An integrated assessment of climate change impacts on Asian honey bee behavior, crop yield contribution, and farmer livelihoods with a focus on beekeeping for agricultural sustainability

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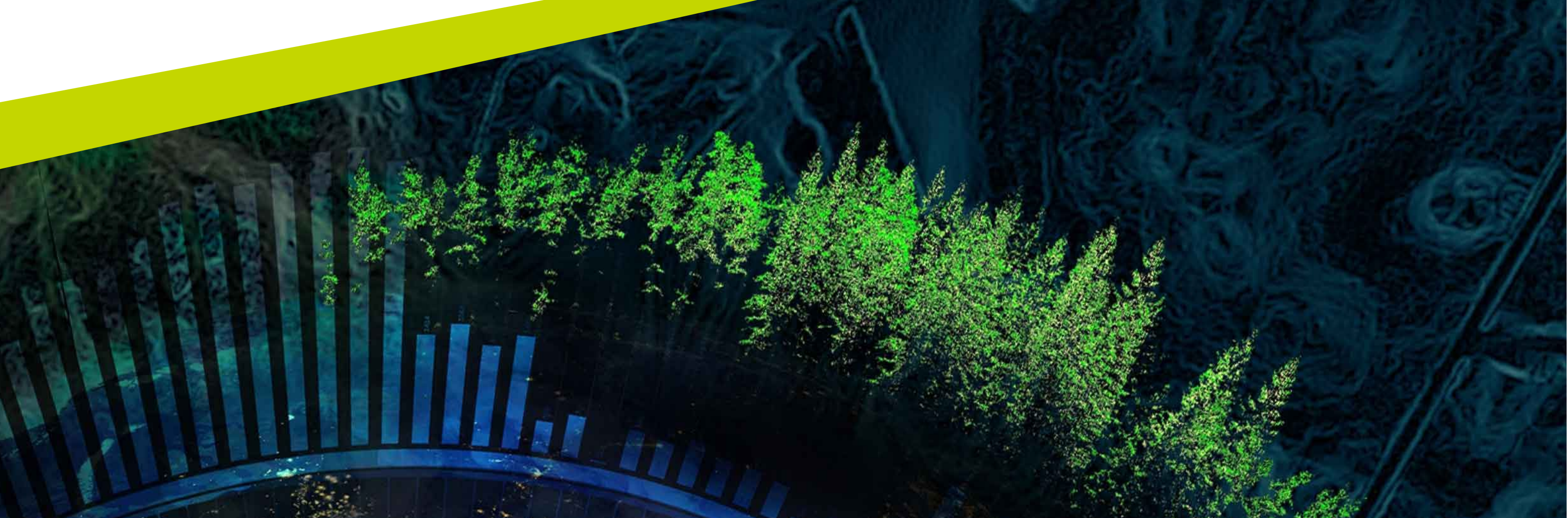
Degree project/Independent project • 30 credits
Swedish University of Agricultural Sciences, SLU
The Faculty of Landscape Architecture, Horticulture and Crop Production Science
Master’s programme in Agricultural science - Agroecology Alnarp 2024



An integrated assessment of climate change impacts on Asian honey bee behavior, crop yield contribution, and farmer livelihoods with a focus on beekeeping for agricultural sustainability

En integrerad bedömning av klimatförändringarnas effekter på asiatiska honungsbins beteende, följaktligen grödans avkastning och jordbrukarnas försörjning med fokus på biodling för hållbar jordbruksproduktion.

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Credits:	30
Level:	Second cycle, A2E
Course title:	Independent project in Agricultural science, A2E – Agroecology – Master's programme
Course code:	EX0848
Programme/education:	Master's programme in Agricultural science - Agroecology
Course coordinating dept:	Department of Biosystems & Technology
Place of publication:	Alnarp, Sweden
Year of publication:	2025
Copyright:	All featured images are used with permission from the copyright owner.
Keywords:	Agent based model, agricultural sustainability ,Asia honey bee, Bee foraging behavior and pollination activity ,Beekeeping, Climate change, crop yield, Sri Lanka

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Foreword

Honey bees stand at the heart of agricultural sustainability, serving as vital agents of pollination and biodiversity maintenance. Their role extends far beyond honey production, underpinning the productivity of countless crops and supporting rural livelihoods worldwide. Yet, climate change has emerged as a profound threat to these pollinators, altering temperature regimes, flowering cycles, and ecological balance. Understanding how such environmental shifts influence honey bee behavior is crucial for safeguarding food systems and ecosystems alike.

This research was conducted in Sri Lanka within the framework of the Master's Programme in Agroecology at the Swedish University of Agricultural Sciences (SLU). During a three-week field visit, data were collected from diverse climatic zones, combining farmer interviews, field observations, and ecological modeling. The study integrates field-based insights, farmer perceptions, and agent-based simulation modeling to present a holistic view of how environmental change is shaping the future of beekeeping and crop production in Sri Lanka. In doing so, it highlights how climate variability particularly temperature fluctuations can influence the behavior of the Asian honey bee (*Apis cerana*), with subsequent implications for pollination dynamics, crop yield, and rural livelihoods.

By blending empirical data with simulation modeling, this thesis seeks to contribute both to scientific understanding and to practical decision-making for sustainable agriculture. The proposed (Decentralized, Empowered, Eco-smart, Participatory Beekeeping Empowerment) represents an innovative framework for developing climate-resilient beekeeping strategies, integrating local knowledge, adaptive technologies, and ecological stewardship.

The preparation of this thesis reflects a journey of intellectual growth, cross-cultural learning, and personal perseverance. It stands as a testament to the collaborative spirit of agroecological research, linking farmers, researchers, and institutions in a shared mission to sustain agricultural ecosystems. It is my hope that the insights presented herein will not only advance academic discourse but also inspire tangible actions toward pollinator conservation and the long-term resilience of beekeeping in Sri Lanka and beyond.

Abstract

Climate change is increasingly disrupting ecological interactions critical to agriculture, with pollinator behavior being an important but still underappreciated concern. Pollinators, particularly honey bees, are vital to global food production and ecological balance. This study used a mixed method approach combining farmer surveys and simulation modelling to investigate how climate change is perceived and predicted to influence the behavior of *Apis cerana* (Asian honey bee) in Sri Lanka, alongside subsequent affects on crop yield and farmer livelihoods reliant on beekeeping. Structured interviews and field surveys were used as primary data collection methods, while secondary data on hive density and crop yield were used for modeling and simulation purposes. Farmer surveys were conducted from seven districts across the country's three major climatic zones (Wet Zone, Intermediate Zone, and Dry Zone) in order to examine farmers' perceptions of Asian honey bee foraging behavior and pollination activity in relation to climate change, and if these differed across climatic zones. An agent-based simulation model using NetLogo was used to explore both past trends and future projections of bee foraging frequency and its impact on crop yield (for pumpkin, cucumber, avocado) under changing temperature conditions across time periods.

Findings from the farmer survey revealed a significant perceived ecological mismatch in the Dry Zone, particularly between crop flowering and pollinator behaviour, while Wet Zone farmers perceived more stable pollination conditions but also reported nectar source decline. The farmer survey also identified regional disparities in climate-adaptive beekeeping practices, with the Dry Zone exhibiting limited modern practices and low awareness. Agent-based modeling confirmed that rising temperatures (especially during 2025–2034) disrupted bee activity and reduced crop yield for all three crops, but particularly in the Dry Zone for pumpkin. However, moderate recovery was projected for 2035–2044 as temperatures stabilized. To address some of the challenges raised in this research, the study proposed the DEEP BEE model (Decentralized, Empowered, Eco-smart, Participatory Beekeeping Empowerment) as a strategic framework to support climate-resilient beekeeping practices in Sri Lanka. Based on needs identified in farmer surveys, the model emphasizes localized training, diversified floral resources, adaptive hive design, and digital extension services as key means to support beekeeping productivity, pollinator conservation, and rural livelihoods.

Keywords: Agent-based model, Agricultural sustainability, Asia honey bee, Bee foraging behavior and pollination activity, Beekeeping, Climate change, Crop yield, Sri Lanka.

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Abbreviations

Abbreviation	Description
SLU	Swedish University of Agricultural Sciences
MRL	Multinomial Logistic Regression Analysis
ANCOVA	Analysis of Covariance
ABM	Agent-Based Model

1 Introduction

Agriculture remains a crucial sector worldwide, supplying vital food, raw materials, and economic stability. Pollination is a fundamental factor in successful farming, as it directly affects both the yield and quality of many crops (Bartomeus et al. 2014). Pollinators contribute to the reproductive success of nearly three-quarters of agricultural crops globally, thereby playing an essential role in both food security and ecosystem stability (Klein et al., 2007a). Recent estimates place the economic value of pollination services between $235 billion and $577 billion per year, underscoring their significance to the agricultural sector (IPBES, 2020). According to Gallai et al., (2009), the value of pollination services for crop production worldwide was estimated at €153 billion in 2005, or 9.5% of global agricultural output at the time.

Among pollinators, honey bees, especially *Apis mellifera* (Western honey bee) and *Apis cerana* (Asian honey bee), play a vital role in the agricultural sector. While *A. mellifera* thrives in temperate climates across Europe, Africa, and the Americas, *A. cerana* is native to Asia and well-adapted to tropical and subtropical climate (Hepburn & Radloff 2011; Park et al. 2015). Both are major pollinators of many crops and contribute to agricultural production and ecosystem function, supporting biodiversity and food security (Katuwal & Pokhrel 2023).

Globally, the decline of pollinators is a critical issue. With the United States losing 59% of its colonies between 1947 and 2005 and central Europe experiencing a 25% decrease between 1985 and 2005, there is compelling evidence of significant regional decreases in managed honey bee populations (Potts et al., 2010). Habitat loss and fragmentation due to agricultural expansion, urbanization, and deforestation have drastically reduced the availability of foraging resources and nesting sites for pollinators (Potts et al., 2010; IPBES, 2016). In addition, the widespread use of agrochemicals, particularly neonicotinoid pesticides, has been shown to impair pollinator behavior and physiology, leading to reduced survival and reproductive success (Goulson et al., 2015).

The impacts of climate change extend to disrupting the timing and geographic distribution of plant-pollinator interactions, which may lead to mismatches in flowering and foraging cycles(Peng et al. 2025). It manifests through rising temperatures, altered precipitation patterns, and increased frequency of extreme weather events. These changes can disrupt the delicate interactions between pollinators and plants, which can result in a decline in pollination and, consequently, crop yields (Goulson et al., 2015). These disruptions can result in mismatches in timing (phenological mismatches) or location (spatial mismatches), where plants and their pollinators no longer coincide in the same place or at the same time (Gérard et al. 2020). Such misalignments can reduce pollination, ultimately affecting crop yield and ecosystem stability (Vadiraj 2025). The situation is particularly concerning in tropical regions, where many pollinator species have evolved to thrive within a narrow range of temperature conditions (Conrad et al. 2021). Because of their limited thermal tolerance, even slight changes in climate can severely impact their survival, distribution, and ability to pollinate, making tropical ecosystems especially vulnerable to the effects of climate change (Kjøhl, Nielsen, & Stenseth, 2011). This study primarily focuses on temperature trends in the context of climate change.

Because of this, climate change and especially temperature is a critical factor influencing changes in pollinator behavior, which can directly impact crop yields especially for crops that depend heavily on pollinators (Kjøhl , Anders Nielsen , & stenseth, 2011). Therefore, it is essential to understand how changes in pollinator behavior due to climate change and especially temperature affect crop productivity and to examine adaptation solutions, particularly in low- and middle-income country contexts. Focusing on beekeeping practices is especially valuable, as beekeepers have firsthand experience with bee activity and foraging patterns. Their insights can provide important information for developing climate-resilient strategies to support farmers and sustain agricultural productivity. Development of climate-resilient beekeeping practices offers a potentially viable solution to mitigate these challenges, given that managed bee colonies can enhance pollination services and improve agricultural yields, and thereby support food security and farmer incomes (Fikadu 2019). However, we still lack an understanding of how to optimize beekeeping practices under varying climate scenarios of temperature change. Understanding the interplay between climate variables, pollinator behavior, crop yields, and socio-economic factors is crucial for developing sustainable strategies that address both ecological and economic resilience.

In the present study, this study selected the tropical country of Sri Lanka to examine climate change and especially temperature impacts on pollinator activity and crop yield. Sri Lanka is especially susceptible to climate change because of its location, restricted geographical area, and economic and social traits. Sri Lanka is an island in the Indian Ocean, about 30 kms off the southeastern coast of India with a land area of 65,610 sq. km and is endowed with a diversity of agro-ecological zones. The nation's agriculture is closely tied to the patterns of climate variables, most notably rainfall and temperature, which fluctuate across the country's three main agro-environmental regions (namely the Dry Zone, Intermediate Zone, and Wet Zone). Climatic zones in Sri Lanka are mainly determined by annual rainfall. The Wet Zone, which includes the southwest part of the island and the higher elevations of the Central Highlands, receives more than 2,500 mm of rain each year. The

Intermediate Zone receives between 1,750–2,500 mm and the Dry Zone, which covers over 60% of the nation, gets less than 1,750 mm annually (Chithranayana & Punyawardena 2008)**.** The country has been exposed to a range of climate-related threats including floods, landslides, droughts, cyclones and tidal surges, compound by the impacts of rising sea levels, and the loss of biodiversity (Samaraweera et al. 2024). Sri Lanka is placed in the 89th and 31st position in the world in the INFORM Risk Index 2021 in all climate-related risk and specific climate-related risk classification, respectively (European Commission. Joint Research Centre. 2021). The Asian honey bee *Apis cerana* is the most common and plentiful type of honey bee in Sri Lanka (Hepburn & Radloff 2011). Asia honey bee pollination is very important for both wild flora and agricultural crops in Sri Lanka. This species has been reported to be an effective pollinator of numerous plants species, including some important horticultural and plantation crops like mustard, coconut and fruit trees like mango, avocado (Aslan et al. 2016). Maximum foraging distances for Asia honey bees have often been reported to be between 1,500 and 2,500 meters (Koetz , 2013) but foraging ranges vary throughout studies (Koetz 2013). The efficient nest thermoregulation system of *A. cerana* controls body and internal hive temperatures between 33°C to 35.5°C (Rojas-Sandoval 2022). This range pertained to the simulation model of the Asian honey bees' foraging frequency, aimed at identifying variations in foraging behavior concerning optimal temperature. *A. cerana* exhibits effective thermoregulatory capabilities, typically maintaining hive temperatures within the range of 33°C to 35.5°C. This species has evolved to withstand tropical and subtropical conditions, making it more resilient than *A. mellifera* in regions with high humidity and fluctuating temperatures (Tan et al. 2012; Katuwal & Pokhrel 2023). Therefore, the presence of diverse climatic conditions within the same country, combined with its agriculture-based economy, provides a suitable context for studying the impact of climate change on pollinator behavior.

In the last decade, Sri Lanka faced a significant loss of pollinators, gravely humping the pollination deficit that threatens the productivity and quality of the major crops of the country (Mawbima, 2025). This issue is particularly pronounced in the North Central Province where pumpkin farmers' plights have led to a practice of manual hand-pollination due to a decline in the abundance of managed honey bees and wild bees as a whole (Mawbima, 2025). Hand-pollination is costly and not as effective as that performed by natural pollinators (Wurz et al. 2021) , making it all the more important to urgently adopt measures to facilitate the protection of pollinator habitats and sustainable agricultural activities. However, in Sri Lanka there is not adequate research regarding climate change impact on pollinator behaviour consiquensly impact on crop yield and farmers livehood.

Therefore, this study focuses on examining farmers' perceptions of the impact of climate change especially temperature on Asian honey bee behavior and, consequently, its effects on crop yield and farmers' livelihoods. It provides an overview of current changes in pollinator behavior and their influence on agricultural productivity. Furthermore, the study seeks insight on potential future trends by predicting how Asian honey bee behavior and crop yields may shift under changing climate conditions in Sri Lanka. Specifically, the purpose of this study was to examine:

1. How do farmers' perceptions of Asian honey bee foraging, behavior, and pollination activity vary across different climatic zones in Sri Lanka?

2. How agenet-based modelling simulations predict Asian honey bees' behavior and, consequently, crop yields to shift with future changing climate conditions (temperature) in Sri Lanka?

Based on the findings and investigation of the adaptive capacity of current beekeeping practices under climate change, the study proposed a sustainable climate resilience strategy for beekeeping in Sri Lanka. These recommendations aim to support Asian honey bee productivity, improve farmers' livelihoods, and promote biodiversity.

2 Materials and Methods

2.1 Research Strategy

This study used a mixed-methods approach, combining both qualitative and quantitative methods, to explore how climate change is perceived and predicted to affect the behavior of Asian honey bees, and how these changes may subsequently influence crop yields and farmer livelihoods in Sri Lanka. The research examined current beekeeping practices and included a simulation model to study how temperature changes impact bee foraging and crop production. Based on these investigations, the aim of this study was to suggest strategies to improve agricultural resilience, based on both farmer perceptions and simulation results.

A conceptual framework is provided (Figure 1) to illustrate the structure of the research concept and linkages among the variables. The framework included ecological and climatic variables, emphasizing the interrelationships between climate change, Asian honey bee behavior, beekeeping practices, and agricultural resilience.

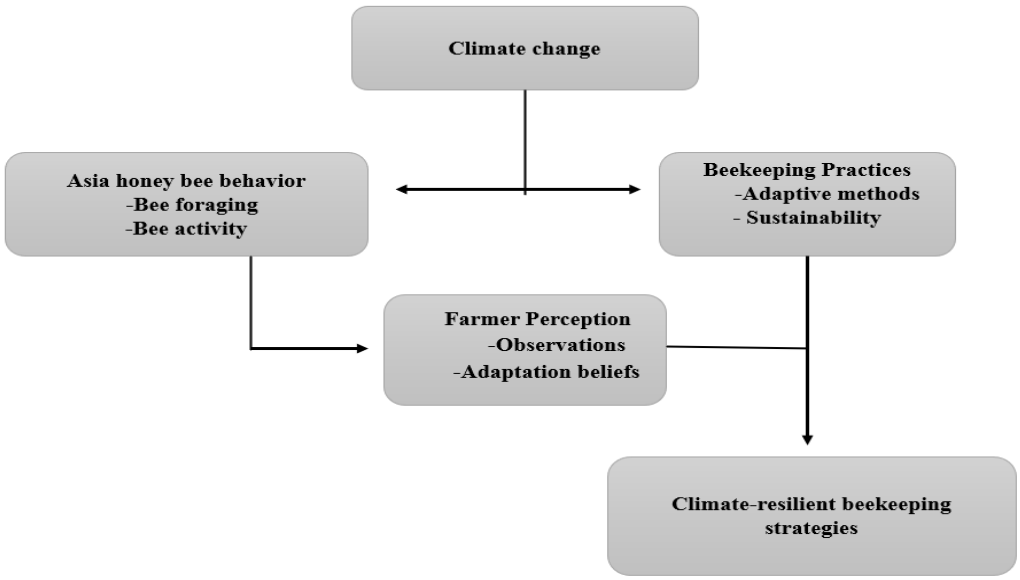


Figure 1:Conceptual framework of the study.

2.2 Sampling technique

Sri Lanka is divided into three primary climatic zones: the Wet zone, intermediate zone, and dry zone, each characterized by distinct rainfall patterns and environmental conditions Across the country, these zones have an impact on livelihoods, biodiversity, and agricultural methods. The island is divided into twenty-five administrative districts, each of which is classified into a different climate zone based on factors including temperature, humidity, and rainfall. To ensure that all three climatic zones are covered in this study, seven districts were chosen based on their active participation in beekeeping practices (Figure 2).

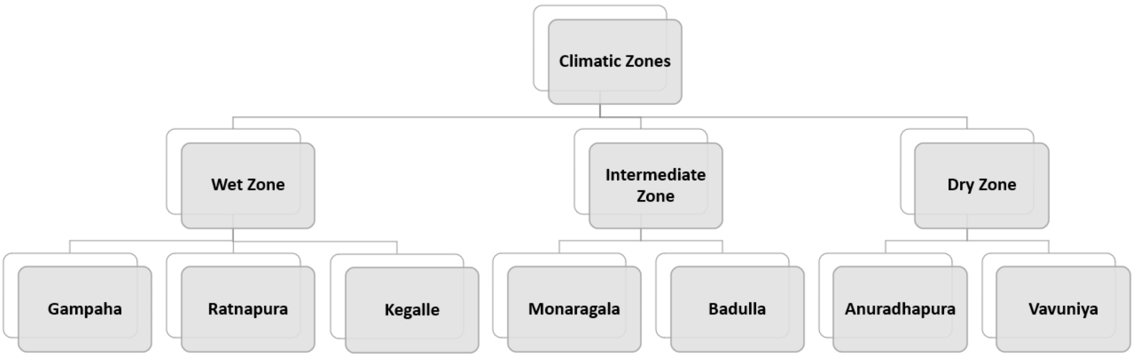


Figure 2:Sampling technique of the study. The wet zone included three administrative districts, while both intermediate zone and dry zone included two administrative districts each.

2.3 Research area and sample

2.3.1 Research Area

To ensure comprehensive coverage of diverse climatic conditions, districts with high engagement in beekeeping practices were strategically selected across the major climatic zones of Sri Lanka, in coordination with the Bee Development Unit in Bidunuwewa (Figure 3). In the Wet Zone, Gampaha, Ratnapura, and Kegalle were chosen due to their favorable environmental conditions and active participation in apiculture. For the Intermediate Zone, Monaragala and Badulla districts were identified, reflecting their growing interest and potential in beekeeping activities. Finally, in the Dry Zone, Anuradhapura and Vavuniya districts were selected, highlighting regions where beekeeping is being increasingly adopted as a livelihood option.

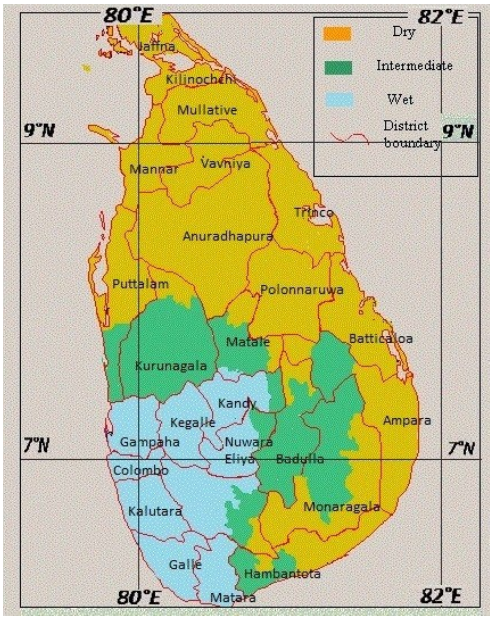


Figure 3:Climatic zones in Sri Lanka (Karunaweera et al. 2014).

2.3.2 Sample size

A total of 110 samples (in the form of interviews with individual beekeepers) were collected from selected districts (Figure 2), with approximately 30 samples obtained from each climatic zone. The actual distribution was 40 from the Wet Zone, 39 from the Intermediate Zone, and 31 from the Dry Zone (Table 1).

Table 1:Sample distribution of the study.

Climatic zone	District	Sample	Sample size
Wet zone	Gampaha	15	
	Kegalle	10	40
	Rathnapura	15	
Intermediate zone	Monaragala	15	39
	Badulla	24	
Dry Zone	Anuradhapura	19	31
	Vavuniya	12	

2.4. Description of data and procedure

Research data were collected through a combination of field surveys, interviews, and secondary sources. Primary data collection involved the use of structured questionnaires and semi-structured interviews conducted with beekeepers. Secondary data were obtained from the Department of Census and Statistics of Sri

Lanka, the Beekeeping Unit in Bidunuwewa, and the CHELSA climate database. All collected data were then processed and organized for both descriptive and advanced analyses, including simulations using the NetLogo agent-based modeling framework.

Primary data consist of firsthand information collected through surveys and interviews focusing on farmers' perception on bee foraging and bee activity, beekeeping methods, and climate change (see Appendix 2 for full questionnaire). Secondary data included official records and reports on bee density across selected districts from 2020 to 2024, and crop yield data obtained from the Department of Census and Statistics Sri Lanka. Climate data was obtained from the CHELSA database (CHELSA, 2025; Karger et al., 2017). The CHELSA dataset provides long-term, high-resolution climate projections that are well suited for modeling and simulation purposes. Mean annual temperature was here used from this database, with mean values calculated on a per distict basis for each of the three climate time periods considered.

2.5 Data collection methods

Data collection was carried out using structured questionnaires to gather quantitative information and semi-structured interviews to gain deeper qualitative insights. To meet the research objectives, both comprehensive quantitative and qualitative data were required. Therefore, a combination of data collection tools was employed, as outlined below.

2.5.1 Interviewer administered questionnaire

An interviewer-administered questionnaire was developed for collecting primary data from beekeepers. The questionnaire consisted of six main sections:

1. General information of the beekeeper
2. Impact of climate change
3. Farming and pollination
4. Beekeeping and climate adaptation
5. Adaptation and future strategies

The questionnaire included a mix of Likert scale questions (graded on a scale of 1-5), multiple-choice questions, ranking questions, and open-ended questions to ensure both depth and breadth of information (see Appendix 2 for full questionnaire).

2.5.2. Field observations

Field observations were conducted in beekeeping areas across the selected districts within each climatic zone (Figure 2). These visits aimed to directly observe beekeeping practices and techniques used by local practitioners, providing valuable contextual and practical insights to complement the survey and interview data.

2.6. Data Processing Techniques

2.6.1. Descriptive Analysis

Descriptive statistics were used as the initial step in the data analysis process to summarize and present the data in a meaningful way. This analytical approach benefits from the availability of extensive datasets and powerful computational tools (Sarmento & Costa 2017). In this study, descriptive analysis was used to give an overview of current beekeeping methods and to show the demographic features of the respondents.

2.6.2. Multinomial Logistic Regression Analysis (MLR)

This method was chosen because the dependent variable comprises multiple categories, and MLR enables the analysis of how each predictor influences the likelihood of selecting one perception category over another. It is appropriate when the dependent variable is nominal and the objective is to model the probability of each category relative to a reference category (El-Habil 2012**)**.

This statistical analysis was conducted to investigate how farmers' perceptions of Asian honey bee foraging behavior and pollination activity vary across climatic zones in Sri Lanka and whether these perceptions reflect observed climate-related changes. To evaluate whether farmer perceptions aligned with observed climate-related changes, the results of the multinomial logistic regression were later compared with outputs from the NetLogo agent-based simulation model (see Section 3.2). Specifically, the key perception variables (e.g., perceived mismatch between flowering and pollinators, nectar source decline) were qualitatively compared against modeled bee foraging frequency and crop yield under historical and projected climate scenarios. This comparison enabled an assessment of whether farmer observed trends corresponded to ecological patterns simulated under rising temperature conditions.

Survey responses were designed to balance simplicity and depth of information. Some variables (e.g., mismatch between flowering and pollinators) were coded as binary (Yes/No) to reduce ambiguity and ensure consistent interpretation across varied respondent education levels, especially in climatic zones. Binary variables were used when the question focused on the presence or absence of an experience (e.g., 'Have you observed a mismatch?'), while ordinal or Likert-scale variables were used for questions aiming to measure the intensity or severity of perceptions (e.g., change in pollinator population, nectar decline). However, binary formats were chosen where they increased clarity and response reliability given the diverse demographic profile of respondents.

It involved three main steps: assessing the internal consistency andintercorrelation of perception variables, testing for multicollinearity, and fitting a multinomial logistic regression model to predict climatic zone classification based on selected farmer reported perceptions.

2.6.2.1 Pre Model diagnostics and variable consistency

1. Cronbach's alpha

Cronbach's alpha examined internal consistency, or how well a set of variables assesses the same underlying notion; a high alpha indicates that the items are highly associated and consistent (a value of ≥ 0.7 is preferred) (Cronbach, 1951 ; Tavakol & Dennick, 2011). It is only applied when there is a suspicion that the variables are measuring the same construct. Bee foraging includes:Q3.3 (Change in pollinators),Q3.4 (Mismatch in flowering) and Q4.13 (Decline in nectar sources) (see appendix). These all relate to aspects of plant-pollinator interactions (i.e., bee foraging and pollination). Thus, it made theoretical sense to check if they form a reliable scale (same construct).

Bee activity contains Q2.4 (Changes in flowering time) and ,Q4.8 (Changes in bee behavior). These two reflected different constructs: one was plant-based (flowering time), and the other was insect-based (bee behavior). Cronbach's alpha was not appropriate for only 2 variables with different underlying meanings. Therefore, bee activity couldn't be checked for internal consistency using Cronbach's alpha for this reason. It should be tested separately.

The resulting alpha coefficient was 0.42, which falls well below the commonly accepted threshold of 0.70. This indicated that the three items did not exhibit strong internal consistency and were not suitable to be combined into a single composite index. Instead, they were retained as independent variables in subsequent modeling. The table displayed variable-level diagnostics from a Cronbach's alpha test that evaluated the internal consistency of three survey questions about bee perceptions of foraging. Among the variables, Q3.4 (Mismatch in flowering and pollinators) had the strongest correlation with the overall scale (item-total correlation = 0.58), indicating it aligned well with the other variables. If this variables were removed, the reliability of the scale would drop significantly (alpha = 0.06), suggesting it was essential. In contrast, Q3.3 (Change in pollinators) had a weaker correlation (0.29), and removing it would slightly improve the overall consistency (alpha = 0.46), indicating it may not fit well with the others (Table 2). Overall, the low alpha values suggested that these items did not form a reliable composite scale and should be treated as separate variables in further analysis.

Table 2:variable level diagnostics from a Cronbach's alpha test.

Item	Item-Total Correlation	Alpha If Dropped
Q3.3 (Pollinators)	0.29	0.46
Q3.4 (Mismatch)	0.58	0.06
Q4.13 (Nectar sources)	0.34	0.41

3. Pairwise correlations

The pairwise correlation test was performed to assess whether there is collinearity (i.e., strong linear relationships) among the three predictor variables related to farmer perceptions of bee foraging and pollination activity.

A pairwise correlation analysis was conducted to assess the degree of collinearity among the three bee foraging perception variables (Q3.3, Q3.4, and Q4.13). The results showed that none of the correlations exceeded 0.3, with the highest absolute correlation being –0.30 between Q3.4 (mismatch between flowering and pollinators) and Q4.13 (decline in nectar sources). The correlation between Q3.3 (change in pollinators) and the other two items was very low (–0.26 and 0.03, respectively) (Table 3). These values are well below the commonly used threshold of 0.8, indicating no strong collinearity among the predictors (Dormann , et al., 2012). Therefore, all three variables can be included in the multinomial logistic regression model without concern for multicollinearity.

Table 3:Pairwise correlation analysis between variables demonstrating that strong linear relationships among the three predictor variables.

	3.3. Have you observed a change in the presence of pollinators on your farm over the last 5-10 years	3.4. observe any mismatch between crop flowering and pollinator activity	4.13. Have you observed a decline in nectar sources for your bees?
3.3. Have you observed a change in the presence of pollinators on your farm over the last 5-10 years	1.00	-0.26	0.03
3.4. observe any mismatch between crop flowering and pollinator activity	-0.26	1.00	-0.30
4.13. Have you observed a decline in nectar sources for your bees?	0.03	-0.30	1.00

The Condition Index (kappa) was calculated to further assess the potential for multicollinearity among the predictor variables related to bee foraging perceptions (Q3.3, Q3.4, and Q4.13). This index provided a single summary value that reflects the overall collinearity structure among the variables. As a general rule, a condition index value greater than 30 indicates serious multicollinearity, while values between 10 and 30 may suggest moderate concern (Belsley, Kuh, & Welsch, 2004). In this analysis, the computed condition index was 2.56, which was well below the critical threshold (Table 4). This result confirmed that the selected variables were sufficiently independent from one another and did not exhibit problematic collinearity. When considered alongside the previously reported low pairwise correlation coefficients, this provided strong justification for including all three variables as independent predictors in the multinomial logistic regression model without compromising model stability or interpretability.

Table 4:Condition Index (kappa)

Test	Value
Cronbach's α (std, check.keys)	0.42
Condition index (kappa)	2.56

This study looked at the determinant of the correlation matrix to further check for multicollinearity among the three bee foraging perception variables (Q3.3, Q3.4, and Q4.13). This test showed a single number that indicated how independent the variables were from each other. If the determinant was very close to zero, it meant the variables were highly related (collinear), which could cause problems in a regression model (Hair, Jr., Black, Babin, & Anderson, 2019). In this case, the determinant value was 0.85, which was far from zero. This meant there was no sign of collinearity, and the variables were independent enough to be used together in the analysis. Based on that, this model estimated the likelihood of farmers' perception of bee foraging behavior and bee activity in the wet and dry zones compared with the intermediate zone independently.

This statistical analysis was conducted to investigate how farmers' perceptions of Asian honey bee foraging behavior and pollination activity vary across climatic zones in Sri Lanka and whether these perceptions reflect observed climate related changes. To evaluate whether farmer perceptions aligned with observed climate-related changes, the results of the multinomial logistic regression were later compared with outputs from the NetLogo agent-based simulation model (see Section 3.2). Specifically, the key perception variables (e.g., perceived mismatch between flowering and pollinators, nectar source decline) were qualitatively compared against modeled bee foraging frequency and crop yield under historical and projected climate scenarios. This comparison enabled an assessment of whether farmer observed trends corresponded to ecological patterns simulated under rising temperature conditions.

Field validation of the simulation model will be essential to ensure reliability of these projections. Future studies should implement systematic monitoring of pollination deficits in major crops (Klein et al., 2007; Potts et al., 2010). For example, government agencies could be requested to collect long-term data on pollinator abundance and diversity, flowering phenology, and hive density across climatic zones. Experimental field plots could directly measure crop yield under pollinator-excluded and open-pollinated conditions, enabling comparison with model-predicted yield gaps (Garibaldi et al., 2013). Additionally, integrating remote sensing data on floral resource availability and rainfall variability with on-ground surveys of nectar sources would provide robust empirical datasets to validate modeled bee foraging frequency (Lawson & Rands, 2019). These combined approaches would allow calibration of simulation outputs with observed ecological responses, strengthening the policy relevance of NetLogo models for predicting climate change impacts on pollination systems.

2.6.3 NetLogo Agent-Based Simulation Model

The interactions between pollinators and crop systems under various climatic conditions were modeled using NetLogo (v6.4.0), a popular framework for agent-based simulations.The simulation allowed for dynamic adjustment of variables such as temperature, bee density, and pollination rates, replicating a virtual agroecosystem influenced by climate trends (Tisue & Wilensky, 2004; Becher et al., 2014). Similar simulation models have previously been applied for bee foraging behavior and examining the effectiveness of the waggle dance in locating nectar sources to explore how various paramters interact to influence the efficiency of foraging and the proportion of nectar collected through waggle dance versus random searching (simulace.info, 2025). Becher et al. (2014) developed a honeybee model, BEEHAVE, which integrates colony dynamics and population dynamics. The present study utilized an agent-based model developed in NetLogo to explore the relationships between environmental variables (temperature), biological agents (bees), and agricultural outputs (crop yield). The purpose of this model was to simulate how variations in temperature and bee hive density influence foraging behavior,crop pollination efficiency, and ultimately crop yield. Furthermore, simulations incorporated predicted future temperatures for major crops in each climatic zone in an attempt to examine climate change influences on bee foraging activity and crop yield. The ABM here developed was also designed to be able to accommodate any crop with varying levels of pollinator dependency, and as such could be flexible for wider use and serve as a useful tool for enhancing understanding of ecological dynamics, or to support the development of climate-resilient strategies for beekeeping and crop production (see Discussion). In this study, avocado was selected as a major pollinator-dependant crop cultived in the Wet Zone due to the significant role of honey bees in enhancing its yield. In the Dry Zone, pumpkin was chosen because honey bee pollination is essential for its fruit production. Cucumber was selected for the Intermediate Zone, where honey bees also play a major role in boosting crop yield (Klein et al. 2007).

In this study, the model exhibited emergent behavior in the form of crop yield resulting from the interplay of bee foraging frequency, the crop pollination dependency value, and the environmental variable. Bees adjust their foraging activity based on temperature and the bee hives density of a particular climatic zone with optimal behavior influenced by defined parameters like optimal temperature and halving-interval (see below). Output was visualized through real-time plots of foraging frequency and crop yield, allowing researchers to observe temporal dynamics over simulation ticks (time points).

ABM parameters and their value states

- **Environment**: Defined by a continuous temperature slider (ranging from 24.0°C to 40.0°C, with a default of 29.9°C).
- **Bee hive density**: Represented by the number-of-bees slider, likely influencing foraging behavior (representing bee hives density, e.g 2.17 per km^2).

- **Foraging**: Controlled through parameters such as,
  - optimal-temp – ideal temperature for bee activity (default: 33.0°C).
  - halving-interval – rate at which foraging efficiency drops with deviation from optimal temperature.
  - Emergence-scaling – scales the bee hives density (default: 5.0). it is a multiplier that adjusts bee population growth and activity in proportion to hive density. In this model, a default of 5.0 was used, consistent with scaling factors applied in BEEHAVE (Becher et al. 2014) and other ABM frameworks where reproduction or recruitment is scaled relative to environmental carrying capacity. It ensures that bee agents "emerge" in the simulation in proportion to realistic hive densities and resource conditions.

- **Crop Yield Calculation**: Two crop yield metrics were tracked (Garibaldi et al. 2013; Klein et al. 2007):

1. **Crop Yield 1** – the number of patch squares in the simulation grid that reached the "pollinated" state by the end of a run. This represents the spatial extent of pollination success.
2. **Crop Yield 2** – the modelled production output (metric tonnes, MT) calculated with:

$$\text{Crop Yield 2} = \text{Baseline Yield} \times [1 + (\text{Pollination Increase Proportion} \times \text{Effective Foraging})]$$

Where:

- Baseline Yield = average production without pollination assistance.
- Pollination Increase Proportion = fractional yield boost per unit of foraging activity.
- Effective Foraging = proportion of optimal foraging achieved, based on temperature proximity to optimal and bee abundance.

Initialization

The model was initiated using a "Setup" button which initializes all agents and parameters. The "Go" button runs the model over discrete time steps called "ticks", updating the environment and output plots in real time.

Process overview and scheduling

At each tick,

1. Temperature and bee numbers were read.
2. Foraging frequency was determined based on the proximity of temperature to the optimal value and the number of bees.

3. Crop yield was computed using both baseline yield and enhancements from pollination.
4. Outputs were logged in the "Foraging Frequency" and "Crop Yield" plots.

Simulation Experiments

Parameters such as temperature, number-of-bees, optimal-temp, and pollination-increase-proportion can be systematically varied to test hypotheses regarding the sensitivity of crop yield to climate and pollinator availability. The interface allowed the export of output data for statistical analysis.

In the simulation, the mean temperature in each climatic zone for the 2020–2024 period was used as the 'optimal temperature' baseline for *Apis cerana* foraging. This assumption was based on the premise that the species is likely ecologically adapted to current climatic conditions within each zone. Additionally, while managed hives were the model's reference, it is recognized that most pollination services in Sri Lanka stem from wild *Apis cerana* populations, which further complicates direct attribution of changes in crop yield solely to managed hives or temperature shifts.

This study simulated varying optimum temperature levels across different climatic zones and time periods. For each period, bee hives density and crop yield were assumed to be similar. The impact of honey bee pollination was evaluated on specific crops chosen for each climatic zone based on their suitability for cultivation. Crop yields were calculated as five-year averages. These inputs were used to model how yield outcomes might change under projected climate shifts. For example, during 2020–2024 in the wet zone, the temperature was 29.92°C with a bee density of 2.17 hives/km², matching the inputs in the NetLogo interface and resulting in a baseline yield of 40.57 MT (Table 5). This was an important simulation calibration point. Each temperature scenario was run three times for enhancing both the accuracy and validity of the results.

Table 5:Parameter input values used to run simulations.

Climatic Zone	Year	Temp (celcius)	Bee density(km2)	Crop yield (MT)
Dry zone Anuradhapura Vavuniya	2020-2024	28.1	0.43	139.7
	2025-2034	24.9		
	2035-2044	27.1		
Intermediate zone Badulla Monaragala	2020-2024	28.9	1.72	29.05
	2025-2029	25.5		
	2030-2034	27.8		
Wet Zone	2020-2024	29.9	2.17	40.57

Gampaha	2025-2029	26.3
Ratnapura	2030-2034	28.6
Kegalle		

2.6.4 Analysis of Covariance (ANCOVA)

Analysis of Covariance (ANCOVA) was used for agent-based model (ABM) outputs to analyze how bee foraging frequency and crop yield trajectories were influenced by different climate scenarios over time. The analysis involved transforming simulation data, visualizing trends, and statistically testing differences. Raw simulation outputs for both bee foraging frequency and crop yield were structured in wide format, with separate columns for each climate-replicate-period combination. The pivot_longer() function in R was used to transform the data into long format so that it could be easily compared across time and climate zones.It calculated summary statistics, including mean, minimum, and maximum, for each climate zone and period over all simulation steps to explore trends in the data. Ribbon plots were used to display these statistics; the central line shows the mean result over replicates and runs, while the shaded area shows the range (min to max).

ANCOVA was used to determine whether the rate of change (slope) in outcomes bee foraging frequency or crop yield differs significantly between climate zones or across time periods. This separates the impact of the climate scenario from the overall impact of time.

The general ANCOVA model used was:

Outcome ~ Time + Group + Time:Group

Time (run) was the covariate, while outcome (such as crop output or bee foraging frequency) was the response variable. Time: Group tests to see if groups' slopes differed, where Group denoted the categorical variable (climate zone or time).

These visualizations provided an intuitive view of how the model outputs evolved over time in different climate scenarios.

Model Comparison Approach:

This study used two linear models to statistically assess whether trajectories (slopes) of bee foraging frequency and crop yield differ across climate zones and periods. There were,

1.Additive model: assumes separate, independent effects of simulation step (Run) and group (Climate or Period).

2.Interaction model: includes an interaction term (Run × Climate or Run × Period), allowing the slope of the outcome over time to vary by group.

The interaction term tested whether the slope (effect of Run) varied significantly by group (either Climate or Period). Significant slope differences are indicated by a low p-value (<0.05). Comparing these models tests whether time and group interact, as in the example of whether the rate of change over time was significantly different across climate change. This comparison was done separately for each period (climate differences) and each climate (period differences). ANCOVA (Analysis of Covariance) was a statistical method that blends ANOVA and regression, enabling comparison of outcome trajectories across groups while adjusting for a continuous variable (Tabachnick et al. 2019). In this study, the simulation step (Run) served as the covariate representing time, and climate zone was the categorical grouping variable.

3.Results

3.1 Farmers’ perceptions of bee foraging behavior and pollination activity across climatic zones in Sri Lanka

The sample distribution considered for farmers' perception about bee foraging behavior and pollination activity across climatic zones. It showed a male-dominated beekeeping sector across all climatic zones. Though regions like Anuradhapura and Ratnapura showed notable female participation. Male beekeepers tend to be older and less educated, especially in the Dry Zone, while younger, better-educated women are increasingly engaging in beekeeping, particularly in the Wet and Intermediate Zones (see Appendix 1).

The Intermediate Zone was selected as the baseline for comparison since it represents moderate climatic zone between the relative extremes of the Dry and Wet Zones. Five predictors were used: perceived change in pollinators, mismatch in flowering and pollinators, decline in nectar sources for bee foraging and pollination measure, change in flowering time, and change in bee behavior for bee activity measure. The odds ratio (OR) showed how likely it was for one group to experience an event compared to another. An OR greater than 1 indicates a higher likelihood of the event in the comparison group relative to the selected baseline, while an OR less than 1 indicates a lower likelihood. An OR equal to 1 suggests no difference between groups. Confidence Interval (CI) provided a range of values within which the true Odds Ratio is expected to lie, with a specified level of confidence typically 95%. A narrow CI indicates a more precise estimate, whereas a wider CI reflects greater uncertainty. If the CI includes the value 1, the result is generally considered not statistically significant at the 0.05 level. Table 6 shows that farmers’ perceptions did not indicate noticeable differences in bee foraging behavior across climatic zones, and temperature was not explicitly identified as the main factor affecting pollination in their responses. This table, however, tests only whether perceptions differ between zones it does not rule out the possibility that beekeepers have noticed changes in foraging behavior overall. The absence of a statistically significant difference across zones may therefore mask underlying perceptions that are present but consistent across all areas.

Based on that, An ordinal scale ranging from 1 to 5 was used to measure Flowering time disruption; higher values indicate more disruption; the odds ratio (OR) showedthe impact of each unit increase on this scale. In Dry Zone, greater perceived disruption in flowering time was linked to a 58% reduction in the odds of farmers being located in those zones compared to intermediate climates (OR = 0.42, 95%

CI [0.17, 1.02], $p < 0.1$) (Table 6). Although only marginally significant, this result indicated that increased flowering disruption may decrease the likelihood of farming in dry regions, possibly due to climatic condition or adaptive decision-making. In Wet climates, flowering disruption showed a positive association (OR = 1.38, 95% CI [0.6, 3.18]), though the result was not statistically significant.

Changing pollinator populations, measured on an ordinal scale ranging from -2 (strong decline) to +2 (strong improvement), were found to have varying associations across climate zones. In Dry Zone, farmers who reported greater declines in pollinators had 39% lower odds of being located in these zones (OR = 0.61, 95% CI [0.35, 1.08], $p < 0.1$) (Table 6). This implies that significant pollinator losses are more likely to occur in Intermediate or Wet Zones, with probability decreasing by 41% for every unit rise in perceived improvement. Wet Zone, on the other hand, displayed a lower and non-significant correlation (OR = 0.98 [0.68, 1.41]) (Table 6).

Table 6:Comparison of Farmers' perceptions of bee foraging behavior and pollination activity across climatic zones in Sri Lanka.

Variable	Comparison	Odd Ratio(OR)[CI]	Significance
Bee Foraging & Pollination			
Pollinator Population	Dry vs Int.	0.61 [0.35, 1.08]	$p < 0.1$ (marginal)
Change	Wet vs Int.	0.98 [0.68, 1.41]	Not significant
Mismatch: Flowering vs	Dry vs Int.	7.72 [1.95, 30.56]	$p < 0.01$
Pollinators	Wet vs Int.	0.18 [0.06, 0.58]	$p < 0.01$
Nectar Source Decline	Wet vs Int.	0.34 [0.15, 0.77]	$p < 0.01$
	Dry vs Int.	1.73 [0.69, 4.36]	Not significant
Bee Activity			
Flowering Time	Dry vs Int.	0.42 [0.17, 1.02]	$p < 0.1$ (marginal)
Disruption	Wet vs Int.	1.38 [0.6, 3.18]	Not significant
Bee Foraging Behavior	Dry vs Int.	4.24 [0.08, 227.91]	Not significant
Change	Wet vs Int.	0.10 [0.03, 0.32]	Not significant

Mismatch Between Flowering and Pollinators' is a binary variable coded as 1 for 'Yes' (mismatch present) and 0 for 'No' (no mismatch). A powerful predictor across zones was the perception of mismatch. Significant ecological disconnection was observed in Dry Zone, where a reported mismatch was linked to 7.72 times higher odds (OR = 7.72 [1.95, 30.56], $p < 0.01$) (Table 6). of being in the Dry Zone compared to Intermediate.The mismatch effect was reversed in Wet Zone, though, with farmers who reported a mismatch having 82% lesser odds of being in Wet Zone(OR = 0.18 [0.06, 0.58], $p < 0.01$) (Table 7). This emphasizes that due to more stable pollination conditions or improved plant-pollinator synchronization, such mismatches tend to be less common or have fewer of an effect in Wet Zones. Some farmers perceived a mismatch between the flowering time of their crops and the foraging behavior of honey bees. This mismatch, as described by the interviewees, referred to situations where flowering occurred at times when honey bee activity was noticeably reduced such as during early mornings, late evenings, or periods of adverse weather. Although *Apis cerana* is capable of foraging year-round in Sri Lanka, these farmers observed that bee activity did not always coincide with peak flowering times, potentially leading to reduced pollination efficiency. Importantly, this mismatch refers specifically to honey bees and not to wild pollinators in general. The farmers' accounts reflect their personal observations and perceptions rather than direct experimental data.

Farmers' perceptions of nectar source decline were assessed on an ordinal scale ranging from -2 (significant decline) to 0 (no decline), with odds ratios interpreted per one-unit increase, indicating a less severe decline. In Wet Zone, a one-unit reduction in perceived nectar source decline severity was associated with a 66% lower likelihood of being in that zone (OR = 0.34, 95% CI [0.15, 0.77], $p < 0.01$) (Table 7). This statistically significant association suggests that stable nectar availability may be a distinguishing factor of Intermediate Zone compared to Wet Zone, potentially indicating greater ecological resilience or better-adapted management practices in Intermediate Zone. In contrast, the relationship was not statistically significant in Dry Zone (OR = 1.73, 95% CI [0.69, 4.36]) (Table 6), although the direction of the association suggested a trend toward greater perceived nectar decline among farmers in Dry Zone. This points to possible localized stressors in Dry Zone but lacks sufficient evidence for firm conclusions.

A binary scale (0 = No change, 1 = Yes, change noticed) was used to gauge how people perceived changes in bee foraging behavior. This variable did not produce statistically significant or consistent correlations across climatic zones. The odds ratio was OR = 4.24 (95% CI [0.08, 227.91]) in the Dry Zone and OR = 0.10 (95% CI [0.03, 0.32]) in the Wet Zone(Table 6). In all climate zone comparisons, the variable change in bee behavior, which is measured on a binary scale (0 = no, 1 = yes), did not yield statistically significant results. A substantial level of statistical uncertainty was indicated by the large confidence intervals that accompanied the odds ratios, (Table 6) which frequently ranged from almost zero to several hundred.

3.2 NetLogo Simulation of Bee foraging frequency and crop yield across Climatic Zones

3.4.1 Interface-Based Simulation

Interface Structure and Parameter Control

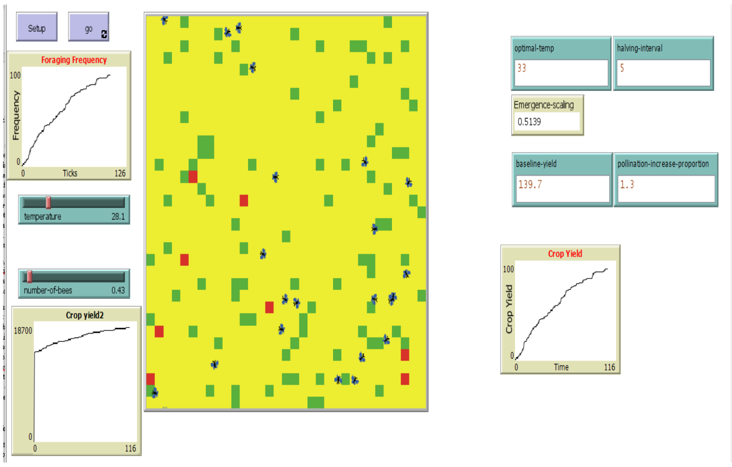
The model interface enabled the real-time manipulation of key ecological and environmental parameters, allowing users to simulate multiple scenarios across three distinct climate zones Dry, Intermediate, and Wet over three projected time periods: 2020–2024, 2025–2034, and 2035–2044.

The central panel featured a spatial grid that visually represented agricultural zones as color-coded patches (Figure 4). Each patch changed color based on real-time conditions green indicating high activity or yield, yellow for moderate conditions, and red for low performance allowing users to monitor the evolving spatial patterns of foraging and productivity. The right and bottom panels displayed real-time output graphs and numeric monitors. These included plots for bee foraging frequency over time, crop yield trajectories, and key zone-specific environmental indicators like temperature and bee density.

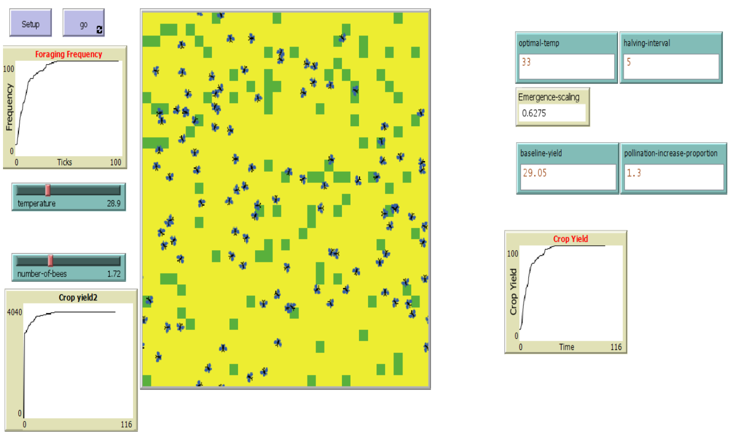
In the Dry Zone for pumpkin (Figure 4), the spatial grid was dominated by yellow patches with scattered green and red cells. The foraging frequency graph indicated a gradual increase that plateaus below optimal levels. The temperature is set at 28.1°C with a bee density of 0.43 hives/km², both values indicating moderately warm but sub-optimal ecological conditions. The crop yield increased slowly, reaching approximately 139.7 MT by the end of the simulation. Notably, the Emergence scaling factor was low (0.5139), and the pollination increase proportion was set at 1.3, indicating some sensitivity to pollinator contributions, but insufficient bee activity to capitalize on this. The interface reflects limited ecological resilience, with low foraging density (few visible agents) and modest yield curves (Figure 4).

The Intermediate Zone for cucumber exhibited a much more active landscape (Figure 4). The spatial grid showed a balanced spread of green patches, indicating better floral coverage and more favorable pollination environments. The foraging frequency curve rose sharply and quickly plateaued near saturation at 100 ticks. The temperature was 28.9°C and bee density was 1.72 hives/km², both significantly higher than in the Dry Zone, enabling robust foraging dynamics. The crop yield trajectory increased rapidly and reached a value of approximately 29.05 MT, closely matching the defined baseline yield. The emergence-scaling factor was moderate (0.6275), supporting active bee reproduction and patch coverage. This was further enhanced by the same pollination-increase-proportion of 1.3, which, combined with higher bee presence, lead to strong ecological interaction (Figure 4).

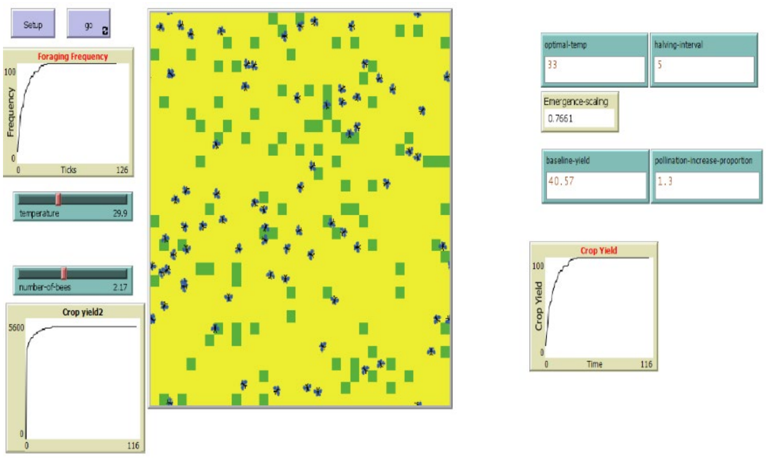
In the Wet Zone for avocado (Figure 4) the spatial grid was densely populated with green patches, and bee agents were evenly and actively distributed. The foraging frequency curve reached saturation early in the simulation, indicating highly efficient pollination behavior. The temperature was set at 29.9°C, and bee density was 2.17 hives/km², the highest among the three zones. The crop yield curve showed a steep and immediate increased, reaching about 40.57 MT, consistent with the maximum baseline yield set for this zone. The emergence-scaling factor was 0.7661, supporting high reproductive success and colony strength. The interface clearly illustrated an abundant and stable ecosystem, where pollinators and crops function synergistically.



(A)



(B)



(C)

Figure 4: Simulation of Bee foraging frequency and crop yield across Climatic Zones for the time period of 2020–2024. (A) Dry Zone for pumpkin, (B) Intermediate Zone for cucumber, and (C) Wet Zone for avocado. The spatial grid represents an abstract simulation landscape rather than a true geographic scale. Colors indicate relative levels of pollination performance: green = high foraging activity/crop yield, yellow = moderate, and red = low.

3.4.2 Bee Foraging frequency

The bee foraging frequency results revealed strong, consistent differences in each of the three crops across all three time periods (2020–2024, 2025–2034, and 2035–2044) (Figure 5). Wet Zone foraging frequency for avocado increased rapidly and reached high values early in each period. By around simulation step 20–30, the frequency plateaus near 100, indicating optimal foraging conditions in Wet Zone. The gray ribbon around the Wet Zone/avocado was narrow in the later steps, indicating low variability and high consistency across replicates once foraging reaches saturation (Figure 5). Slightly wider ribbons early on suggest some stochastic variation in initial foraging behavior, but it stabilized quickly. This indicated a reliably strong foraging performance in Wet Zone over all time periods. The results showed that bee foraging frequency declined during 2025–2034 due to temperature variations, but returned to normal levels in 2035–2044.

The Intermediate Zone for cucumber also showed a steep rise in foraging frequency, but not as steep or as high as the Wet Zone. The maximum foraging frequency stabilized around 80–90. The gray ribbon was slightly wider than in the Wet Zone for avocado, suggesting moderate variability across simulation runs (Figure 5). Early runs showed more spread, which narrows over time as behavior stabilizes. This indicated reasonably favorable conditions for bees, though not as ideal as the Wet Zone. Similar to the Wet Zone for avocado, bee foraging frequency declined during 2025–2034 and increased in 2035–2044. However, it did not return to the levels observed in 2020–2025.

The Dry Zone for pumpkin showed a much slower and more linear increase in foraging frequency. Even by the end of the simulation, the frequency only reached around 60–70 at most. The gray ribbon in the Dry Zone for pumpkin was the widest among all climate zones, especially in earlier periods of the simulation runs (Figure 5). This revealed greater variability and less predictability in foraging under the Dry Zone for pumpkin; suggesting that dry conditions significantly limit foraging activity.

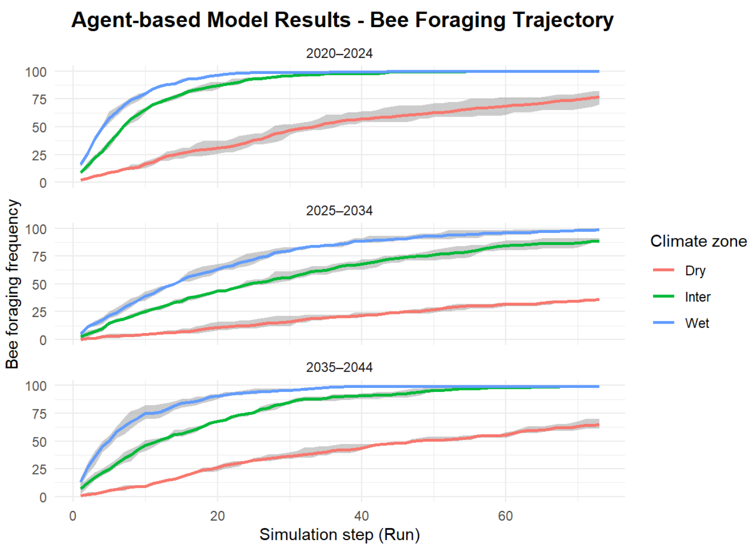


Figure 4:Agent Based modelling result of bee foraging trajectory in the Wet zone for avocado, Intermediate zone for cucumber, and Dry zone for pumpkin.

ANCOVA tests were conducted to compare slopes (trajectories) between climate zones and periods to validate these observed trends. Highly significant p-values confirmed the trends observed in Figure 5 that the rate of increase in foraging frequency differs significantly across time periods for crops in climate zones (Table 7), and across crops generally (Table 8).

Table 7:ANCOVA foraging results by time period.

Period	p_value
2020–2024	p=<0.001
2025–2034	p=<0.001
2035–2044	p=<0.001

Table 8:ANCOVA foraging results by climate zone / crop

Period	p_value
Dry zone / pumpkin	p=<0.001
Intermediate zone / cucumber	p=<0.001
Wet zone / avocado	p=<0.001

3.4.3 Crop Yield

The crop yield trajectories varied clearly by climate zone and remain consistent across all three periods (2020–2024, 2025–2034, 2035–2044). Each climate zone exhibited a distinct growth pattern for its specific crops. In the Dry Zone for pumpkin, crop yield varied across different time periods. It started at around 14,000 units and steadily increased to approximately 16,500 units by the end of the 2020–2024 simulation period. However, during 2025–2034, the yield declined to about 15,000 units. In the projection period of 2035–2044, crop yield for pumpkin rose again, showing a noticeable increase compared to 2025–2034, although the growth was less substantial than that observed in 2020–2024 (Figure 6). Yields in the Intermediate Zone for cucumber were significantly lower, starting around 3,000 units and only gradually increasing to about 4,000 (Figure 6). The avocado crop in Wet Zones also showed relatively low yields (similar to or slightly above the Intermediate zone), beginning near 4,000 and plateauing early (Figure 6). Both of these zones experienced a slight decline in crop yield during the 2025–2034 period. In 2035–2044, yields increased slightly, but the growth was less pronounced compared to the increase observed in 2020–2024.

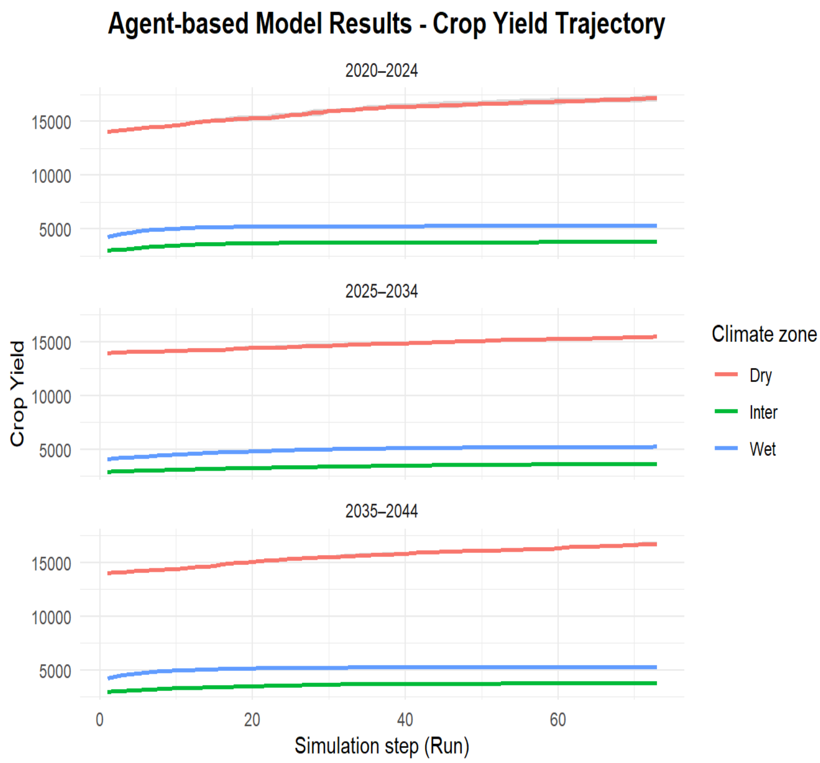


Figure 5:Agent based model results of crop yield trajectory in the Wet zone for avocado, Intermediate zone for cucumber, and Dry zone for pumpkin.

ANCOVA was used to formally assess whether crop yield trends (slopes) over time differ between climates and across periods. All p-values were well below 0.001, indicating that crop yield trends differ significantly between climate zones during each time period (Table 9). This result confirmed that each crop responds differently to climate, even when time was accounted for. These results showed that the effect of time (simulation steps) on crop yield varies significantly within each climate zone (Table 10). It suggested that even within a given climate, the rate of yield change shifts across the three time periods,

Table 9:ANCOVA for crop yield by Period.

Period	p-value
2020–2024	p=<0.001
2025–2034	p=<0.001
2035–2044	p=<0.001

Table 10:ANCOVA for crop yield by Climate zone.

Climate	p-value
Dry zone (Pumpkin)	p=<0.001
Intermediate zone / cucumber	p=<0.001
Wet zone(avacado)	p=<0.001

4.Discussion

4.1 Climate zone-based disparities in Asia honey bee behavior and farmer perceptions

Table 6 was shown that most striking outcome was the significant perceived mismatch between perceived flowering times and pollinator activity in the Dry Zone, reflecting a perceived severe ecological asynchrony. This aligned with earlier studies that link phenological mismatches to climate-induced variability in rainfall and temperature (Goulson et al. 2015). Despite this, fewer farmers in the Dry Zone reported noticing changes in flowering. This might be because the farmers who were most affected have already stopped beekeeping; therefore, they were not captured for inclusion in this not respond survey(Méndez et al. 2013). However, farmers in the Dry Zone did not strongly feel that nectar sources had declined (as shown by the odds ratio of 1.73), unlike in the Intermediate Zone. However, simulation models indicated that bees did not forage much in the Dry Zone for pumpkin. This supported the idea that there really was less nectar and fewer pollinators there. This gap between perception and ecological reality may stem from limited awareness, exacerbated by low educational levels because this area was a remote area in Sri Lanka and an aging beekeepers population (mean age above 55, education mean = 0.4) (see Appendix 1), which can limit adaptive capacity and environmental literacy (Yildirim et al. 2025).

Moreover, a significant proportion of survey respondents in the Dry Zone (see Appendix 3) identified prolonged drought as the most challenging environmental condition. This observation was supported by simulation data, which confirms that such drought conditions suppress bee foraging frequency. As a result, these harsh environmental stressors contributed to reduced ecological resilience, a trend reflected in the broader confidence intervals observed in both farmer responses and foraging trajectory data.

The Intermediate Zone served as the baseline due to its moderate climatic conditions and balanced demographic characteristics. Simulation results showed robust ecological functioning with relatively stable bee foraging patterns and yields for cucumber, supported by higher educational attainment (M = 1.6 for males, M = 2.0 for females) (see appendix 1) and more awareness of pollinator declines. Interestingly, farmers in this zone perceived a more significant decline in pollinators than those in the Dry Zone, possibly due to the dependency of bees on species like the red gum tree, which is now declining due to deforestation. Despite having favorable climatic conditions, the deterioration of floral resources may offset these benefits (Potts et al. 2010). This suggests that land-use changes, not just climate, are driving pollinator stress in this zone.

The Wet Zone presented that simulation outputs for avocado showed high ecological stability, foraging saturation and dense bee activity. This aligned with farmers' low perceived mismatch between flowering and pollinators (Table 6), likely due to the zone's rich biodiversity and stable microclimates. Klein et al. (2007); Potts et al. (2010) mentioned that pollinator abundance and activity are often higher in biodiverse and stable ecological zones. However, the significant perception of nectar source decline (Table 6) suggested that even flora-rich ecosystems were vulnerable to species composition shifts or phenological disruptions. Because the majority of respondents said the most challenging environmental condition for bees was heavy rainfall in this area (see appendix 3). Lawson & Rands (2019) indicated that changing rainfall patterns have an impact on pollen degradation and nectar source decline.Demographically, this zone had the youngest and most educated female participants (mean female age = 41.6, education M = 2.0)(see appendix 1), indicating evolving gender roles and possibly better adaptive awareness (Perera et al., 2018). Despite these positives, the marginally significant perception of flowering time disruption (OR = 2.43, $p < 0.1$) indicated that climate change awareness was rising even in this relatively stable environment.

It is important to note that the structure of survey questions can influence how farmers interpret and respond to them. Binary questions (e.g., presence/absence of mismatch) simplify complex realities and may limit variability in response, potentially influencing regression sensitivity. In contrast, ordinal scales provided a more nuanced understanding but required higher respondent interpretation. A mixed structure was deliberately chosen to balance clarity and depth across a diverse population. Future studies could explore combining binary screening questions with follow-up ranking or open-ended responses to capture both presence and severity of experiences.

Across all zones, perceptions of bee behavior change failed to produce consistent or significant results , highlighting both the subjective nature of farmer observations and the complexity of bee behavior under changing climatic and ecological conditions (Klein et al., 2007). The results imply that either farmers may not always associate climate-related changes with bee behavior, or bee behavior changes are impacted by a variety of specific ecological characteristics that are difficult to generalize across climatic zones. As a result, there wasn't enough information to make any valid or significant inferences about how bee activity was perceived in the Dry, Intermediate, and Wet zones.

4.2 Future Changes in Bee Foraging Frequency and crop yield under Climate Change

This study highlighted how projected climatic variability was likely to alter bee foraging behavior and crop yield for three major pollinator-dependant crops representative of each climate zone in Sri Lanka. Bee foraging frequency was found to vary significantly with temperature fluctuations, a finding that aligns with previous research indicating that temperature is a critical factor in pollinator activity patterns(Hegland et al. 2009; Scaven & Rafferty 2013). Notably, in the period 2035–2044, while temperatures rose, they did not surpass the baseline period of 2020–2024, resulting in an increase in bee foraging activity but still lower than the 2020–2024 benchmark. This suggests that bee foraging may respond nonlinearly to temperature increases, and that thresholds exist beyond which further warming no longer supports increased activity.

The decline in foraging frequency was particularly pronounced in the Dry Zone for pumpkin, where elevated temperatures exceeded the optimal range for bee activity. These results reinforce findings from Nicholson & Egan (2020), who observed that natural hazard-induced climatic stressors such as extreme heat and drought often exert negative impacts on pollinator abundance and behavior, especially in vulnerable regions. In line with this, studies of Asian honey bees have showed that elevated temperatures can modify foraging time and reduce pollen collection efficiency (Abou-Shaara 2014).

The simulation model used in this study also demonstrated a significant relationship between bee foraging frequency and crop yield of the selected three crops. Crops selected for each climatic zone such as pumpkin in the Dry Zone exhibited yield declines during periods of reduced bee activity (2025–2034), reflecting the critical role of pollination services. These results were consistent with earlier work by (Garibaldi et al. 2013), who showed that reductions in pollinator visitation rates lead directly to decreased fruit set, especially in crops dependent on animal pollination. Bee foraging and crop yield of cucumber were mostly stable in Intermediate Zone, but some changes still occurred due to projected climate shifts. This supports the view of Nicholson & Egan (2020) who emphasized the need for more research focused on specific regions especially in developing countries where data is lacking. Their review found that most pollination studies are centered on wealthy, temperate countries, even though pollinator declines pose a greater threat to agriculture production in tropical and dry areas. Ultimately, this study confirmed that bee foraging frequency was a key driver of crop productivity under changing climatic conditions. With increasing global temperatures and the likelihood of more frequent climate-related extreme events, safeguarding pollination services through climate-resilient land management and pollinator conservation strategies is imperative.

While this study focused on temperature as a key environmental driver in bee foraging simulations, it acknowledges that temperature alone does not fully explain observed variations in bee activity. In reality, foraging behavior is influenced by a complex interaction of factors including floral resource availability, rainfall patterns, and presence of wild pollinator populations. Furthermore, the simulation model used current mean temperatures in each zone as the optimal baseline temperature for *Apis cerana* activity, recognizing that this species is likely adapted to local conditions due to evolutionary and ecological factors. Importantly, given projections that Sri Lanka's temperatures may remain below the optimal 33°C for hive thermoregulation, temperature might not be the most limiting factor in the long term. Hence, while temperature was selected as the focal variable for simulation modeling, this does not imply it is necessarily the dominant driver of pollination deficits across all zones. Future modeling efforts would benefit from including additional interacting variables and accounting for the contributions of wild bee populations, which remain a major source of pollination in Sri Lanka.

4.3 Limitation for crop yield

This study aimed to simulate the contribution of managed Asian honey bees (*Apis cerana*) to crop yield of selected crops under varying environmental conditions. While our simulation provided useful insights into how bee activity might influence yield, it is important to recognize that pollination services do not act in isolation. Abiotic elements like soil fertility, water availability, and climate variability interact intricately with biotic agents like wild pollinators to affect crop output, which is by nature multifactorial.Therefore, attributing crop yield variation solely to the managed Apis cerana without accounting for these interacting variables may oversimplify the true ecological scenario.

Nicholson & Egan (2020) mentioned in a study that there is a major research gap in understanding how pollination services for crops, especially in developing regions, are influenced by natural hazard events. Only a small fraction (5%) of the reviewed studies explicitly examined crop pollination services, emphasizing the urgent need to connect ecological data with agronomic outcomes. This study findings contributed to this gap by showing how yield responses may shift with the behavioural dynamics of managed *Apis cerana* under rising temperatures a likely scenario under future climate regimes.

Importantly, the interaction between climate variables and pollinator efficiency further complicates measurement. For example, Gasim & Abdelmula (2018) showed that under heat stress, the yield loss in faba beans was significantly greater in the absence of pollinators, suggesting a buffering effect of pollination under abiotic stress. This supports the hypothesis that pollinator services may offer resilience to environmental extremes, although the degree of resilience likely depends on species-specific traits and the presence of alternative pollinators.

However, isolating the effect of pollinators on yield is difficult in real-world ecosystems due to the confounding influence of external factors such as irrigation, nutrient inputs, and pest management. Therefore, while simulations like this are valuable for hypothesis generation, they must be interpreted within the broader context of agroecological variability. A more integrated approach incorporating wild pollinator diversity, climate data, and farm management practices is essential to accurately predict and enhance pollination services under future climatic conditions.

4.4 Adapting current beekeeping practices to climate change

The adaptive capacity of beekeeping practices to ecological and climatic changes in Sri Lanka showed distinct regional variations. In the Wet and Intermediate Zones, beekeepers demonstrated a considerably high adaptive capacity to climate change (i.e. the practices beekeepers employed to cope with and respond to its impacts). This was evident in the widespread adoption of modern and ecologically sound beekeeping practices. The majority of beekeepers practiced modern hives in the wet zone (26 out of 40 respondents in the Wet Zone); similarly, the Intermediate Zone practices predominantly modern hives (23 out of 39 respondents in the intermediate zone)(see appendix 3). Both the significantly Wet and Intermediate Zones employ a combination of traditional and modern techniques (see appendix 4). They used special pest defense techniques. However, in the Dry Zone, most respondents practiced traditional methods, with 22 out of 30 indicating this preference. Few of them (4 respondents out of 30) (see appendix 3) practiced the modern methods. This trend appears closely linked to demographic and educational factors, as most beekeepers in the Dry Zone were over 50 years old and possess relatively low levels of formal education (see appendix 1). These factors likely contributed to an unwillingness or inability to adopt new technologies, a phenomenon supported by other studies highlighting similar barriers to agricultural innovation among older or less-educated farmers (Meijer et al. 2015).

In both the Wet and Intermediate Zones, beekeepers demonstrated the use of alternative methods to attract honey bees, primarily through the planting of beeattractive flora and the provision of artificial nesting sites. Specifically, 33 respondents in the Wet Zone and 29 (see apprndix 3) in the Intermediate Zone reported cultivating plants that were favorable to pollinators, alongside establishing artificial nests to support colony establishment and growth(see appendix 5). Conversely, the majority of respondents in the Dry Zone (20 out of 27) (see appendix 3) indicated that they did not adopt any alternative methods for attracting bees. This disparity may be influenced by differences in environmental conditions, resource availability, or awareness regarding the ecological importance of such practices. The implementation of alternative honey bee attraction methods is not only instrumental in conservation and expansion of honey bee populations (Decourtye et al. 2010), but also plays a crucial role in enhancing regional biodiversity and promoting ecological resilience and sustainable approach to climate change adaptation, especially in vulnerable zones .

The findings of the survey clearly indicated that all climatic zones under study Dry, Wet, and Intermediate have experienced honeybee colony losses due to extreme climatic conditions. Notably, the Dry Zone reported the most severe losses, with 16 respondents confirming significant hive losses. This was comparatively higher than the Wet Zone (13 respondents) and the Intermediate Zone (8 respondents), suggesting that regions with harsher and more prolonged drought conditions are more vulnerable to colony decline (see appendix 3). Sometimes, bees left the hive box due to heat stress (see appendix 6) These results aligned with prior research indicating that arid and semi-arid climates are associated with increased bee mortality due to heat stress and forage scarcity (Sibaja Leyton et al. 2024; Walters et al. 2024).

Despite these clear environmental threats, most beekeepers across all zones were not practicing effective climate adaptability strategies. The primary reasons cited were a lack of awareness and limited access to necessary resources or facilities. This trend reflects findings by Gemedi et al. (2025), who highlighted the critical role of beekeeper education and extension services in enhancing climate resilience in beekeeping. Only a minority of respondents reported implementing mitigation strategies, such as providing artificial sugar supplements during prolonged droughts, ensuring access to water resources, or relocating hives to shaded areas or covering them with natural leaves or black polyethylene(see apendix 6). Although these practices are basic, they can be vital for buffering colonies against environmental stressors(Hilmi et al. 2011; *Good beekeeping practices for sustainable apiculture* 2021). However, the low adoption rate of such practices underscores a significant gap in adaptive capacity at the grassroots level. The absence of adaptive practices among beekeepers is a serious concern, especially as research increasingly shows that climate change is altering bee foraging patterns, reducing colony productivity, and weakening pollination services(Klein et al. 2007a; Potts et al. 2010a) . If beekeepers in climate-vulnerable zones like Dry Zone do not adopt proactive adaptation strategies, they will face increasing losses and long-term threats to their livelihoods.

In addition to ecological concerns, the survey results also underscored the significant economic implications of pollinator decline and the vital role beekeeping plays in sustaining rural livelihoods. A substantial majority of farmers reported a notable decrease in their income, which they directly attributed to the reduction in Asia honey bee populations. This trend was particularly evident in the Dry Zone, where the impact was most severe (see appendix 3). These findings are consistent with global literature emphasizing the economic dependence of agricultural systems on pollination services, especially for smallholder farmers(Klein et al. 2007; Gallai et al. 2009).

Beekeeping has long been recognized as an accessible and sustainable livelihood strategy, especially in climate-vulnerable regions (Hilmi et al. 2011). Beyond honey production, beekeeping opens avenues for value-added products that can enhance income diversification. For instance, in Vavuniya (Dry Zone) , one respondent a local woman, has begun producing lip balm and moisturizing cream using beeswax. While this initiative highlights the entrepreneurial potential of beekeeping, it has yet to reach market-level development due to a lack of processing facilities and institutional support. This example illustrated both the opportunity and the infrastructural barriers that small-scale beekeepers face in expanding their enterprises (Hilmi et al. 2011).

The broader implications of this finding affirm that honeybees are not only crucial for maintaining biodiversity but are also integral to rural livelihoods. Several studies have highlighted how beekeeping contributes to poverty alleviation, agriculture production, and gender empowerment in low-resource settings (Sagwa 2021). According to the study, climate change has a direct effect on pollinators, significantly impacting their survival and livelihoods. Notably, the majority of survey respondents strongly agreed that beekeeping should be promoted as a climate adaptation strategy. This widespread endorsement reflects an understanding of its dual ecological and economic value. Promoting beekeeping can serve as a community-level response to climate change impacts, enhancing resilience while supporting sustainable development goals (Kijera 2025).

4.5 Proposal of a DEEP BEE Model for sustainable, climate-resilient beekeeping in Sri Lanka

This study demonstrated that climate change significantly impacts the foraging behavior and overall activity of the Asian honey bee, which in turn affects crop yields and the livelihoods of farmers, particularly in relation to beekeeping practices. In Sri Lanka, current beekeeping methods were not adequately adapted to address the challenges posed by climate change. There was a noticeable gap between grassroots beekeepers and centralized institutions, resulting in unequal access to information and support at the community level. To address this issue, the proposed **DEEP BEE** model (Decentralized, Empowered, Eco-smart, Participatory Beekeeping Empowerment) offers a comprehensive framework aimed at promoting climate-resilient and biodiversity friendly beekeeping systems in Sri Lanka, with a particular focus on underserved rural communities. The model placed a strong emphasis on a decentralized strategy to close the crucial gap between local beekeepers and institutions at the national level (Purcell & Anderson 1997; *Good beekeeping practices for sustainable apiculture* 2021). In order to begin implementing this model in practice, stakeholders (such as beekeepers at the local level, the Department of Agriculture, the Beekeeping Development Unit, and provincial and district Agricultural Extension Officers) will need to further refine and interpret it. Simulation results from the agent-based model (ABM) identified the climatic zones / crops most impacted by predicted mismatch, limited foraging frequency, and declining crop yields under projected climate conditions. These findings justify prioritizing Decentralized Knowledge Hubs (DKHs) in such climate-vulnerable regions to ensure targeted interventions (Figure 7).

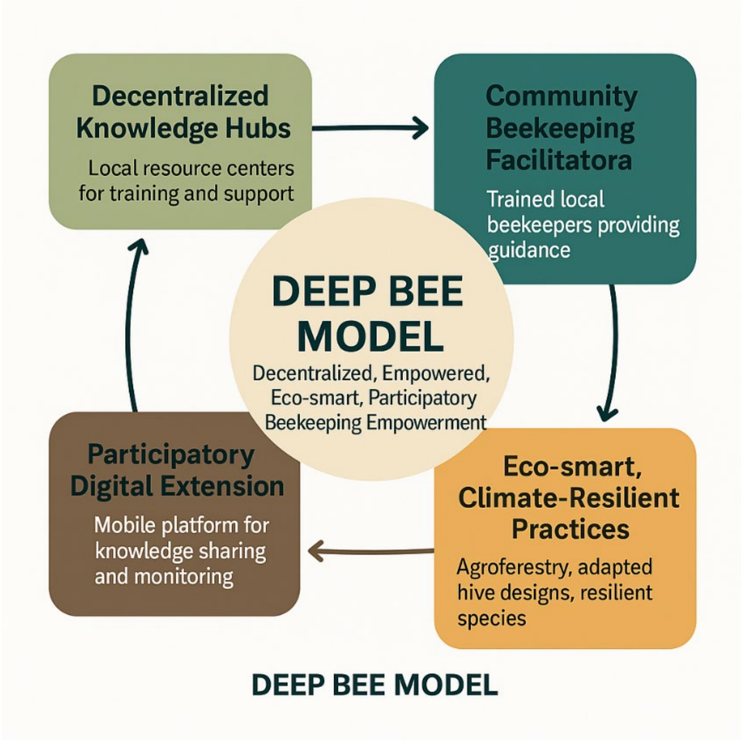


Figure 6:Proposal of the DEEP BEE Model for Sustainable, Climate-Resilient Beekeeping in Sri Lanka.

The model ensured that practical knowledge, climate adaptation techniques, and resources reach remote areas by establishing Decentralized Knowledge Hubs (DKHs) and training Community Beekeeping Facilitators (CBFs), especially those in the Dry Zone that were often excluded from mainstream extension services (Figure 7). These localized centers foster trust and enable peer-led knowledge transfer, a method that has been proven effective in other South Asian agricultural interventions (Purcell & Anderson 1997). The ABM highlighted how temperature fluctuations directly influence bee foraging efficiency, validating the need for climate-smart training content that addresses zone specific challenges. CBFs, guided by simulation-derived data, can deliver precise technical knowledge on adaptive strategies like hive relocation, use of clay hive boxes, and agroforestry design suited to each climatic context.

Moreover, the model integrates eco-smart practices, including the promotion of multi-season agroforestry systems to ensure year-round floral availability, which is essential for bee health and pollination services. Such diversification not only improves pollinator resilience but also strengthens local agriculture production and rural incomes, aligning with findings from the (Potts, Fonseca, & Ngo, 2016) global assessment on pollinators. The ABM confirmed that areas with more consistent floral resources and optimal bee density experienced higher foraging frequency and better crop yields, reinforcing the ecological rationale behind the eco-smart components of the model.

A notable innovation in the DEEP BEE model is the climate-specific adaptation of hive materials and designs. For example, the introduction of clay hive boxes in high-temperature zones addresses the thermal stress bees experience, improving survival and productivity (*Good beekeeping practices for sustainable apiculture* 2021). ABM scenarios demonstrated how elevated temperatures reduced foraging activity, particularly in the Dry Zone, and how temperature stabilization improved behavior over time. This underscores the model's focus on technological adaptations rooted in environmental modeling Simultaneously, the model highlighted the urgent need for structured breeding programs to develop and disseminate climate-resilient bee species an initiative currently lacking in Sri Lanka but essential for long-term sustainability under climate change .

The inclusion of a participatory digital extension system ("BeeConnect") facilitates two-way communication between institutions and farmers, overcoming barriers of literacy and infrastructure. A critical application of the ABM lies in its ability to inform BeeConnect. Simulation results can be translated into simple visual tools within the app, providing farmers with early warnings about anticipated drops in bee foraging activity due to climate stressors like excessive heat. This participatory digital platform can then be used to disseminate tailored recommendations, such as when to provide supplemental feeding, protect hives, or enhance floral resources. In doing so, BeeConnect transforms simulation insights into actionable knowledge, enhancing real time decision making for beekeepers. This feature was inspired by successful digital agricultural platforms in the Global South that have enhanced access to timely information and market data (USAID, 2018).

the DEEP BEE model addressed both institutional and environmental challenges of rural beekeeping in Sri Lanka. It represented a holistic strategy that enhances ecological sustainability, empowers local actors, and strengthens resilience against climate variability. The integration of agent based modeling within this framework ensures that interventions are data informed and spatially targeted. The model's components were informed by proven best practices in climate adaptation, rural extension, and participatory governance, making it a viable framework for national adoption(Figure 7).

Beyond these immediate applications, the agent-based model developed in this study has broader potential. Because the NetLogo framework allows adjustment of parameters such as crop pollination dependency, hive density, and temperature sensitivity, the model can be extended to simulate other pollinator-dependent crops (e.g., coconut, mango, or tea) or to test scenarios under additional climate stressors such as rainfall variability or extreme weather. This flexibility makes the ABM a decision-support tool not only for researchers but also for institutional stakeholders seeking to anticipate regional risks and prioritize interventions.

Moreover, integrating socio-economic variables into the model could enhance its relevance for real-world decision-making. Parameters such as honey market prices, costs of hive materials, or household income loss due to reduced pollination could be simulated alongside ecological dynamics. By linking ecological resilience with economic outcomes, the ABM would provide valuable insights for government authorities designing subsidy schemes, for NGOs promoting livelihood resilience, and for farmer cooperatives lobbying for policy support. In this way, the DEEP BEE framework becomes not just an ecological or technical strategy, but a participatory platform where ecological data, farmer knowledge, and stakeholder priorities converge to guide sustainable beekeeping under climate change.

5. Conclusion

This study provided an integrated assessment of how climate change is perceived and predicted to influence the behavior of Asian honey bees (*Apis cerana*) and its consequent impacts on crop yields and farmer livelihoods in Sri Lanka, with a focus on beekeeping. By combining farmer perceptions, statistical modeling, and agent-based simulation, the research delivers a multifaceted understanding of pollinator dynamics under climate change that is important for developing sustainable, climate-resilient beekeeping strategies and enhancing agricultural productivity and rural livelihoods in Sri Lanka. Key findings revealed that significant perceived ecological mismatch in climate zones according to the farmers' perception. The dry zone, plagued by high temperatures and limited floral resources, showed perceived severe phenological mismatches and reduced bee foraging activity.The Intermediate Zone, while climatically balanced, was perceived by farmers to suffer from the degradation of floral diversity, pointing to the role of land-use changes in pollinator stress. The wet zone offered the most stable environment for pollination according to farmers perceptions, yet even here, rising rainfall intensity was considered a threat to nectar availability and foraging success.

Simulation results confirmed that temperature played a critical role in regulating bee foraging behavior and, by extension, crop pollination success. Bee activity and crop yield both declined under unfavorable temperature shifts, especially during the 2025–2034 projection. However, some recovery was noted in 2035–2044, emphasizing the non-linear and zone-specific effects of climate change. These findings underscored the need for regionally tailored strategies that recognize both climatic variability and socio-economic constraints. While beekeeping was recognized by farmers as a valuable climate adaptation tool, adaptive capacity remains uneven across zones. Traditional practices dominated in more vulnerable regions, hindered by demographic factors such as age and low education. In contrast, beekeepers in Wet Zone exhibited more adaptive behaviors, including the use of modern hive systems and bee-friendly vegetation in comparison to other zones.

To address these disparities, this thesis proposed the DEEP BEE model; a decentralized, eco-smart, and participatory framework to strengthen climate-resilient beekeeping. This model not only bridges institutional gaps but also could help to enhance biodiversity and economic stability for rural communities. Its wider refinement and adoption by Local level stakeholders (Beekeepers), institutional stakeholders (e.g. Department of Agriculture, Beekeeping Development Unit; Provincial and district Agricultural Extension Officers) could help to adapt climate resilient strategies by identifying possible risks and adaptation strategies in a more timely manner,and contributing towards strengthened relationships between institutions and beekeepers.

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Popular science summary

This study explores how climate change affects the behaviour of the Asian honey bee (*Apis cerana*), and how those behavioural changes, in turn, influence crop yields and farmer livelihoods in Sri Lanka. Honey bees play a crucial role in agriculture by pollinating many fruit, vegetable, and field crops. However, rising temperatures and unpredictable weather are beginning to disrupt this delicate relationship between bees, plants, and farmers.

Through field surveys with beekeepers across Sri Lanka's Wet, Intermediate, and Dry zones, and Agent-based modelling , the research examined how temperature variations influence bee foraging activity and crop productivity. Farmers in the Dry zone reported increasing mismatches between crop flowering and bee activity, while those in the Wet Zone noticed fewer nectar sources and changing rainfall patterns. Simulation results confirmed these perceptions: when temperatures rose beyond the bees' optimal range (around 33°C), foraging activity and pollination efficiency declined, leading to lower yields of pumpkin, cucumber, and avocado.

These findings suggest that climate change threatens both pollination services and rural livelihoods, especially where farmers depend on small scale beekeeping and pollinator dependent crops. The study suggests the solution for promoting climate resilient and biodiversity friendly beekeeping systems in Sri Lanka. It proposes a framework called the DEEP BEE Model (Decentralized, Empowered, Eco-smart, Participatory Beekeeping Empowerment), which promotes climate-resilient and community-based beekeeping. This model encourages locally adapted hive designs, better floral resource management, and digital training for farmers. By combining scientific modelling with farmer knowledge, this research highlights the urgent need to protect pollinators as part of broader climate adaptation strategies.

Acknowledgements

There are several individuals whose support and contributions have been vital throughout the entire process of my thesis project. I extend my heartfelt thanks to each and every one of them.

First and foremost, I would like to express my deepest gratitude to my supervisor, Paul Egan, for entrusting me with this research as part of the SIANI project. His guidance and encouragement have been instrumental from the outset. I am especially thankful for his efforts in introducing me to many valuable contacts, which greatly facilitated my data collection and networking efforts in Sri Lanka.
I would also like to sincerely thank my co-supervisor, Hanna Thosteman, for her insightful guidance and unwavering support throughout the research process. Her constructive advice has been crucial to the success of this work.

My appreciation extends to Özgür, who provided invaluable help with data analysis, and to Lotta, who generously shared her knowledge and insights on beekeeping practices.

A special note of thanks goes to the Director of the Beekeeping Unit Mr. Vimukthi in Sri Lanka, whose dedication and coordination enabled my collaboration with provincial and district agricultural officers across different climatic zones. I am deeply grateful to these officers, whose efforts made it possible for me to reach and engage with beekeepers in diverse regions.

Furthermore, I extend my sincere appreciation to all the beekeepers who participated in this study. Their enthusiastic participation, warm hospitality, and openness were truly inspiring. Their generosity and willingness to share their experiences will stay with me always.

Finally, I am profoundly thankful to my family and my husband for their constant love, patience, and unwavering support throughout this journey. I truly could not have accomplished this without them.

Appendix 1

Demographic Summary of beekeepers by Climate Zone and District

Climate Zone	District	Male	Male Age (M ± SD)	Male Edu. (M ± SD)	Female	Fem. Age (M ± SD)	Fem. Edu. (M ± SD)
Dry Zone	Anuradhapura	8	57.9 ± 8.0	0.2 ± 0.7	11	49.3 ± 10.4	0.7 ± 0.6
	Vavuniya	9	51.6 ± 9.7	0.4 ± 0.5	2	39.5 ± 0.7	0.0 ± 0.0
	Total	17	54.5 ± 9.2	0.4 ± 0.6	13	47.8 ± 10.2	0.6 ± 0.7
Intermediate Zone	Badulla	17	50.5 ± 12.1	1.7 ± 0.8	1	56.0 ± NA	3.0 ± NA
	Bandarawela	6	52.2 ± 14.0	1.2 ± 0.8	NA	NA	NA
	wellawaya	10	50.9 ± 12.8	1.7 ± 0.5	5	45.8 ± 6.1	1.8 ± 0.4
	Total	33	50.9 ± 12.3	1.6 ± 0.7	6	47.5 ± 6.8	2.0 ± 0.6
Wet Zone	Gampaha	11	48.5 ± 12.1	2.0 ± 0.8	4	40.5 ± 5.4	1.8 ± 1.0
	Kegalle	9	53.0 ± 11.5	2.2 ± 1.0	1	45.0 ± NA	1.0 ± NA
	Rathnapura	12	55.8 ± 13.7	2.1 ± 0.8	3	42.0 ± 10.6	2.7 ± 0.6
	Total	32	52.5 ± 12.6	2.1 ± 0.8	8	41.6± 6.9	2.0± 0.9

Appendix 2

Survey Questionnaire

District/Province: _______________

Section 1: General Information

1.1. Name (Optional): ……………………………….

1.2. Age: …………………………………..

1.3. Gender: ☐ Male ☐ Female ☐ Other

1.4. Education level:

No Formal Education		Primary Education		Secondary Education		Higher Education	

1.5. Type of Farming: ☐ Smallholder ☐ Commercial ☐ Mixed

1.6. How many years have you been farming? ……………………………………

1.7. What types of pollinators do you observe in your area? (rank the following pollinators from **most common (1) to least common (5 or more, as applicable)**

Bees		Butterflies		Beetles		Birds		Bats		Other (please specify):

1.8. Do you practice beekeeping?

Yes		No	

Section 2: Climate Change impact

2.1. Have you noticed any changes in climate patterns affecting your crops?

☐ Yes ☐ No

If yes, what changes? (rank from **most common (1) to least common (5 or more, as applicable)**

Increased temperature		Irregular rainfall		More frequent droughts		Extreme weather events (storms, floods)	

2.2. How have these climate changes affected your crops? (rank from **most common (1) to least common (5 or more, as applicable)**

Lower Yields		Poor Quality Produce		Increased Pests and Diseases		Delayed Flowering/Fruiting		No Significant Impact	

2.3. Have you considered other factors affecting crop yield besides climate change?

Yes		No	

If yes, rank the following factors from most impactful (1) to least impactful:

☐Soil fertility
☐Pests and diseases
☐Water availability/irrigation
☐Farming practices/techniques
☐Use of fertilizers and pesticides
☐Market access and prices
☐Other (please specify): ___________

2.4. Have you noticed changes in the flowering time of your crops due to climate change?
On a scale of 1 to 5, please rate the level of impact you have observed:
(1 = No impact, 5 = Very high impact)
☐**1** – No impact (flowering time remains the same)
☐**2** – Slight impact (minor shifts in flowering time)
☐**3** – Moderate impact (noticeable but manageable changes)
☐**4** – High impact (significant shifts affecting crop growth)
☐**5** – Very high impact (major disruptions in flowering and yield)

Section 3: Farming and Pollination

3.1. What crops do you cultivate:
……………………………………………… Land size : …………….

3.2. How dependent are your crops on pollination services? (On a scale of 1 to 5, please rate the level of dependency you have observed)
(1 = Not dependent, 5 = Highly dependent)

☐ Not dependent (crops grow and yield without pollination)
☐ Slightly dependent (pollination has a minimal effect)
☐ Moderately dependent (pollination somewhat influences yield)
☐ Highly dependent (pollination is crucial for good yield)
☐ Extremely dependent (crops will not produce without pollination)

3.3. Have you observed a change in the presence of pollinators on your farm over the last 5-10 years? (On a scale of 1 to 5, please rate the level of presence you have observed)
(1 = Significantly decrease, 5 = Significantly increased)

Significantly Decreased		**Slightly Decreased**		**No Change**		**Slightly Increased**		**Significantly Increased**	

3.4. Do you observe any mismatch between crop flowering and pollinator activity?

Yes		No		Not Sure	

Section 4: Beekeeping and Climate Adaptation

4.1. Do you keep bees or use beekeeping services for pollination?

Yes (own bees)		Yes (rent hives)		No	

If No, would you consider beekeeping as a method to improve pollination?

☐ Yes ☐ No ☐ Not sure

4.2. Do you adjust crop planting schedules to align with bee activity?

Yes		No	

4.3. What alternative methods do you use to attract pollinators?

Planting wildflowers		Avoiding pesticide use		Providing artificial nests		No special measures	

4.4. What type of beekeeping do you practice?

Traditional Hives		Modern Hives		Mixed Methods	

4.5. How many years have you been practicing beekeeping:

……………………..

4.6. What species of bees do you keep?

Apis cerana (Asian honeybee)		Apis dorsata (Giant honeybee)		Apis mellifera		Trigona (Stingless bee)		Other…………….

4.7.How many hives do you currently manage :

…………………………………

4.8. Have you observed any changes in bee behavior due to climate variations?

Yes		No	

4.9. What kind of changes have you noticed? (rank from **most common (1) to least common (5 or more, as applicable)**

Reduced Honey Production		Increased Mortality		Reduced Pollination Activity		Shifts in Foraging Patterns		No Change	

4.10. What measures have you taken to adapt to these changes? (rank from **most common (1) to least common (5 or more, as applicable)**

Providing Artificial Feed		Relocating Beehives		Changing Hive Management Practices		No Specific Measures	

4.11. Have you experienced hive losses due to extreme weather events?

Yes, severe losses		Yes,some losses		No	

4.12.How do you manage your hives during prolonged droughts?

☐ Provide supplementary sugar feeding
☐ Ensure access to water sources
☐ Reduce hive disturbances
☐ Move hives to areas with better floral resources
☐ Other: ___________

4.13. Have you observed a decline in nectar sources for your bees?

Yes, significant decline		Yes, slight decline		No	

4.14. Have you experimented with different bee strains to improve pollination efficiency?

Yes		No	

4.15.If yes, which traits were you selecting for in breeding? (Rank in importance)

Honey production		Resistance to disease		Tolerance to extreme weather		Pollination efficiency		Other

4.16. Have you received any training or support for bee breeding programs?

Yes		No	

If yes, what are they?
..

4.17. Have you practiced bee breeding?

Yes		No	

If yes, what breeding techniques have you used?

Artificial insemination		Selective queen breeding		Natural colony selection		**Other…………**

4.18.What are the main challenges in implementing breeding programs for bees?

☐ Limited access to breeding stock
☐ Lack of technical knowledge
☐ High costs
☐ Other: ___________

4.19. Would you be interested in participating in a bee breeding program to improve resilience against climate change?

Yes		No	

4.20. How often do you use pesticides on your farm? (scale of 1 to 5)

Never		**Rarely (Once or twice a year)**		**Occasionally (Several times a year)**		**Frequently (Monthly)**		**Very Frequently (Weekly or more)**	

If you use pesticides, do you take any measures to protect pollinators?

Apply pesticides at night		Use bee-friendly pesticides		No specific measures	

4.21.Have your bee colonies experienced disease outbreaks in recent years?

Yes		No	

If yes, which diseases have affected your hives?

☐ Varroa mite infestation
☐ Nosema disease
☐ Foulbrood (American or European)
☐ Chalkbrood
☐ Other: ___________

4.22.What strategies do you use to manage bee diseases?

☐ Regular hive inspections

☐ Using natural remedies
☐ Using chemical treatments
☐ Breeding for disease resistance
☐ Other: ________

4.23.What are the biggest challenges in beekeeping today? (rank from **most common (1) to least common)**

Climate change		Pesticide exposure		Lack of floral resources		Hive diseases (mites, infections)		Other:

Section 5: Socioeconomic Impact

5.1. Have changes in pollination affected your income from farming (scale of 1 to 5)

No Change		Slight Decrease		Moderate Decrease		Significant Decrease		Severe Decrease	

5.2. how much of your honey production from per hive?.....................

5.3. How much of your annual income is dependent on honey production and pollination services?

Less than 25%		25-50%		50-75%		More than 75%	

5.4. Have climate changes led to financial losses in beekeeping?

Yes		No	

If yes, how have you coped with these losses?

...

5.5.Have you received any external assistance (government support, NGOs, beekeeping organizations) to address pollination deficits?

……………………………………………………………………………

Section 8: Adaptation & Future Strategies

8.1. Have you observed differences in survival rates between different bee species or strains in extreme weather conditions?

☐ Yes ☐ No

8.2.Which environmental conditions are most challenging for your bees? (Rank from most to least challenging)

☐ High temperatures

☐ Prolonged drought
☐ Heavy rainfall and flooding
☐ High winds and storms
☐ Other: ___________

8.3. Have you adopted any strategies to protect bees from climate change? (rank from **most common (1) to least common)**

Relocating hives		Providing supplementary feeding		Reducing hive exposure to extreme heat		No specific measures	

8.4. Do you believe beekeeping should be promoted as a climate adaptation strategy?
☐ Yes ☐ No

8.5. What challenges that you face for practicing beekeeping? (rank from **most common (1) to least common)**

Lack of knowledge		High initial costs		Lack of access to beekeeping equipment**)**		lack of extension services	Other	

Appendix 3

Descriptive statistic analysis for survey data

Count of 4.4.What type of beekeeping do you practice	
Dry	**30**
Mixed Methods	4
Modern Hives	4
Traditional Hives	22
Intermediate	**39**
Mixed Methods	14
Modern Hives	23
Traditional Hives	2
Wet	**40**
Mixed Methods	11
Modern Hives	26
Traditional Hives	3
(blank)	
(blank)	
Grand Total	**109**

Q6.2._Which_environmental_conditions_are_most_challenging_for_your_bees	
Dry	**30**
High_temperatures	1
Prolonged_drought	29
Intermediate	**39**
Heavy_rainfall_and_flooding	23
High_temperatures	6
Prolonged_drought	10
Wet	**40**
Heavy_rainfall_and_flooding	35
Prolonged_drought	5
(blank)	
(blank)	
Grand Total	**109**

4.3.What alternative methods do you use to attract pollinators

Count of Planting_wildflowers	
Dry	**28**
No	20
Yes	8

(blank)	
Intermediate	**39**
No	10
Yes	29
Wet	**39**
No	6
Yes	33
(blank)	
Grand Total	**106**

Count of Providing_artificial_nests	
Dry	28
No	20
Yes	8
(blank)	
Intermediate	39
No	10
Yes	29
Wet	39
No	6
Yes	33
(blank)	
Grand Total	106

Count of No_special_measures	
Dry	27
No	20
Yes	7
(blank)	
Intermediate	37
No	10
Yes	27
Wet	37
No	6
Yes	31
(blank)	
Grand Total	101

Count of Q4.11.Have_you_experienced_hive_losses_due_to_extreme_weather_events	
Dry	**30**
No	2
Yes,_severe_losses	16
Yes,some_losses	12
Intermediate	**39**
No	7

Yes,_severe_losses	8
Yes,some_losses	24
Wet	**39**
No	11
Yes,_severe_losses	13
Yes,some_losses	15
(blank)	
(blank)	
(blank)	
Grand Total	**108**

4.10.What measures have you taken to adapt to these changes (Ranking)

Row Labels		Count of Providing Artificial Feed
Dry		21
	1	16
	3	2
	4	3
(blank)		
Intermediate		36
	1	35
	2	1
(blank)		
Wet		33
	1	25
	2	5
	3	2
	4	1
(blank)		
Grand Total		90

Row Labels		Count of Changing Hive Management Practices
Dry		25
	1	16
	3	2
	4	3
(blank)		4
Intermediate		32
	1	31
	2	1
(blank)		
Wet		33
	1	23
	2	5
	3	2

	4	1
(blank)		2
Grand Total		90

Row Labels		Count of No Specific Measures
Dry		29
	1	15
	3	2
	4	3
(blank)		9
Intermediate		27
	1	23
	2	1
(blank)		3
Wet		35
	1	22
	2	5
	3	2
	4	1
(blank)		5
Grand Total		91

Count of Q5.1._Have_changes_in_pollination_affected_your_income_from_farming	
Dry	**29**
Moderate_Decrease	2
No_Change	5
Other	1
Significant_Decrease	20
Slight_Decrease	1
(blank)	
Intermediate	**38**
Moderate_Decrease	2
No_Change	7
Severe_Decrease	3
Significant_Decrease	19
Slight_Decrease	7
(blank)	
Wet	**38**
Moderate_Decrease	2
No_Change	14
Significant_Decrease	14
Slight_Decrease	7
Special_training_fron_DOA	1
(blank)	

(blank)	
(blank)	
Grand Total	**105**

Appendix 4

Types of Beekeeping practices in Sri Lanka (A) Modern Wooden hive box in Intermediate zone (B) Modern wooden hive box with pest defence techque in Wet zone (C) Traditional hive using clay pots in intermediate zone (D) Traditional hive using Jaggory trunk in dry zone

(A)

(B)

(C)

(D)

Appendix 5

Alternative methods practicing for attract Asia honey bee (A) Planting bee attaction flora (B) using artificial nest

(A)

(A)

(B)

Appendix 6

Asian honey bee exited the hive box due to the high temperature inside

Covering hive boxes with black polythene during extended droughts in dry zones.

Appendix 7 (Fact Sheet)

Background

Sri Lanka, with its three climatic zones (Wet, Intermediate, Dry), is highly vulnerable to climate change impacts (Chithranayana & Punyawardena 2008).

The Asian honey bee (Apis cerana) is the country's most common pollinator, crucial for crops like pumpkin, cucumber, and avocado.

Research Aim

To investigate how climate change particularly temperature shiftsaffects Asian honey bee behavior, crop yield, and farmer livelihoods, and to propose strategies for climate-resilient beekeeping.

Research Questions

1.How do farmers' perceptions of Asian honey bee foraging, behavior, and pollination activity vary across different climatic zones in Sri Lanka?

2.How agenet-based modelling simulations predict Asian honey bees' behavior and, consequently, crop yields to shift with futurechanging climate conditions (temperature) in Sri Lanka.

Methodology

1. Farmer Surveys 🧑‍🌾 🐝

110 beekeepers interviewed across Wet, Intermediate, and Dry Zones.
Captured perceptions of bee activity, pollination, and climate impacts.

2. Data Collection 📊

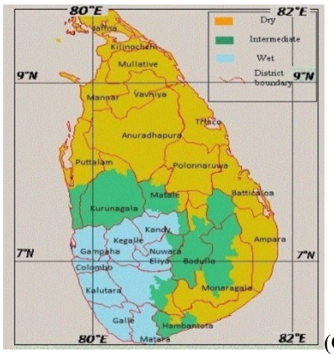
Hive density & crop yield records.
Climate projections from the CHELSA database.

3. Simulation 🔬

Agent-Based Model (NetLogo) simulated how changing temperatures (2020–2044) affect bee foraging & crop yields.

4. Analysis 📈

Applied Multinomial Logistic Regression (MLR) & ANCOVA to compare farmer perceptions with simulation outcomes.



(Climatic zones in Sri Lanka (Karunaweera et al. 2014).

Key Findings

🌡️ Temperature stress: Bee foraging declines when temperatures move away from the 33–35 °C optimum. Biggest crop yield losses projected in Dry Zone (pumpkin), moderate in Intermediate (cucumber), and least in Wet Zone (avocado).

🧑‍🌾 Farmer perceptions: Many report mismatches between flowering and bee activity. Dry Zone farmers perceive severe ecological asynchrony; Wet Zone farmers note nectar decline.

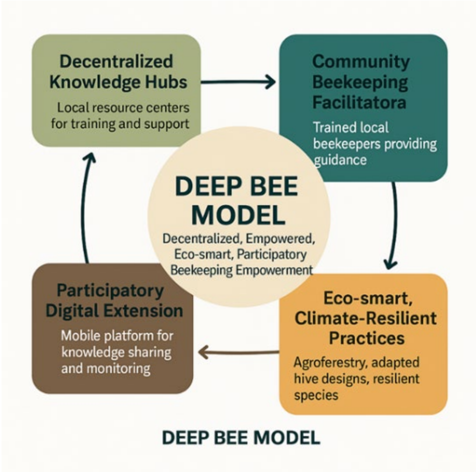
📉 Simulation results: Agent-based modeling shows strong drops in bee foraging and crop yield during 2025–2034, with partial recovery after 2035.

🛠️ Practice gaps: Dry Zone relies on traditional hives, with low adoption of climate-adaptive methods. Modern practices are more common in Wet and Intermediate Zones.

💸 Livelihood risk: Bee colony losses from drought and heavy rains reduce both honey yields and crop pollination, threatening rural incomes.

Suggetions

1. The DEEP BEE Model (Decentralized, Empowered, Eco-smart, Participatory Beekeeping Empowerment)
    - 🏫 Decentralized Knowledge Hubs (DKHs): Local centers for training and resources.
    - 🤝 Community Beekeeping Facilitators (CBFs): Peer-led support networks.
    - 🌱 Eco-smart practices: Year-round floral resources, multi-season agroforestry.
    - 🐝 Adaptive hive designs: Heat-resilient (e.g., clay hives) and shaded hive placement.
    - 🔬 Breeding programs: Climate-resilient bee strains.
    - 📲 BeeConnect digital platform: Real-time weather alerts, adaptive advice, and two-way farmer–extension communication.



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