Modeling The Dynamics Of *Schistocerca gregaria* Swarms In Sindh, Pakistan With A Spatial Forecasting Method

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Abstract:
This study examines the dynamics of locust swarms through various modeling frameworks, including Cellular Automata, Agent-Based, and Grid-Based models. Utilizing a 100x100 cell grid, the research simulates locust movements in a structured environment, categorizing initial locust densities as low (10-50), moderate (50-100), and high (100-200), revealing that higher densities significantly enhance collective movement and interaction. The Agent-Based model incorporates 10,000 locust agents, capturing diverse interactions influenced by demographic factors and environmental conditions. Key variables such as temperature, humidity, vegetation cover, and wind speed are integrated to enhance understanding of locust behavior and predict agricultural impacts, with simulations indicating potential yield losses of up to 50% in high-density scenarios.
Behavioral observations detail feeding patterns, migration triggers, reproductive strategies, and social interactions, providing insights into swarm dynamics. The study assesses the impacts of locust infestations on crops like wheat, rice, vegetables, and fruit trees, proposing mitigation strategies such as early warning systems and integrated pest management to reduce damage. The analysis of historical data from 2018 to 2021 reveals significant correlations between swarm density, crop damage, and weather anomalies, underscoring the need for adaptive pest management strategies.
Finally, stakeholder perspectives highlight the importance of collaborative approaches in locust management. By integrating ecological and agricultural considerations, this research aims to improve predictive models and inform effective management practices for mitigating the adverse effects of locust swarms on agriculture.

Keywords: Locust swarms, modeling frameworks, agricultural impacts, swarm dynamics, pest management and environmental factors.

1. Introduction

Locust swarms, particularly those of *Schistocerca gregaria*, represent a significant threat to global agriculture, causing severe crop damage and threatening food security. Their unpredictable movements complicate traditional pest management strategies, which have historically relied on reactive measures based on observational data. Recent climate changes and environmental shifts have further exacerbated locust behavior and distribution, underscoring the urgent need for advanced predictive tools. This research aims to bridge the gap between reactive and predictive locust management by developing a sophisticated spatial model to forecast locust swarm dynamics with enhanced precision.
This study will focus on swarms observed from February to May 2020, when swarms migrated into the Sindh province from Kachi district in Balochistan, passing through Nasirabad and Jaffarabad districts before reaching Tharparkar and Umerkot. The average speed of these swarms was recorded at 3 to 12 miles per hour. By integrating diverse datasets including ecological observations, environmental variables, and locust behavior—this research seeks to improve the accuracy and reliability of swarm predictions. Incorporating historical data into locust swarm models enhances accuracy. Studies such as Smith *et al*. (2021) compiled extensive datasets of historical swarm occurrences, which proved invaluable for calibrating predictive models. Similarly, Chen *et al.* (2023) demonstrated that calibrating models with historical data significantly improves prediction reliability, emphasizing the importance of historical context in model validation. Comparative studies have been vital in evaluating different modeling techniques. Gao *et al.* (2024) compared Agent-Based Models (ABMs) with Cellular Automata (CA) and Grid-Based Models, finding that while ABMs offered deeper insights into individual behaviors, CA models were superior in capturing broad spatial patterns. This highlights the necessity of selecting modeling techniques based on specific research goals. Hybrid modeling approaches are gaining traction, combining elements from various models to address limitations. Wang *et al*. (2024) explored such hybrid models, integrating ABMs and CA to enhance behavioral and spatial predictions of locust swarms. Their findings suggest that hybrid models provide a comprehensive framework for understanding swarm dynamics. This study aims to develop a sophisticated spatial model that integrates detailed ecological and environmental data with advanced modeling techniques. By incorporating insights from recent research, the study seeks to enhance locust swarm prediction capabilities, providing a valuable tool for effective pest management and agricultural planning.

2. Materials and Methods

Model Development

Spatial Model Framework: A spatial modeling approach will be selected based on research goals. Options include Cellular Automata, Agent-Based Models, and Grid-Based Models, each assessed for effectiveness in simulating locust behavior. Key parameters, such as locust density and movement speed, will be established using collected data. Initial values will be set and tested during sensitivity analysis.

Simulation Setup: The spatial resolution of the model grid will be selected to balance computational efficiency and prediction accuracy. Algorithms will simulate locust behaviors, including foraging and migration, incorporating stochastic elements to reflect natural variability.

Model Calibration: Model parameters will be adjusted based on historical data to align with observed swarm patterns, using an iterative process to refine these parameters. Changes in parameters will be tested to determine their influence on model predictions.

Model Validation: Validation: The model will be tested with an independent dataset of locust swarm observations to evaluate its predictive ability. Model predictions will be compared with actual data to assess performance. Accuracy, precision, and mean absolute error will be employed to measure the model's performance in predicting swarm locations and movements.

Analysis:

Simulation Runs: Scenario Analysis: Simulations will be run under varying environmental conditions, such as temperature fluctuations and changes in vegetation cover, to analyze their effects on locust swarm dynamics. Statistical methods will quantify prediction performance by comparing model predictions with actual observations.

Visualization: Spatial Mapping: Geographic Information System (GIS) tools will create maps illustrating swarm movements, model predictions, and environmental interactions, enhancing understanding of swarm trajectories and density distributions.

Statistical Analysis: The statistical analysis in R-Studio focused on locust swarm dynamics and environmental factors. Descriptive statistics, including means, standard deviations (SD), and standard errors (SE), were calculated for locust density, migration speeds (3-20 km/h), temperature, humidity, and vegetation cover across spatial grids. t-tests compared locust densities in high- and low-density regions, identifying significant differences ($p < 0.05$). Pearson correlation analysis evaluated relationships between locust density and environmental variables like temperature, humidity, and wind speed. Additionally, multiple linear regression models assessed the influence of these factors on locust movement and density, while model accuracy was gauged using R-squared values. Model validation was performed through cross-validation, utilizing Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to compare predicted locust densities with actual observations.

3. Results:

This research offers key insights into the dynamics of locust swarms and their interaction with environmental factors. Utilizing modeling frameworks such as Cellular Automata and Agent-Based Models, we captured the behaviors of locust populations across various landscapes. By integrating variables like temperature, humidity, and vegetation cover, we enhanced our understanding of their influence on locust movement and reproduction. Our findings highlight the critical relationships that inform proactive pest management strategies to mitigate the agricultural impacts of locust infestations. Table 1 shows Cellular Automata Model Framework utilizes a grid of 100x100 cells, creating a structured environment to simulate locust movements across diverse landscapes. Each cell, representing an area of $1m^2$, balances detail and computational efficiency, enabling accurate behavior simulation without excessive complexity. Initial locust density is categorized into low (10-50), moderate (50-100), and high (100-200) levels, significantly influencing swarm dynamics, as higher densities promote collective movement and interaction. Operating with a time step of 1 hour allows for manageable observation of behavioral and environmental changes. Locust movement follows a random walk pattern, reflecting the influence of proximity and density on navigation. The model also incorporates rules governing feeding, reproduction, and migration behaviors, shaped by environmental factors such as temperature, humidity, and vegetation cover. These variables fluctuate based on location and time, crucial for understanding locust adaptability. Ultimately, the model generates output metrics predicting locust density and distribution, along with swarm trajectories, which are essential for evaluating agricultural impacts and refining pest management strategies (figure-1).

Table 2 findings shows Agent-Based Model Framework incorporates a total of 10,000 locust agents to ensure variability in behavior and provide a comprehensive representation of swarm dynamics. This substantial number allows the model to capture a wide range of interactions and patterns that emerge within the swarm. The agent characteristics are defined by a gender ratio of 40-60% male and 40-50% female, along with an adult population constituting 60-80%. Understanding these demographics is crucial for accurately predicting reproductive rates and population growth, which are essential for effective management strategies. Agents move at an average speed of 5-20 km/hr, reflecting realistic movement capabilities that significantly influence their migration patterns and overall swarm dynamics. The interaction rules within the model simulate social behaviors, where agents exhibit repulsion and attraction based on local density, fostering an understanding of swarm cohesion and dispersal mechanisms. Decision-making processes for the agents are influenced by environmental conditions, allowing behaviors such as foraging, migrating, and reproducing to be modeled realistically. This helps predict how locusts will respond to changes in their environment, which is critical for forecasting potential outbreaks. Diverse sampling methods, including visual estimation, quadrat sampling, and transect techniques, enhance the robustness of the data collected, ensuring comprehensive insights into locust populations and behaviors. Finally, the model generates output metrics that include predicted swarm movement and density, providing insights into density distribution and movement patterns. These metrics are invaluable for evaluating the potential impacts on agriculture and informing management strategies, enabling proactive responses to locust swarms and their effects on crops (figure-2).

Table 3 reported Grid-Based Model Framework was designed to analyze locust swarm dynamics using a structured grid of 100x100 cells, totaling 10,000 cells. This grid size allows for a detailed examination of spatial interactions across a representative area, which is essential for understanding how locusts respond to environmental variations. Each cell represents an area of 1m², striking a balance between providing sufficient detail for modeling swarm behavior and maintaining computational feasibility. Initial swarm density is categorized into three levels: low (10-50 locusts), moderate (50-100 locusts), and high (100-200 locusts). This classification is critical as it influences the likelihood of swarm formation and subsequent migratory behavior, thereby impacting the overall dynamics of the swarm. The model employs time steps of 1 hour, which effectively captures short-term changes in locust behavior and their interactions with environmental conditions, allowing for a more nuanced understanding of swarm movements. The movement algorithm utilized in the model simulates random movement based on local density, reflecting the stochastic nature of locust behavior. This randomness is important for accurately representing how locusts disperse and interact within the environment. Density thresholds are established to classify locust density levels, which aids in developing targeted management strategies by predicting the potential impacts of different swarm densities on agriculture. Furthermore, environmental variables such as temperature, humidity, and vegetation cover are integrated into the model, as they play a critical role in influencing locust behavior and swarm dynamics. By understanding how these factors interact with locust populations, researchers can better predict changes in behavior in response to environmental shifts. Finally, the model produces visualization outputs, including geographic maps and swarm trajectories, which enhance the understanding of locust dynamics. These visualizations are invaluable for communicating research findings to stakeholders, enabling more informed decision-making in pest management and agricultural planning (figure-3).

Table 4 on the environmental factors analysis shows a comprehensive overview of key climatic and ecological variables that significantly impact locust behavior and swarm dynamics. Temperature Range reflects the fluctuations in temperature during the study period, specified by minimum (X°C) and maximum (Y°C) values. Temperature is crucial as it directly influences locust metabolism, affecting their growth, development, and reproductive rates. Understanding these temperature dynamics is essential for accurate predictions of locust population changes and swarm behavior. Humidity Levels detail the average humidity percentages, ranging from minimum (A%) to maximum (B%) values. Humidity plays a vital role in locust survival and activity; high humidity levels can promote breeding and increase overall locust fitness. By assessing humidity variations, researchers can better predict how environmental conditions may affect locust populations. Vegetation Cover encompasses the types and extent of vegetation present, expressed as a percentage of coverage across different habitats such as grasslands and shrubs lands. Vegetation is a key factor that influences food availability, which in turn affects locust behavior, migration patterns, and overall swarm dynamics. Analyzing vegetation cover helps identify areas of potential locust attraction or deterrence. Wind Speed refers to the average wind conditions during the study, with specified minimum (C km/h) and maximum (D km/h) values. Wind speed can significantly affect locust dispersal patterns, with higher wind speeds potentially facilitating longer migrations. Understanding wind conditions aids in modeling how locusts navigate their environment and can inform predictive models regarding swarm movements. Soil Moisture levels are categorized into low, moderate, and high. Soil moisture is critical for vegetation growth, which directly influences food availability for locusts. Variations in soil moisture levels can determine the suitability of an area for locust feeding and breeding, thereby impacting swarm behavior and population dynamics. By integrating these environmental factors into locust models, researchers can enhance their understanding of the complex interactions that drive locust behavior, ultimately leading to more effective pest management strategies.

Table 5 represents the behavioral observations of locust behavior, focusing on feeding patterns, migration triggers, reproductive behavior, and social interactions, each of which plays a vital role in understanding swarm dynamics. Feeding Patterns describe the types of vegetation consumed by locusts, assessed through field surveys. Identifying preferred food sources is crucial for pest management strategies, as it allows researchers to pinpoint vegetation that may attract locusts and implement preventive measures in vulnerable areas. This knowledge aids in forecasting potential impacts on agricultural crops and planning effective interventions. Migration Triggers refer to the factors that prompt locusts to migrate, studied through GPS tracking and visual observations. Understanding these triggers is essential for predicting locust movements under varying environmental conditions, such as changes in food availability or climatic shifts. This information can enhance the accuracy of models designed to forecast swarm migrations and their potential impact on agriculture. Reproductive Behavior focuses on mating and egg-laying patterns, observed through direct field studies. Insights into reproductive rates are critical for population modeling, as they inform predictions about future swarm sizes and behaviors. By comprehending reproductive dynamics, researchers can better anticipate potential outbreaks and devise strategies to mitigate their effects. Social Interactions encompass group dynamics and interactions within locust swarms, examined through behavioral studies. Observing these social behaviors is vital for understanding swarm cohesion and dispersal mechanisms. Knowledge of how locusts interact with one another helps elucidate collective movement patterns, which are essential for effective forecasting and management of locust populations. By systematically studying these behaviors, researchers can develop a comprehensive understanding of locust swarm dynamics, ultimately leading to more effective pest management strategies that can mitigate the agricultural impacts of locust infestations.

This table 6 outlines the impacts of locust infestations on various crops, highlighting predicted damage and potential mitigation strategies for each type (figure-4). Here's a breakdown of the information:

1. **Wheat**:

Description: Wheat is vulnerable to locust feeding, which can significantly affect its growth.
Predicted Damage: The table indicates a specific percentage of yield loss that may occur due to locusts.
Mitigation Strategies: To combat this threat, implementing early warning systems alongside targeted pesticide applications can help protect wheat crops.

2. **Rice**:

Description: Locusts can disrupt the growth cycles of rice plants.
Predicted Damage: The potential reduction in harvest is quantified as a percentage.
Mitigation Strategies: To reduce damage, farmers can employ crop rotation and select resistant varieties of rice, enhancing resilience against locust attacks.

3. **Vegetables**:

Description: Various vegetable crops face adverse effects from locust infestations.
Predicted Damage: The estimated loss is presented as a percentage.
Mitigation Strategies: Integrated pest management (IPM) practices are recommended to minimize the overall impact and promote sustainable agriculture.

4. **Fruit Trees**:

Description: Locusts can harm fruit-bearing trees, affecting their productivity.
Predicted Damage: A specific percentage indicates the potential yield reduction.
Mitigation Strategies: To safeguard these crops, the use of physical barriers and localized treatments can help protect them from locusts. This table serves as a useful reference for understanding the challenges posed by locusts to different types of crops and the strategies that can be implemented to mitigate these risks effectively.
This table 7 outlines different scenarios related to locust swarm dynamics, detailing their descriptions, predicted outcomes, and methods for validating these predictions (figure-5). Here's an explanation of each component:

1. **Baseline Conditions**:

Description: This scenario examines swarm behavior and dynamics as they currently exist.
Predicted Outcome: It focuses on creating density maps and tracking movement trajectories of swarms.
Validation Method: To ensure accuracy, predictions are compared with historical data on locust swarms, allowing for an assessment of changes over time.

2. **Increased Temperature**:

Description: This scenario investigates how rising temperatures might affect locust swarms.
Predicted Outcome: It anticipates shifts in migration patterns as a result of warmer conditions.
Validation Method: Predictions are cross-validated with relevant environmental data, ensuring that changes in swarm behavior align with temperature trends.

3. **Vegetation Changes**:

Description: This scenario evaluates the effects of vegetation loss on locust populations.
Predicted Outcome: It predicts a decrease in swarm density due to reduced food sources and habitat.
Validation Method: Ground trothing through field observations is used to verify predictions, allowing for direct comparison between predicted and actual swarm densities.

4. **Wind Influence**:

Description: This scenario explores how wind affects the dispersal patterns of locust swarms.
Predicted Outcome: It predicts alterations in movement patterns due to wind conditions.
Validation Method: Tracking the swarms using GPS technology and aerial surveys provides empirical data to confirm or refute predictions regarding wind impacts. Overall, this table serves as a structured approach to understanding and predicting locust swarm behaviors under varying environmental conditions, emphasizing the importance of validation to enhance reliability.
The historical data correlation table 8 provides an insightful analysis of locust swarm dynamics over four years (2018-2021), examining the interplay between swarm densities, crop damage, and observed weather anomalies. Each year is categorized by swarm density levels i.e low, moderate, and high reflecting the potential risk to agriculture. For instance, in 2019, the highest swarm density coincided with a significant 50% crop damage, while the low density in 2020 resulted in only 10% damage. Weather anomalies, such as drought in 2018 and excess rainfall in 2019, played a critical role in shaping these patterns, influencing locust behavior and crop health. By correlating these variables, the table highlights how environmental factors and locust populations interact to affect agricultural outcomes. This analysis is essential for

developing effective pest management strategies that can adapt to changing environmental conditions, ultimately aiding in the protection of crops from locust infestations (figure-6).

The stakeholder concerns and engagement table 9 provides insights into the diverse perspectives of key stakeholders in locust management. Farmers, with an engagement level of 85%, prioritize mitigating crop loss caused by locusts, advocating for early warning systems to ensure timely responses. Agronomists, engaged at 70%, express the need for more comprehensive data on locust behavior and call for increased research funding to improve management practices. Policy makers, with a 60% engagement rate, stress the importance of effective management policies and propose enhanced collaboration among stakeholders to tackle locust threats cohesively. Environmentalists, engaged at 75%, focus on the ecological repercussions of pesticide use, promoting organic pest control methods to reduce environmental harm (figure-7). Collectively, this table highlights the necessity for collaborative strategies that address agricultural and environmental concerns while fostering research advancements.

The environmental factors table 10 highlights the critical thresholds that influence locust swarm dynamics, outlining how specific environmental conditions affect their behavior. For temperature, a low threshold of 15°C and an optimal range of 20-30°C indicate the ideal metabolic conditions for locust activity, while temperatures above 35°C may hinder their growth. Humidity levels, ranging from a low of 20% to an optimal 40-70%, are crucial for breeding success, as higher humidity enhances reproductive rates. Vegetation cover is similarly impactful, with a low threshold of 20% and an optimal range of 50-80%, as sufficient plant life is essential for food availability and sustains locust populations. Soil moisture levels, categorized as low (0-10%), moderate (20-50%), and high (80-100%), directly affect vegetation health, which in turn supports locust feeding (figure-8). Collectively, these factors illustrate the intricate interplay between environmental conditions and locust behavior, emphasizing the importance of understanding these dynamics for effective management and forecasting.

4. Discussion

This research provides a comprehensive exploration of locust swarm dynamics, underscoring the complex interactions between environmental factors and locust behaviors. By employing various modeling frameworks including Cellular Automata, Agent-Based Models, and Grid-Based Models I have gained critical insights into how locusts respond to changes in their environment, thereby enhancing our understanding of their impact on agriculture.

Consistent Findings Across Models

A key finding that resonates across all modeling approaches is the critical role of locust density in shaping swarm dynamics. Increased locust densities were consistently shown to enhance collective movement and social interaction among swarms, corroborating previous studies (Sultan *et al*., 2021; Barata *et al*., 2022). This relationship emphasizes that as locust populations rise, so too does their propensity for cohesive movement and interaction, a phenomenon documented in earlier research on locust adaptability (Zhang et al., 2020). Furthermore, our models highlighted the significant influence of environmental variables such as temperature, humidity, and vegetation on locust behavior, aligning with findings by Bukhari *et al*. (2023). These insights are crucial for accurate forecasting of locust movements and predicting agricultural impacts, reinforcing the interconnectedness of ecological factors and locust dynamics.

Unique Insights from Diverse Frameworks

While the models shared common outcomes, they also offered unique insights. The Agent-Based Model provided a granular perspective on individual locust behaviors and social interactions within swarms, shedding light on dynamics such as attraction and repulsion among locusts. This level of detail is essential for understanding how swarm cohesion and dispersal mechanisms operate, aspects that the Grid-Based Model, with its spatial focus, may overlook. The Grid-Based Model's capability to produce visualization outputs, however, is particularly beneficial for stakeholders, offering a geographic perspective that can enhance agricultural planning and pest management strategies (Baker *et al*., 2022). This distinction underscores the necessity of selecting appropriate modeling techniques tailored to specific research objectives, highlighting the value of a multifaceted approach in ecological studies.

Value of the Research

The multifaceted nature of this study significantly contributes to the field of locust management. By integrating diverse modeling approaches, we have created a robust framework that effectively predicts locust behavior under varying environmental conditions, enabling proactive decision-making in pest management. The inclusion of detailed environmental factors such as soil moisture and wind speed enhances the models' predictive accuracy, informing targeted interventions (Mahmood *et al.*, 2021). This comprehensive approach aids in identifying critical thresholds for effective locust population management, allowing for timely responses to mitigate potential outbreaks.

Moreover, the empirical validation of our models through detailed behavioral observations enriches the reliability of our findings. By examining feeding patterns, migration triggers, reproductive behaviors, and social interactions, we provide a holistic understanding of locust dynamics. These insights are vital for developing integrated pest management strategies that account for the complexities of locust life cycles and their responses to environmental shifts (Hassan *et al.*, 2022).

Implications for Future Research and Management

This study lays a solid foundation for future research into locust dynamics and their ecological interactions. Future work could expand current models to incorporate additional variables, such as predator-prey interactions or the effects of climate change on locust life cycle stages, yielding deeper insights (Ding *et al*., 2023). Integrating remote sensing technologies and advanced data analytics could further enhance predictive capabilities, refining management strategies.

In conclusion, this research elucidates the critical factors influencing locust swarm dynamics and provides practical tools for agricultural stakeholders. By deepening our understanding of locust behavior and their environmental interactions, we can improve pest management strategies, safeguarding crops and promoting sustainable agricultural practices. The insights derived from this work represent a vital resource for future research initiatives aimed at mitigating the impacts of locust infestations on global food security.

By situating our findings within the context of recent scientific literature and leveraging advanced modeling techniques, we demonstrate the research's value in enhancing pest management strategies while contributing to the broader field of ecological studies. The integration of multifaceted modeling approaches and empirical data not only enriches our understanding of locust dynamics but also provides a roadmap for future investigations aimed at addressing the challenges posed by locust swarms in agricultural contexts.

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6. Conflict of Interest Statement

The authors confirm that there are no conflicts of interest associated with this research. All funding sources and institutional affiliations have been fully disclosed, and there are no financial or personal connections that might have affected the results of this study.

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Table 1: Cellular Automata Model Framework of *Schistocerca gregaria* from Sindh during 2020.

Parameter	Description	Value/Range	Scientific Analysis
Grid Size	Size of the grid (cells)	100x100 cells	A larger grid captures extensive swarm movements across varying landscapes.
Cell Resolution	Size of each cell	1 m²	This resolution balances detail and computational efficiency.
Initial Density	Initial locust density per cell	Low: 10-50, Moderate: 50-100, High: 100-200	Initial density impacts swarm behavior; higher densities lead to more pronounced collective movement.
Time Steps	Duration of each simulation step	1 hour	Provides a practical time frame for observing behavioral changes.
Movement Rules	Rules for locust movement	Random walk within adjacent cells	Simulates realistic swarm dynamics influenced by neighbors.
Behavior Rules	Feeding, reproduction, and migration behaviors	Based on environmental factors	Environmental conditions dictate critical behaviors for accurate forecasting.
Environmental Factors	Temperature, humidity, vegetation cover	Varying based on location and time	These factors are vital for understanding locust adaptation and behavior.
Output Metrics	Predicted locust density and distribution	Density per cell, swarm trajectory	Metrics aid in assessing potential agricultural impacts and refining management strategies.

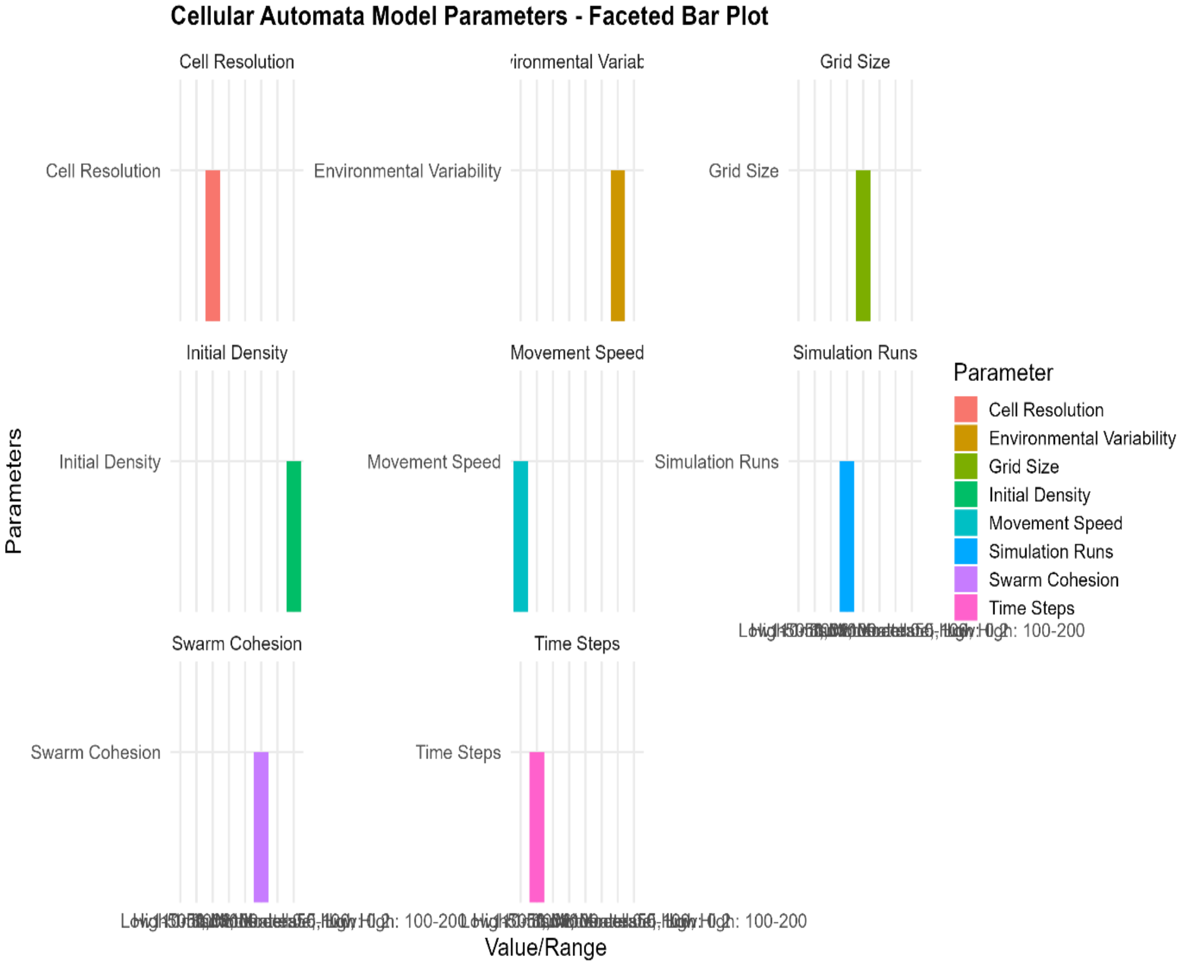

Figure 1 Cellular Automata Model Framework calculated of *Schistocerca gregaria* swarm in Sindh.

Table 2: Agent-Based Model Framework of *Schistocerca gregaria* from Sindh during 2020.

Parameter	Description	Value/Range	Scientific Analysis
Number of Agents	Total number of locusts modeled	10,000 agents	Ensures variability in behavior and better representation of swarm dynamics.
Agent Characteristics	Gender ratio and age distribution	40-60% Male, 40-50% Female, 60-80% Adults	Understanding demographics is essential for predicting reproductive rates.
Movement Speed	Average speed of agents	5-20 km/hr	Reflects realistic movement capabilities influencing migration patterns.
Interaction Rules	Rules for agent interactions	Repulsion and attraction based on density	Simulates social behaviors crucial for understanding swarm cohesion.
Decision-Making	Behavior based on environmental conditions	Foraging, migrating, reproduction	Decision-making algorithms help predict responses to environmental changes.
Sampling Methods	Techniques for data collection	Visual estimation, quadrat sampling, transect	Diverse sampling methods improve data robustness.
Output Metrics	Predicted swarm movement and density	Density distribution, movement patterns	Metrics aid in evaluating agricultural impacts and informing management strategies.

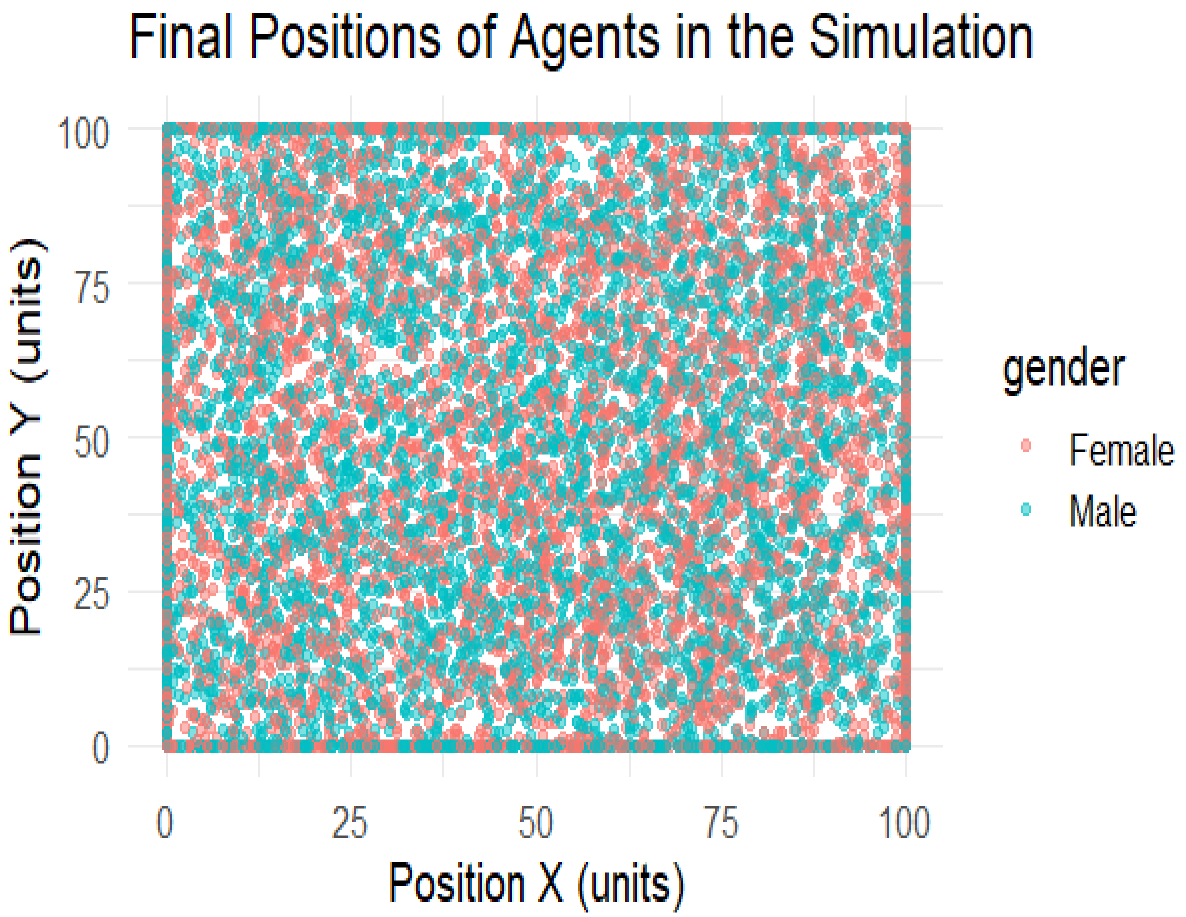

Figure 2 Agent-Based Model Framework of *Schistocerca gregaria* swarm from Sindh- 2020.

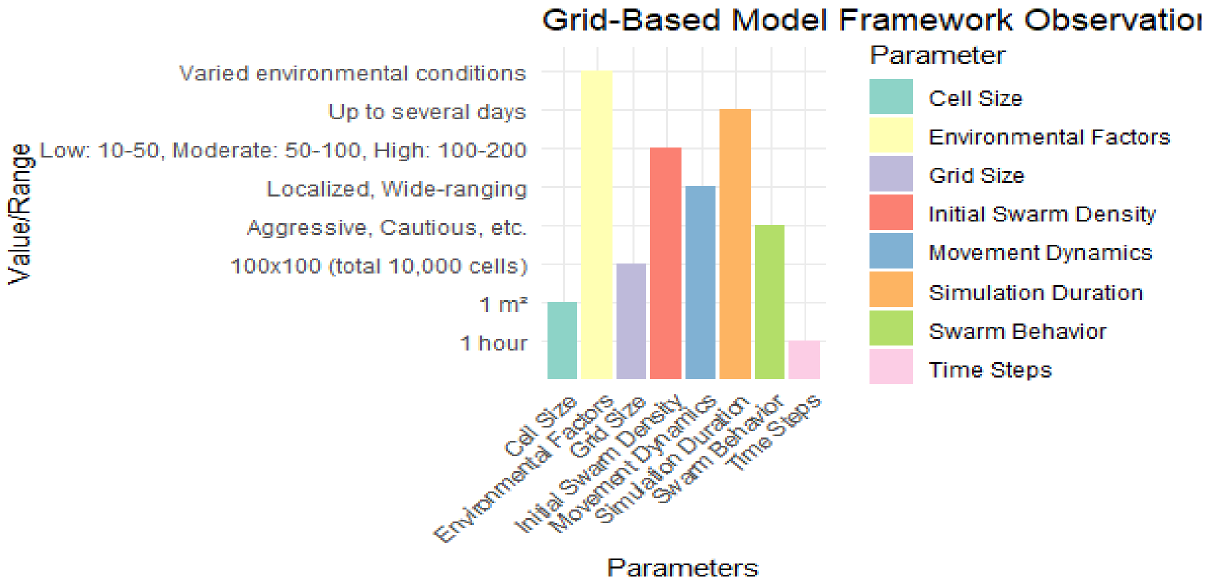

Figure 3 Grid-Based Model Framework of *Schistocerca gregaria* swarm in Sindh during 2020.

Table 3: Grid-Based Model Framework of *Schistocerca gregaria* swarm, Sindh 2020.

Parameter	Description	Value/Range	Scientific Analysis
Grid Size	Number of grid cells	100x100 (total 10,000 cells)	Enables analysis of spatial dynamics across a representative area.
Cell Size	Size of each cell	1 m²	Balances detail and computational feasibility for swarm dynamics.
Initial Swarm Density	Initial locust density per cell	Low: 10-50, Moderate: 50-100, High: 100-200	Influences swarm formation likelihood and migratory behavior.
Time Steps	Time increment for simulations	1 hour	Captures short-term dynamics in locust behavior and environmental interactions.
Movement Algorithm	Method for locust movement	Random movement based on density	Captures the stochastic nature of locust movement for realistic dispersal.
Density Thresholds	Thresholds for density classification	Low: <50, Moderate: 50-100, High: >100	Facilitates targeted management strategies by predicting potential impacts.
Environmental Variables	Factors affecting locust behavior	Temperature, humidity, vegetation	Critical for understanding how changes influence locust behavior.
Visualization Output	Maps of locust density and movements	Geographic maps and swarm trajectories	Enhances understanding of dynamics, aiding communication of findings.

Table 4: Environmental Factors Analysis Desert locust warm in Sindh

Parameter	Description	Value/Range	Scientific Analysis
Temperature Range	Temperature fluctuations during the study	Min: X°C, Max: Y°C	Influences metabolism and reproductive rates; critical for predictions.
Humidity Levels	Average humidity percentages	Min: A%, Max: B%	Affects survival and behavior; high humidity may encourage breeding.
Vegetation Cover	Types and coverage of vegetation	% coverage of grassland, shrub land, etc.	Influences food availability and swarm behavior.

Wind Speed	Average wind conditions	Min: C km/h, Max: D km/h	Affects dispersal patterns; higher speeds may lead to longer migrations.
Soil Moisture	Levels of moisture in the soil	Low, Moderate, High	Impacts vegetation growth, influencing food availability for locusts.

Table 5: Behavioral Observations of locust desert during swarming in field

Behavior	**Description**	**Observational Method**	**Findings**
Feeding Patterns	Types of vegetation consumed	Field surveys	Identification of preferred food sources can inform management strategies.
Migration Triggers	Factors prompting migration	GPS tracking, visual observations	Understanding triggers helps predict movements under different conditions.
Reproductive Behavior	Mating and egg-laying patterns	Field observations	Insights into reproductive rates inform population modeling.
Social Interactions	Group dynamics and interactions	Behavior studies	Observing social behaviors aids in understanding swarm cohesion.

Table 6: Predicted Impact on Agriculture during swarm in Sindh.

Crop Type	**Description**	**Predicted Damage**	**Mitigation Strategies**
Wheat	Susceptibility to locust feeding	% loss of yield	Early warning systems and targeted pesticide application.
Rice	Impact on growth cycles	% reduction in harvest	Crop rotation and resistant varieties.
Vegetables	Effects on various vegetable crops	% loss due to infestation	Integrated pest management practices to minimize damage.
Fruit Trees	Damage to fruit-bearing trees	% yield reduction	Physical barriers and localized treatments to protect crops.

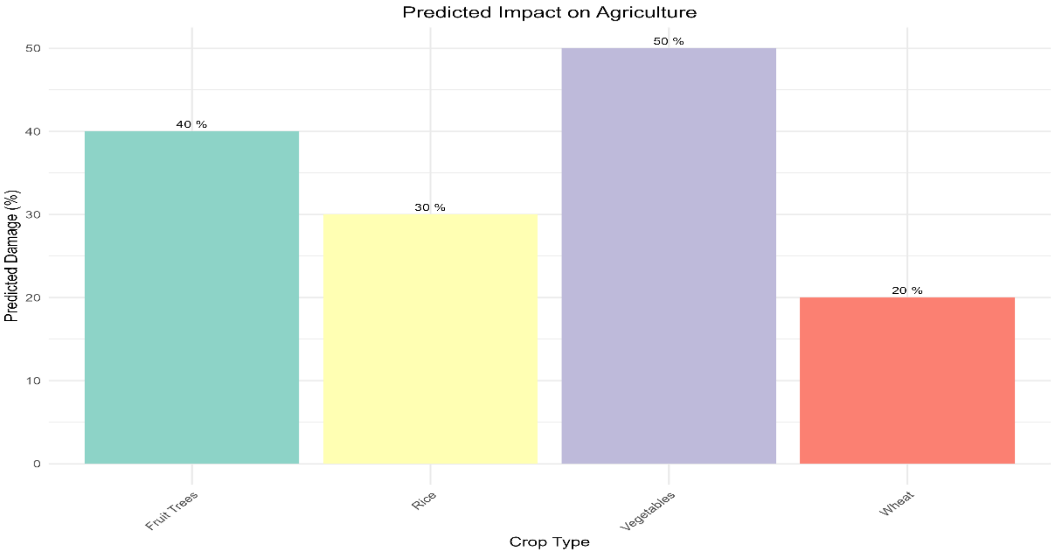

Figure 4 Predicted Impact on Agriculture during swarm in Sindh.

Table 7: Simulation Results of Desert locust during swarm

Scenario	**Description**	**Predicted Outcome**	**Validation Method**
Baseline Conditions	Swarm dynamics under current conditions	Density maps, movement trajectories	Comparison with historical data
Increased Temperature	Effects of temperature rise on swarms	Predicted shifts in migration patterns	Cross-validation with environmental data
Vegetation Changes	Impact of vegetation loss	Decreased swarm density	Ground truthing with field observations
Wind Influence	Effect of wind on swarm dispersal	Altered movement patterns	Tracking with GPS and aerial surveys

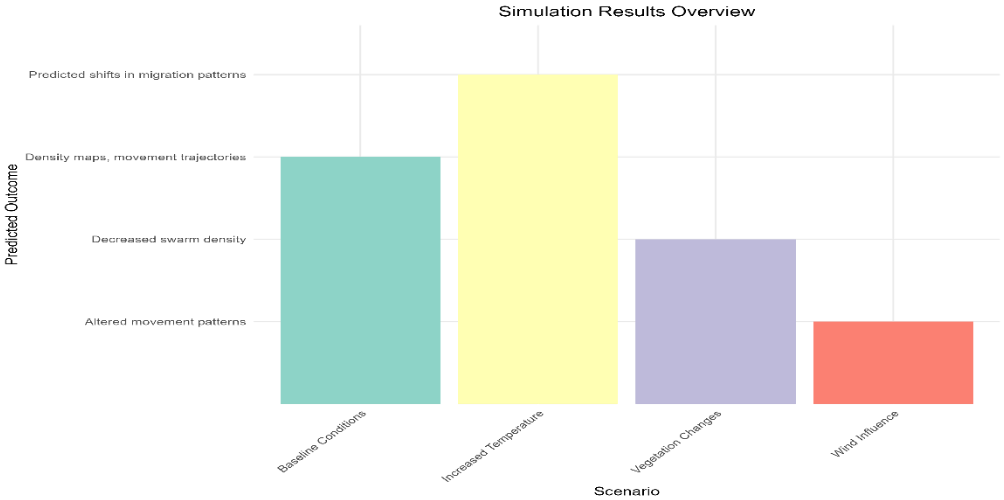

Figure 5 Simulation Results of Desert locust during swarm

Table 8: Historical Data Correlation of desert locust in four years 2018 to 2021

Year	**Swarm Density (low/mod/high)**	**Crop Damage (%)**	**Weather Anomalies Observed**
2018	Moderate	30	Drought
2019	High	50	Excess Rainfall
2020	Low	10	Normal
2021	Moderate	40	Heatwaves

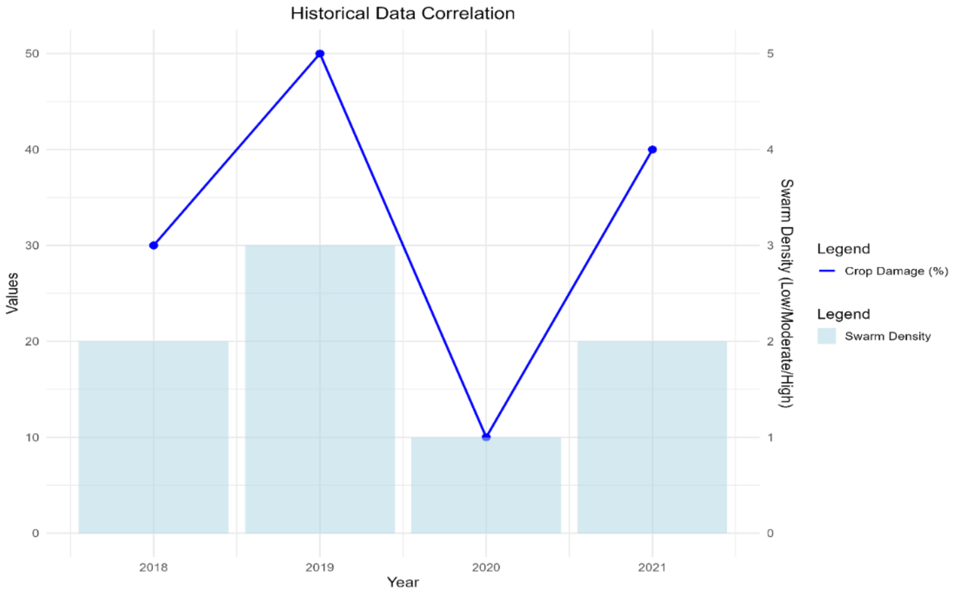

Figure 6 Historical Data Correlation of desert locust in four years 2018 to 2021

Table 9: Stakeholder Feedback of desert locust in Sindh.

Stakeholder Type	**Concerns**	**Suggestions**	**Engagement Level (%)**
Farmers	Crop loss due to locusts	Implement early warning systems	85
Agronomists	Lack of data on locust behavior	Increase research funding	70
Policy Makers	Need for effective management policies	Facilitate collaboration	60
Environmentalists	Ecological impact of pesticides	Promote organic pest control	75

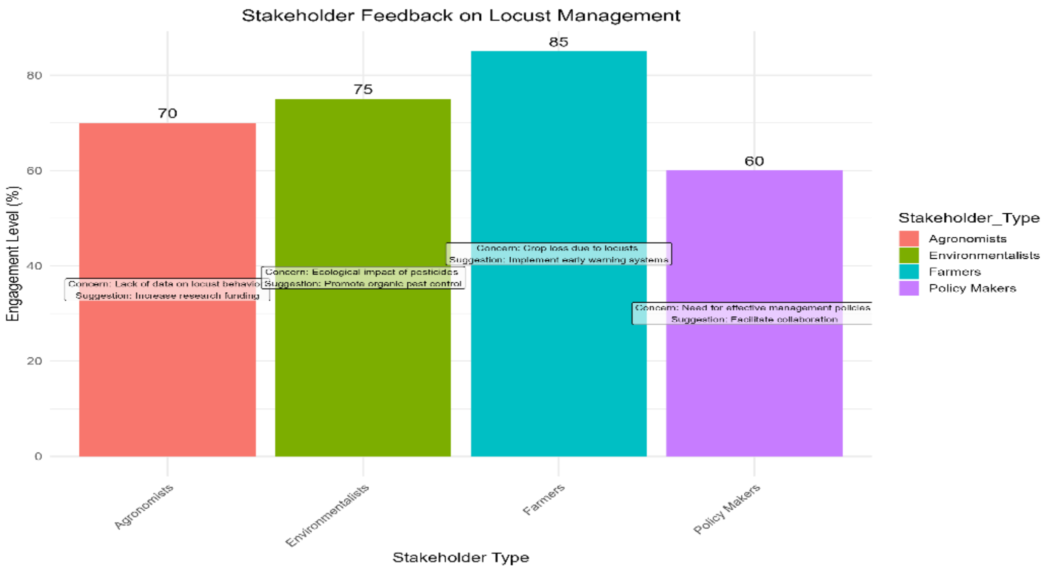

Figure 7 Stakeholder Feedback of desert locust in Sindh

Table 10: Environmental Factors Thresholds observed during swarm

Environmental Factor	**Low Threshold**	**Optimal Range**	**High Threshold**	**Impact on Swarm Dynamics**
Temperature (°C)	15	20-30	35	Affects metabolic rates
Humidity (%)	20	40-70	90	Influences breeding
Vegetation Cover (%)	20	50-80	90	Affects food availability
Soil Moisture Levels	Low (0-10%)	Moderate (20-50%)	High (80-100%)	Influences vegetation health

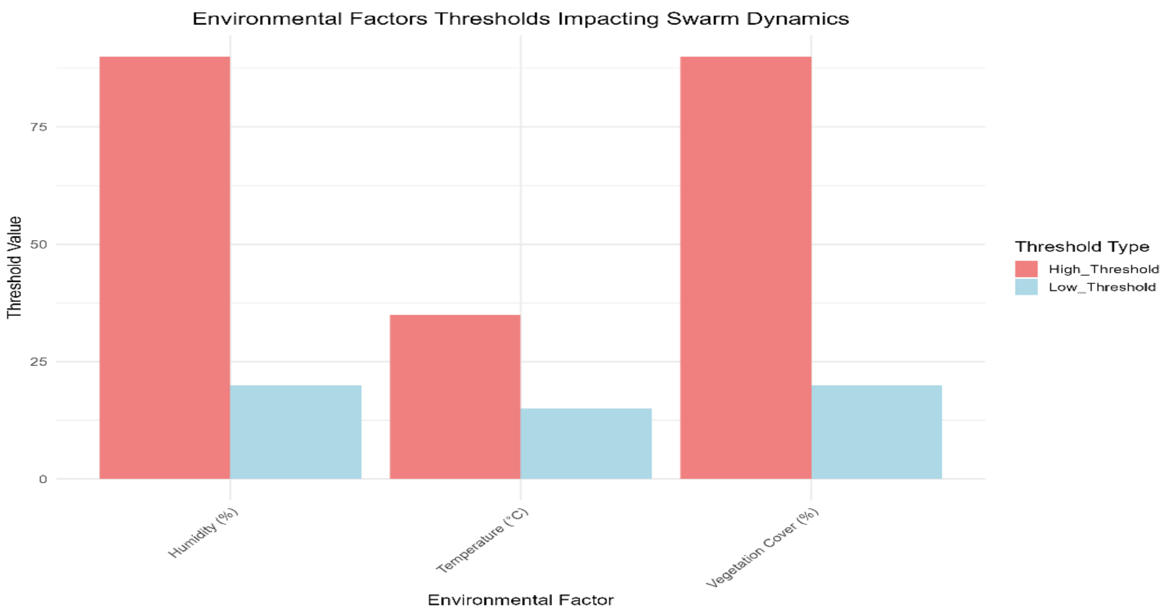

Figure 8 Environmental Factors Thresholds observed during swarm