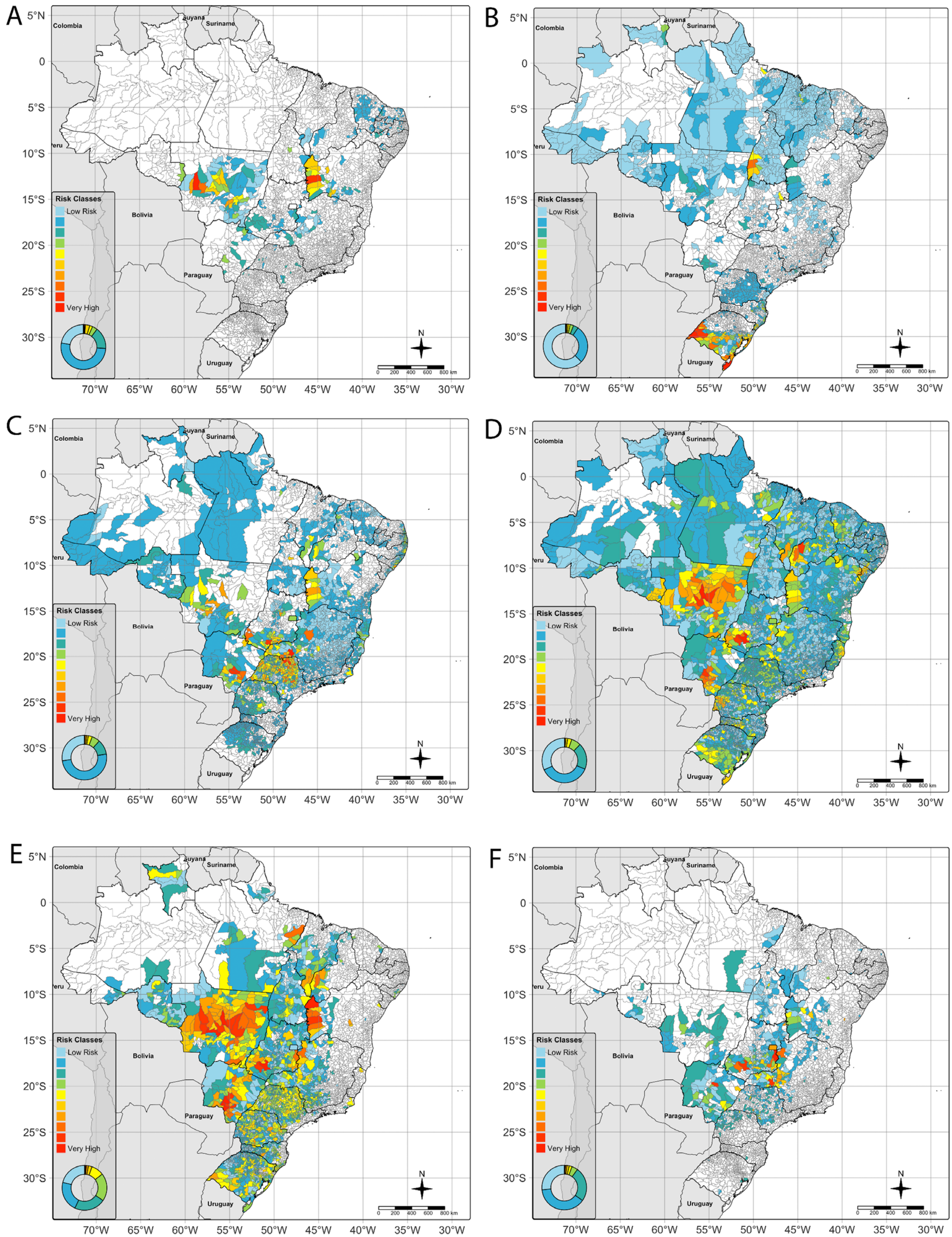

FIGURE 12 | Quantitative risk zoning for *Spodoptera frugiperda* across Brazilian: (A) Herbaceous cotton (seed), (B) Rice (paddy), (C) Sugarcane, (D) Corn (grain), (E) Soybeans, (F) Sorghum (in husk). The color scale (blue to red) denotes increasing levels of economic risk associated with pest pressure, based on the integration of crop importance and predicted suitability.

Author Contributions

George Correa Amaro and Owusu Fordjour Aidoo conceived and designed the research. George Correa Amaro, Ricardo Siqueira da Silva, and Owusu Fordjour Aidoo wrote and built the models. Philipe Guilherme Corcino Souza, Eunice Stella Nyarko, Kwame Adjei-Mantey, Lakpo Agboyi, Frederick Leo Sossah, and Roger Sigismund Anderson collected data sets. George Correa Amaro, Owusu Fordjour Aidoo, and Ricardo Siqueira da Silva made the corrections. All authors reviewed and approved the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data sets generated during and/or analyzed during the current study are available upon a reasonable request from the corresponding author.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.