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Modeling Climate-Induced Range Shifts with Bioclimatic Predictors

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ABSTRACT: Climate change is accelerating shifts in the distribution and intensity of agricultural pests and diseases, threatening global food security and crop resilience. This study investigates the role of climate variables including temperature, moisture, and extreme events in shaping pest dynamics using biologically relevant climate indicators. Historical and projected climate data (ERA5, WorldClim v2.1) were combined with pest occurrence records (GBIF) and cropping system data to build species distribution models (SDMs) under multiple Shared Socioeconomic Pathways (SSPs). Derived climate indicators such as Growing Degree Days (GDD), Standardized Precipitation Index (SPI), and heatwave duration were found to be more predictive of pest suitability than raw climate variables. Results reveal significant historical range expansions for pests like Spodoptera frugiperda, correlated with increased thermal accumulation. Future projections under high-emission scenarios (e.g., SSP585) indicate up to a 42% increase in pest-suitable areas by 2041–2060. Overlaying pest risk maps with cropping system changes highlights regions with heightened exposure risk due to cropland expansion and altered planting calendars. Climate extremes, particularly droughts and heatwaves, emerged as key modulators of pest reproduction and outbreak frequency. The study underscores the value of integrating climate indicators into spatial pest risk assessments and supports the development of early warning systems for climate-resilient agriculture. It also identifies critical modeling limitations, including data gaps and ecological oversimplifications, while recommending interdisciplinary collaboration and real-time data integration for future model improvements.

Keywords: Climate Change, Pest Distribution, Species Distribution Modeling, Growing Degree Days, Extreme Weather, Agricultural Resilience, SPI.

INTRODUCTION

Climate change has emerged as one of the most pressing challenges facing agricultural systems worldwide. The rising global average temperature, shifts in precipitation regimes, and increasing frequency of extreme weather events are not only impacting crop productivity directly but are also significantly reshaping the dynamics of agricultural pests and diseases. These alterations in pest and pathogen behavior have broad implications for plant health, food security, and sustainable agricultural development. As these threats become more widespread and unpredictable, understanding their underlying drivers and integrating climate-informed strategies into agricultural planning becomes essential.

Over the past two decades, a growing body of literature has documented the significant and often accelerating changes in the distribution and intensity of pests and diseases, directly linked to climate change. The role of temperature and moisture availability is particularly well-documented. Rising temperatures have been shown to facilitate the expansion of many insect vectors and fungal pathogens into regions previously deemed unsuitable. For instance, vector-borne diseases such as malaria and dengue are now reported in higher altitudes and latitudes due to the increasing thermal suitability of these regions (Agyekum et al., 2021; Mordecai et al., 2020). Similarly, studies have indicated that species are not only shifting geographically but are also migrating vertically, altering ecological balances in mountainous and highland ecosystems (Caminade et al., 2018).

These shifts are not limited to vectors of human diseases but extend to a wide range of agricultural pests and pathogens. Climate-driven changes in temperature and precipitation patterns have increased the susceptibility of many crops to fungal and bacterial infections. High humidity and fluctuating temperatures are optimal conditions for many pathogenic organisms. For example, fungal species such as Alternaria and Corynespora, and bacterial pathogens like Xanthomonas oryzae, exhibit heightened reproductive success and wider spread under warmer and wetter conditions (Franklinos et al., 2019; Limantol et al., 2016). The adaptation and proliferation of these organisms in novel environments pose new challenges for plant disease control and require revised management frameworks.

Historical analyses of climate variability further reinforce these findings. Increases in rainfall have been linked with greater severity of disease outbreaks, particularly for pathogens that thrive in moist environments (Fagodiya et al., 2022). Fluctuating temperatures affect pathogen life cycles, sometimes accelerating reproduction or enabling multiple generations within a single growing season. Crop species such as soybean and groundnut, known for their sensitivity to climatic changes, have experienced significant yield losses tied to disease outbreaks during anomalous weather periods (Kanna et al., 2023). Beyond empirical observations, farmer perceptions in various regions consistently confirm that changing climatic conditions have exacerbated pest and disease pressures, further threatening food security (Limantol et al., 2016).

Among the most responsive biological groups to climate shifts are insect pests and fungal pathogens. Research has shown that common agricultural pests, including the Asian Citrus Psyllid and various lepidopteran larvae, have expanded their ranges and life cycles due to rising temperatures (Bibi et al., 2021). Likewise, fungi such as Botrytis cinerea flourish in elevated humidity, with outbreaks intensifying during wetter seasons (Akhtar et al., 2021). The expansion of these organisms into previously unaffected areas demonstrates the pressing need for updated surveillance systems and forecasting models that account for changing environmental conditions.

The role of extreme weather events in accelerating or triggering pest and disease outbreaks has gained increasing recognition. Events such as heatwaves, droughts, and floods disrupt ecological balances, often leading to conditions that favor pest survival and reproduction. Heatwaves, for example, can enhance mosquito activity and have been associated with outbreaks of vector-borne diseases such as West Nile and Zika virus (Drakou et al., 2020). Flooding, although capable of temporarily suppressing pest populations, can also promote the spread of waterborne diseases through the creation of stagnant water habitats (Shirzadi et al., 2020). Conversely, prolonged droughts increase plant stress, reducing natural resistance and creating ideal conditions for pest infestations (Ogundeji et al., 2019). These interactions between extreme events and biological responses underscore the importance of incorporating climate extremes into pest management frameworks.

International organizations have responded to this emerging threat by integrating climate risks into their pest assessment and agricultural planning frameworks. The Food and Agriculture Organization (FAO) emphasizes that climate change must be considered a core component of pest and disease risk management. Their strategies increasingly advocate for the inclusion of climate variables in pest monitoring and forecasting systems to enhance preparedness and resilience (Limantol et al., 2016). Similarly, the Intergovernmental Panel on Climate Change (IPCC) highlights the importance of adaptive capacity and early warning systems in its climate adaptation frameworks, acknowledging that pest dynamics are a critical pathway through which climate impacts manifest in agriculture (Haque et al., 2024). These institutions promote a multidisciplinary approach, combining scientific modeling with traditional agricultural knowledge to better manage pest risks.

Central to these efforts is the integration of climate modeling into pest risk analysis. Climate projections show considerable shifts in temperature and precipitation patterns across most agroecological zones, suggesting that the distribution and intensity of pest outbreaks will continue to evolve. Studies increasingly support the use of predictive models that incorporate climate variables to estimate pest suitability and outbreak potential (Ludwig et al., 2019). For instance, modeling exercises in North America project the potential establishment of exotic mosquito species capable of transmitting new diseases, largely due to warming trends. Earth observation data and satellite-derived indicators have also been effectively used to detect environmental conditions conducive to pest outbreaks, offering real-time insights for decision-makers (Colston et al., 2019).

These developments signal a shift from reactive to proactive pest management strategies. By understanding and anticipating how climate influences pest behavior, it becomes possible to deploy targeted interventions, adjust cropping calendars, and modify planting strategies to reduce vulnerability. This is particularly relevant for tropical and subtropical regions where temperature thresholds for pest development are frequently surpassed, and where agricultural systems are already under stress due to socio-economic factors.

In this context, the present study investigates how thermal suitability, moisture regimes, and extreme climate events influence the geographical and temporal distribution of key agricultural pests and diseases. Building on the growing evidence base and leveraging global climate datasets, the research integrates climate-derived indicators such as Growing Degree Days (GDD), Standardized Precipitation Index (SPI), and heatwave duration into spatial distribution models. By coupling these models with pest occurrence data and cropping system shifts, the study aims to project future pest risk zones under various climate scenarios. The novelty of this research lies in its biologically informed modeling approach that emphasizes climate-pathogen mechanisms rather than relying solely on raw climate variables. This approach provides new insights into pest ecology under climate change and contributes to the development of adaptive risk management strategies tailored to future agricultural challenges.

METHOD

This chapter outlines the methodological framework employed to examine the influence of climate change on pest and disease distributions, emphasizing the integration of climate data, species occurrence records, and species distribution models (SDMs). The study utilizes a multi-source data approach combining historical and projected climate datasets, presence-only species occurrence records, and climate-derived ecological indicators. The core objective is to build robust, biologically informed models to assess and predict spatial pest risk dynamics under varying climate scenarios.

Climate Data Sources and Processing

Historical climate data were sourced from ERA5 and ERA5-Land products available through the Copernicus Climate Data Store. These datasets provide hourly and daily variables such as temperature, precipitation, humidity, wind speed, and solar radiation at high temporal resolution. For consistency and ease of application, these data were aggregated to monthly means or totals, depending on the variable, and then used to compute climate indicators relevant to pest ecology.

For future climate scenarios, the study used CMIP6 projections provided by WorldClim v2.1, which include downscaled data across Shared Socioeconomic Pathways (SSPs): SSP126, SSP245, SSP370, and SSP585. Temporal horizons of 2021–2040 and 2041–2060 were selected to assess mid-term impacts. WorldClim's downscaling ensures better ecological relevance across localized regions. Where needed, additional high-resolution data sources like CHELSA were considered to enhance spatial granularity, especially in topographically complex landscapes (Karger et al., 2017).

The preprocessing of climate data involved validation through comparison with local meteorological records. Cross-validation methods and statistical comparisons were conducted to assess biases, with corrections applied where discrepancies were identified. This included statistical downscaling and bias adjustment techniques, especially for precipitation variables, known for high inter-model variability (Bandhauer et al., 2021). Consistency between datasets was also evaluated to ensure reliable integration into the modeling framework.

Derivation of Climate-Ecological Indicators

Rather than relying solely on raw climate variables, the study employed biologically meaningful indicators known to affect pest development and survival. These include:

- Growing Degree Days (GDD): Calculated using daily minimum and maximum temperatures, with pest-specific base temperature thresholds.

- Heat Threshold Days: Number of days per month exceeding critical temperature limits (>34°C), associated with pest mortality or reproductive suppression.
- Minimum Night Temperatures: Important for assessing survival rates of nocturnal pests and vectors.
- Standardized Precipitation Index (SPI): Derived from monthly precipitation totals to quantify drought intensity and duration.
- Rainfall Extremes: Percentile-based measures (e.g., p95, p99) indicating heavy rainfall events conducive to fungal pathogen outbreaks.
- Heatwave and Dry Spell Duration: Using consecutive day counts of extreme heat or no rainfall, based on IPCC-endorsed definitions.

These derived metrics were computed using a combination of climate processing scripts in R and Python, ensuring compatibility with spatial modeling software.

Pest Occurrence Data and Bias Correction

Species presence data were obtained from the Global Biodiversity Information Facility (GBIF). Target pests included *Spodoptera frugiperda* (fall armyworm) and *Xanthomonas oryzae* (bacterial leaf blight), selected for their agricultural importance and data availability. GBIF records were filtered by date (2000–2020), species accuracy, and geolocation precision.

Bias in occurrence data common due to higher sampling near urban or accessible areas was addressed through several techniques. Spatial filtering was applied to reduce clustering in over-sampled regions. Additionally, sampling bias grids based on human accessibility were used to adjust background point selection. This process ensures the SDMs do not overfit well-sampled areas and reflect true environmental associations (Lazoglou et al., 2020).

Environmental background data for model calibration were selected to match the sampling effort and geographic extent of occurrence data. This helped maintain the ecological validity of the modeled species-environment relationships. Where feasible, climatic layers were used to further weight presence points based on local environmental heterogeneity.

Species Distribution Modeling (SDMs)

The study employed MaxEnt, a machine-learning algorithm designed for presence-only data. MaxEnt estimates the most likely distribution of a species by contrasting the environmental conditions of known occurrence points against a background environment. The suitability of MaxEnt for ecological applications is well-supported, particularly where absence data are unreliable or unavailable (Datta et al., 2020).

Climatic predictors derived from ERA5 and WorldClim were input as covariates in MaxEnt. Model complexity was controlled through regularization parameters to prevent overfitting. Variable selection was informed by ecological relevance, multicollinearity diagnostics (e.g., VIF), and expert input.

Model performance was assessed using Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). Models scoring AUC > 0.80 were considered to have strong discriminatory power. Ensemble modeling techniques were also applied, aggregating predictions from multiple MaxEnt runs and, where feasible, combining with other algorithms to improve robustness and reduce uncertainty.

Projection and Validation of Future Scenarios

SDMs were projected onto future climate layers under each SSP scenario. The selected horizons (2021–2040 and 2041–2060) allow detection of near- and mid-term changes in pest suitability zones. These projections assumed constant species-climate relationships but were adjusted to include cropping system shifts as an interacting factor, such as crop calendar changes and expansion of suitable host regions.

To validate future projections, hindcasting methods were used where models were trained on earlier periods and tested against known occurrence shifts in more recent years. Additionally, environmental similarity indices (e.g., MESS maps) were generated to identify extrapolation risks when applying models to future conditions.

Integration with Cropping Systems

To assess potential exposure risks, SDM outputs were overlaid with current and projected cropland distributions using data from FAO and spatial agriculture databases. Crops such as rice and maize were prioritized due to their relevance to the selected pest species. This integration enabled the identification of high-risk zones where climatic suitability and host availability intersect.

Limitations and Mitigation

Several methodological challenges were acknowledged, including uncertainties in climate model outputs, incomplete pest occurrence data, and the assumption of species equilibrium with climate. These were addressed through sensitivity analyses, ensemble modeling, and application of robust statistical filters. Although SDMs offer valuable insights, their predictive power is constrained by ecological complexities not captured in static models.

RESULT AND DISCUSSION

This chapter presents the findings derived from climate-driven species distribution modeling for selected agricultural pests, focusing on how climate change influences historical and projected pest distributions. Results are grouped into four key themes: historical trends, future distribution projections, cropping system shifts, and the role of moisture and climate extremes. The analysis incorporates derived climate indicators, pest occurrence data, and relevant land-use dynamics.

Historical Trends in Pest Distribution

Growing Degree Days (GDD) were calculated across all regions with available ERA5 data and showed a marked upward trend from 2000 to 2020. For *Spodoptera frugiperda* (fall armyworm), increased GDD is linked to accelerated development cycles and expanded potential habitat. Warmer temperatures now enable multiple generations per season in areas that previously supported only one, particularly in temperate zones (Skendžić et al., 2021). This results in a higher reproductive potential, increasing pest pressures and complicating control efforts.

Historical pest distribution data corroborate these trends. For instance, *Helicoverpa armigera* has demonstrated a northward range shift, invading areas in Northern Europe and parts of North America previously too cool for its survival (Lehmann et al., 2020). Regional case studies, such as the range extension of *Dichomeris ligura* in Southern Europe, further affirm temperature-driven expansions, underscoring the biological sensitivity of pest species to even minor climatic shifts.

Occurrence data from GBIF revealed the broad spatial distribution of pest species over time. However, while GBIF effectively identifies general patterns, its limitations are acknowledged due to sampling bias, underreporting, and uneven geographic representation (Shabani et al., 2016). Despite these caveats, GBIF presence data align with observed GDD trends, suggesting strong coherence between thermal suitability and pest spread.

Future Pest Distribution Projections

Using CMIP6 downscaled scenarios, SDMs were projected for two future horizons: 2021–2040 and 2041–2060. Projections under SSP585 (high emissions) consistently displayed the most pronounced expansion in pest range.

For *S. frugiperda*, the model predicts a 42% increase in suitable habitat by 2041–2060 under SSP585, with significant range increases in Southeast Asia, Sub-Saharan Africa, and southern Europe. Similarly, *Xanthomonas oryzae* is projected to expand its range by 38%, particularly in high-rainfall tropical zones.

Table 1. Projected Suitable Habitat Range for S. frugiperda and X. oryzae under Different SSP Scenarios and Time Horizons

Species	SSP	Horizon	Projected Range (km^2)	% Change from Baseline
S. frugiperda	245	2021–2040	1,200,000	+18%
S. frugiperda	585	2041–2060	1,800,000	+42%
X. oryzae	370	2021–2040	950,000	+25%
X. oryzae	585	2041–2060	1,400,000	+38%

These findings align with studies validating the use of CMIP6 in biological modeling, where projections correspond with historical patterns and observed biological responses (Narouei-Khandan et al., 2019). However, the models are not without uncertainty. Factors such as species-specific responses, data gaps, and variability in climate outcomes contribute to uncertainty in risk maps. Consequently, adaptive strategies should be based on ensemble predictions and scenario ranges rather than single projections.

Host and Cropping System Shifts

Overlaying pest suitability projections with spatial cropland datasets revealed important trends in exposure risk. Areas with ongoing or planned cropland expansion especially for crops such as maize and rice are often coincident with zones of increasing climatic suitability for pests.

For example, *Spodoptera* species are projected to colonize newly cultivated areas in parts of Central Africa and Southeast Asia where maize production is expanding. These findings emphasize the critical role of land-use change in pest dynamics.

Climate regime changes are also expected to exacerbate crop-specific vulnerabilities. Maize, a staple in many of the affected regions, faces elevated risk under warmer and wetter conditions due to increased susceptibility to pests like *Diabrotica virgifera*. The intersection of climatic and host availability variables amplifies pest establishment probability.

Further analysis highlighted the importance of planting calendar shifts. Earlier planting in response to altered rainfall regimes results in tighter synchrony between pest lifecycles and crop phenology, potentially intensifying pest pressures (Skendžić et al., 2021). These shifts must be factored into forecasting models and integrated pest management (IPM) strategies.

Moisture and Climate Extremes Influence

Moisture-related indicators, particularly SPI anomalies, were evaluated for their relationship with pest outbreaks. Strong correlations were observed between high SPI values (indicating above-normal rainfall) and increased incidence of fungal diseases such as rusts and leaf blights, particularly in cereal crops (Wei et al., 2019). These findings support the use of SPI as a predictive variable in fungal pathogen risk modeling.

Extreme temperature events such as heatwaves and prolonged dry spells significantly influenced pest dynamics. Heatwaves were shown to accelerate reproduction rates and shorten developmental cycles of many insect pests, while drought conditions often stressed crops and reduced their resistance to infestations (Skendžić et al., 2021). These dynamics introduce temporal unpredictability in pest behavior and demand flexible, climate-informed management.

To quantify these risks, threshold indices such as Relative Humidity (RH) and Vapor Pressure Deficit (VPD) were incorporated into the analysis. These indices provide biologically relevant thresholds for pathogen development, improving the ecological realism of the models (Wei et al., 2019). Furthermore, statistical analysis demonstrated that outbreak windows were strongly correlated with the frequency of extreme weather events. High-frequency events led to pest population surges, reinforcing the role of climate extremes in shaping pest epidemiology.

The findings of this study confirm that climate change is fundamentally reshaping the distribution and intensity of agricultural pest and disease outbreaks through multiple, interacting mechanisms. By employing biologically relevant climate indicators and modeling pest distributions under a range of socio-economic scenarios, the analysis contributes to the growing body of research that links environmental variability to emerging risks in food production systems. However, the complexity of ecological systems, combined with the inherent limitations of predictive modeling, calls for a cautious and context-aware interpretation of results.

One of the central challenges in climate-driven pest modeling lies in its oversimplification of complex ecological interactions. Many SDMs are built on the assumption of direct climate-species relationships, often overlooking interactions with natural predators, competitors, and habitat factors that can modulate pest populations. This simplification, while necessary for computational feasibility, can limit the ecological realism of projections (Eigenbrode & Adhikari, 2023). More advanced ecological models that incorporate trophic interactions and habitat dynamics are necessary to improve accuracy, but they require significant data and technical capacity that may not be available across all regions.

Another critical limitation is the quality and completeness of input data. The reliance on historical climate records and presence-only occurrence data (e.g., GBIF) introduces biases, particularly in under-sampled or data-poor regions (Klinges et al., 2024). These data limitations can lead to underestimation or overestimation of pest suitability in certain areas, affecting the reliability of spatial forecasts. Additionally, pest data are often collected under varying protocols, and reporting practices differ across countries, further complicating global-scale assessments (Eigenbrode & Adhikari, 2023).

The uncertainty associated with future projections also presents a major constraint. Differences among Shared Socioeconomic Pathways (SSPs) reflect divergent trajectories in emissions, policy, and development. This variability leads to a wide range of possible pest distributions, making it difficult to offer universal recommendations. For instance, while SSP585 consistently predicted the most significant expansions in pest habitat, lower-emission scenarios like SSP126 yielded more moderate outcomes. Decision-makers must therefore plan for a range of possibilities rather than rely on deterministic forecasts.

Despite these challenges, the use of derived climate indicators has proven advantageous over raw averages in ecological modeling. Indicators such as Growing Degree Days (GDD), heat stress thresholds, and Standardized Precipitation Index (SPI) offer deeper insight into pest life cycle triggers and stress responses than raw monthly means (Wu et al., 2023). These metrics capture critical thresholds that affect pest physiology and development, improving the precision and utility of risk assessments. Moreover, their contextual relevance enhances model applicability at local scales, where microclimatic variations are often more influential than regional averages (Klinges et al., 2024).

Given the increasing availability of real-time climate data and technological advances in remote sensing and geographic information systems (GIS), there is substantial opportunity to improve pest forecasting systems. Integrating climate data with historical occurrence records and socio-economic datasets can produce more robust, multi-dimensional models that account for both environmental and human factors (Pratap et al., 2024; Raza et al., 2019). Machine learning algorithms that update dynamically with incoming data can further refine predictions and support adaptive management.

Real-time systems like agro-meteorological platforms already demonstrate the value of timely climate information for decision-making in agricultural operations (Amith et al., 2022). These systems help optimize the timing of pest control measures, planting schedules, and irrigation based on near-term weather forecasts, thus translating scientific models into practical tools. However, the effectiveness of such systems depends on their accessibility, the reliability of local weather data, and the willingness of stakeholders to adopt and integrate such tools into routine practice.

Another key recommendation is to foster interdisciplinary collaboration. Pest modeling is inherently multidisciplinary, requiring input from climatologists, ecologists, agronomists, data scientists, and local farming communities. Collaborative research designs ensure that models are not only scientifically sound but also grounded in practical realities and stakeholder needs (Feit et al., 2019). This transdisciplinary approach enhances model interpretability, uptake, and impact.

New technologies also provide opportunities to overcome modeling limitations. For example, remote sensing tools can generate high-resolution data on vegetation cover, crop health, and environmental stressors, which can be fed into ecological models to improve spatial accuracy (Semeraro et al., 2023). These technologies enable researchers to monitor pest-prone areas in near real-time, facilitating more responsive interventions. Additionally, socio-economic variables such as land use change, infrastructure development, and farming practices must be increasingly integrated into pest risk models, as they directly influence pest dynamics and management capacity (Abbass et al., 2022).

Ultimately, while climate-driven pest modeling presents considerable potential, its effective application hinges on continuous refinement of inputs, methodologies, and cross-sectoral collaboration. The complexity of pest ecology under climate stressors necessitates flexible, scalable, and context-sensitive forecasting systems. This study highlights the importance of adopting biologically informed climate metrics, integrating cropping system dynamics, and supporting model outputs with high-resolution data and stakeholder engagement. Together, these strategies can enhance the predictive power and practical relevance of pest risk assessments, contributing to resilient agricultural systems in a changing climate.

CONCLUSION

This study provides compelling evidence that climate change is actively reshaping the spatial and temporal dynamics of agricultural pests and diseases through complex interactions involving temperature, moisture, and extreme weather patterns. Using a climate-informed modeling framework, we demonstrated how biologically relevant indicators such as Growing Degree Days, Standardized Precipitation Index, and heat threshold exceedance can effectively capture the ecological thresholds critical to pest development and distribution. These indicators, when integrated into Species Distribution Models (SDMs), offer more accurate and locally relevant projections than conventional raw climate variables.

Historical analyses showed a clear correlation between warming trends and northward or altitudinal shifts in pest ranges, notably in species like Spodoptera frugiperda and Helicoverpa armigera. Future projections, particularly under high-emission scenarios (e.g., SSP585), forecast significant range expansions, potentially exposing new agroecosystems to heightened pest pressure. These trends were further amplified when coupled with cropping system changes, such as the expansion of maize and rice cultivation into climatically suitable zones. Moisture variability and climate extremes captured through SPI and heatwave indices emerged as key drivers in triggering outbreak windows and enhancing pest reproductive cycles.

The study also acknowledges several limitations, including ecological oversimplifications, biases in occurrence data, and uncertainties inherent in climate scenario projections. Despite these challenges, the integration of high-resolution climate data, refined ecological indicators, and cropping system overlays establishes a valuable methodological framework for climate-driven pest risk assessment.

Scientifically, this research contributes to the growing body of literature advocating for dynamic, multi-layered approaches to pest forecasting. By bridging climatology, plant pathology, and agroecological modeling, it advances the precision and applicability of pest risk maps under climate change scenarios. Practically, the findings offer guidance for policymakers, researchers, and extension services in designing early warning systems, spatial targeting of interventions, and climate-resilient crop management strategies.

Looking forward, future research should explore ensemble modeling approaches that incorporate trophic interactions, real-time data assimilation, and socio-economic variables. Such developments will be essential to capturing the full spectrum of climate-pest dynamics and ensuring adaptive capacity in agricultural planning. Ultimately, the ability to anticipate and manage climate-driven pest threats will be central to safeguarding global food systems in an increasingly unstable climate.?

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