HONEY BEE HABITAT SUITABILITY: UNVEILING SPATIAL AND TEMPORAL VARIATIONS, PREDICTING FUTURES, AND MITIGATING NATURAL HAZARD IMPACTS

A Thesis submitted by

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ABSTRACT

Honey bees (*Apis mellifera*) are pivotal for global agriculture and ecosystem services, contributing significantly to pollination and the sustainability of crop production. Despite their significance, studies assessing the spatial and temporal variations in land suitability for honey bees and evaluating the impact of climate change and natural hazards are limited. This study in Southern Queensland, Australia, aimed to create a GIS-based framework for assessing apiary land suitability, predicting future suitability under changing climate, and identifying priority habitats for conservation against natural hazards. The specific objectives encompass the following: 1) to assess land suitability for beekeeping, considering spatial and temporal variations in criteria, using GIS-based multi-criteria decision analysis (MCDA); 2) to predict honeybee distribution using bioclimatic and environmental variables for two future time spans: 2020-2039 and 2060-2079; and 3) to pinpoint high-priority areas for protection from bushfires and floods, implementing effective mitigation strategies. The assessment conducted using fuzzy Analytical Hierarchy Process (fuzzy AHP) and fuzzy overlay with apiary site locations, environmental, and bioclimatic variables, reveals insights into seasonal land suitability. In spring, fuzzy AHP deems 67.8% of the study area as moderately suitable, while fuzzy overlay indicates 69.4% as marginal to moderate. Fuzzy AHP's validity (60-70%) outperforms fuzzy overlay (80% in spring, <60% in other seasons). Through ensemble modelling conducted using honey bee presence and pseudo absence data, the research identifies key bioclimatic and environmental variables shaping honey bee habitats, emphasising the critical synergy between climate and environment in determining suitability. Projections for the future (2060-2079) are concerning, with a 100% transition of highly suitable land into moderately (0.5%), marginally (17.6%), or not suitable areas (81.9%) for honey bees, necessitating urgent conservation efforts and policy implementation. The study also pioneers an investigation into threats faced by honey bees in the form of bushfires and floods. Results show that a significant portion of honeybee suitable areas is threatened by bushfires (97.6%). On the other hand, 5% of honeybee habitats are under the threat of flood hazard, while 1% face threats from both hazards. This study urges safeguarding honeybee habitats during natural disasters, offering vital insights and actionable strategies. Future research suggestions encompass examining the long-term effects of climate change on floral resources for honey bees. A cornerstone in honeybee protection, this study provides a robust framework for sustainable apiary management amid climate change and environmental threats.

CERTIFICATION OF THESIS

I, Sarasie Priyanwada Tennakoon Tennakoon Mudiyanselage, declare that the Thesis entitled *"Honey bee habitat suitability: unveiling spatial and temporal variations, predicting futures, and mitigating natural hazard impacts"* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Date: 12 January 2024

Endorsed by:

Professor Armando Apan
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DEDICATION

The most beautiful aspects of this world are made-up by two things. Rays of the Sun, and Milk of a Mother.

Maxim Gorky

This thesis is dedicated to my beloved mother, Chintha Tennakoon, who is the most beautiful aspect in my life.

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ABBREVIATIONS

AHP	Analytic Hierarchy Process
ALA	Atlas of Living Australia
ANP	Analysis Network Process
AUC	Area Under the Relative Operating Characteristic Curve
CR	Consistency Ratio
CTA	Classification Tree Analysis
DEM	Digital Elevation Model
ESRI	Environmental Systems Research Institute
FDA	Flexible Discriminant Analysis
FPC	Foliage Projective Cover
Fuzzy AHP	Fuzzy Analytic Hierarchy Process
GAM	Generalized Additive Model
GBIF	Global Biodiversity Information Facility
GBM	Generalised Boosting Method
GDA	Geocentric Datum of Australia
GIS	Geographic Information System
GLM	Generalised Linear Model
MARS	Multivariate Adaptive Regression Spines
MCDA	Multi-Criteria Decision Analysis
MGA	Map Grid of Australia
NARCliM	New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling
NRM	Natural Resource Management
PROMETHEE	Preference Ranking Organisation Method for Enrichment of Evaluations
RE	Regional Ecosystem
REDD	Regional Ecosystem Description Database
RF	Random Forest
ROC	Relative Operating Characteristic curve
SAW	Simple Additive Weighting
SDM	Species Distribution Modelling

SRE	Surface Range Envelope
TFN	Triangular Fuzzy Numbers
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TSS	True Skills Statistics
USDM	Uncertainty Analysis for Species Distribution Models
VIF	Variance Inflation Factor
WGS	World Geodetic System
WPM	Weighted Product Model

CHAPTER 1 – INTRODUCTION

1.1 Background

Pollinators contribute significantly to global food production and play a crucial role in maintaining biodiversity and ecosystem stability (Potts et al., 2016). Among all the pollinator species, bees are regarded as the most important owing to their physiology, abundance, and complete reliance on floral resources (Klein et al., 2018). Amongst the various bee species, the European or Western honey bee (*Apis mellifera*) (Hymenoptera: Apidae), hereafter referred to as the honey bee, stands out as the most commonly utilised in apiary management and for providing pollination services (Rucker et al., 2012). Honey bees are found nearly everywhere except Antarctica and certain oceanic islands (Hung et al., 2018). Honey bees visit the largest range of crop varieties (Breeze et al., 2014) and can be used to improve yield and to produce nuts, fruits, and vegetables of uniform quality (Rucker et al., 2012). Species other than honeybees are crucial for pollination; however, their reliability in large-scale monocrop fields is low. The uncontrollability of wild bees also makes them less dependable (Ausseil et al., 2018).

Thus, the honey bee industry has become an integral component of agriculture around the world (Demircan et al., 2016). According to the 2020 figures, the estimated worldwide economic value of crop pollination services ranges from US$267 billion to US$657 billion (Porto et al., 2020). Honey bees not only contribute to the success of modern agriculture by facilitating crop pollination (Gaines-Day & Gratton, 2016) but also produce honey as their primary product, which is highly nutritious and offers immense therapeutic benefits (Eteraf-Oskouei & Najafi, 2013). The bee honey is highly valued as a nutritious food, a healthy substitute to sugar, and a medicine. Natural honey can be used as a safe substitute for sugar especially in fruit beverages due to its properties as an antioxidant and a sweetener rich with nutrients (Sharma et al., 2016). The minor nutrients of honey have made it an important medicinal substance with variety of properties (e.g., antioxidant, antibacterial, antiviral, anti-inflammatory, immunomodulation, and anticancer) (Miguel et al., 2017).

The major honey bee species being used by the Australian apiarists is *Apis mellifera* (Figure 1.1) and commonly found all over the continent as managed colonies and feral colonies due to integration into the natural environment over 200 years (Paton, 1993). The honey bee industry in Australia contributes to the economy producing honey as the main product along with beeswax, propolis, royal jelly, bee venom, pollen, queen and packaged bees, nucleus hives and honeycomb sections worth US$101.3 million in 2019 (Clarke et al., 2021). However, the real contribution to the economy far exceeds this figure when considering the value of agricultural produce derived from pollination services provided by beekeepers. As a result, the industry's annual valuation exceeds US$8.9 billion (Department of Agriculture Fisheries and Forestry, 2023).

Figure 1. 1 The European honey bee (Apis mellifera) (Trepte, 2009)

Honey bees forage on different flowering species for food and fulfill their nutritional requirements through nectar and pollen produced in flowers (Donkersley et al., 2014; Morgano et al., 2012). Nectar serves as the source of carbohydrates occasionally containing trace minerals and allelochemicals (Kearns & Inouye, 1993; Seeley, 2009), while pollen provides bees with lipids, proteins, vitamins, and mineral nutrients (Brodschneider & Crailsheim, 2010; Khoury et al., 2013). Accordingly, nectar is the energy source for bees, eventually being converted into honey (Di Pasquale et al., 2013), while pollen plays a crucial role in the physiological development (Brodschneider & Crailsheim, 2010), longevity (Keller et al., 2005), population (Keller et al., 2005), and immunity of bees (Alaux et al., 2010). Moreover, for honeybees, access to a variety of floral resources rather than to a single species is essential for health, immunity, and longevity (Alaux et al., 2010). In Australia, native flora contributes to 70% of the national honey production (Spicer & McGaw, 2020). The dominant species is

Eucalyptus, while Brassicaceae, Echium, Macadamia, and Acacia are also important food sources for honey bees (Sniderman et al., 2018). More specifically, Grey Ironbark (*Eucalyptus paniculata*), Narrow-leaved Ironbark (*Eucalyptus crebra*) (Figure 1.2), Spotted Gum (*Corymbia maculata*), Blue Gum (*Eucalyptus globulus*), and Paper-barked Tea Tree (*Melaleuca quinquenervia*) (Figure 1.3) are some of the top floral species for honey bees in Australia (Rhodes & Trueman, 1999).

Figure 1. 2 Narrow-leaved Ironbark (*Eucalyptus crebra)*(Aardvark, 2008)

Figure 1. 3 Paper-barked Tea Tree (*Melaleuca quinquenervia*) (Henry, 2011)

Irrespective of the contribution to global food security, biodiversity, and ecosystems, honey bees, and thus the apiary industry, are under threat by a multitude of factors encompassing pests and diseases (Genersch, 2010), habitat loss, land use intensification, pollution, poor nutrition (Polykretis et al., 2016) and climate change (Vanbergen & The Insect Pollinators Initiative, 2013). During the last few decades, a significant decrease in the population of honey bee colonies has been documented in various regions across the globe (Meixner, 2010; Polykretis et al., 2016). Moreover, as revealed by several studies, pollinator species including honey bees are forecasted to decline in number in the future which is mainly explained by the deterioration of natural ecosystems and the alarming trend of losing larger portions of the Earth's biodiversity (Neov et al., 2019). There is growing concern about the preservation of this important species; however, there are still untouched areas that require further study.

1.2 Statement of the problem

The majority of the apiarists around the world are migratory in order to reach food sources for honey bees due to the spatial and temporal variations in floral resources and to provide paid pollination services (Albayrak et al., 2021; Goodman, 2014). Even the same species may exhibit different patterns of flowering due to differences in climatic, topographic, and edaphic factors (Somerville, 2010). Due to this variability, apiarists must drive long distances and observe the sites to determine their suitability before locating the hives (Goodman, 2014).

Land suitability assessments based on thorough investigation and analysis, rather than visual observations, are regarded as more beneficial. Many studies have focused on conducting land suitability analysis in a wide array of fields (Azizi et al., 2014; Mandal et al., 2018; Yalew et al., 2016). Land suitability evaluation plays a crucial role in preventing discrepancies between the real requirements and the implemented practices within a specific area. By identifying the inherent potentials and limitations of the land, this evaluation helps align the actual land use with its capabilities (Kahsay et al., 2018). Furthermore, it is important to have a mechanism in place to assess the level of suitability of a site when compared with other optional sites available. This will guide the apiarists choose the best locations to place the hives. The suitability of sites may also vary according to the time of the year due to temporal variations in the resource base, especially the floral resources (Birtchnell & Gibson, 2008). This emphasises the need to detect changes in the suitability of sites with seasonal variations (i.e., during spring, summer, autumn, and winter).

Multi-Criteria Decision Analysis (MCDA) is widely used in land suitability analysis and is capable of handling multiple criteria to make decisions based on human judgment. When selecting apiary sites, multiple factors must be considered including bees' biotic needs and requirements for apiary management (Sarı et al., 2020). Geographic Information System (GIS), coupled with MCDA, has proven to be an effective method in suitability assessment by previous studies due to its capability of assessing spatial data in regard to different aspects such as ecological, climatic, topographic, social and economic factors (Estoque & Murayama, 2011). Moreover, GIS and MCDA together can produce suitability maps as the output which are essential for proper land use planning.

In Australia, studies on land suitability assessment to establish apiary sites have not been conducted regardless the increasing demand for commercial pollination, honey and other products. Most importantly, the Queensland government's decision to look for alternative sites to keep the apiary sites off the national parks stresses the importance of a methodology to assess land suitability for apiary sites. This study paves the way to integrate the knowledge of experienced beekeepers and technology to find a solution to this problem. No study so far has attempted to identify the habitat suitability of any bee species in Australia in particular the most important species for apiary industry, *Apis mellifera*. Most importantly, no research has been attempted to assess land suitability changes due to temporal (seasonal) variations in floral resources and other related biophysical factors. So far, Fuzzy AHP has not been applied and tested for accuracy in land suitability for apiary sites.

Over the past 50 years, the species diversity of pollinators (including the managed honeybees) has declined, while the demand for commercial pollination has increased by three times (Goulson et al., 2015). Global climate change is believed to trigger the loss of food for honey bees in addition to the clearing of habitats (Hegland et al., 2009; Le Conte & Navajas, 2008; Lever et al., 2014). Climatic change can alter the spatial and temporal patterns of flowering and these changes will be more common as the climate change progresses (Aldridge et al., 2011; Craufurd & Wheeler, 2009; Tun et al., 2021). In Australia, the average temperature is increasing by 0.1 - 0.2ºC per decade with greater effects in Queensland and parts of Western Australia (Suppiah et al., 2007). In addition to the rise in temperature that affects flora and plant phenology, global warming can trigger bushfires that can completely or partially damage floral resources for a considerable time (Jalaludin & Morgan, 2021). Therefore, the estimation of the impacts of climate change on floral resources is imperative to assess the future honey production under declining resources. Climate change, particularly the increasingly frequent warm periods during winter, can lead to mismatches between the colony phenology of the honey bee and their floral resources, affecting colony brood rearing activity and subsequently impacting the reproduction of the invasive brood parasite Varroa destructor (Nürnberger et al., 2019). Moreover, climate change has a potential impact on the distribution and severity of honey bee pests, such as the small hive beetle (*Aethina tumida*). As climate change alters soil temperature and moisture, key factors governing small hive beetle pupation performance, areas currently unaffected may become increasingly suitable for SHB invasion (Cornelissen et al., 2019). In contrast, climate change might bring potential positive opportunities in certain aspects of bee keeping. In either case, reliable knowledge is required to develop mitigation and adaptation measures. However, existing literature contains only limited work on assessing the impacts of climate change on floral resources and beekeeping. Particularly, in Australia, there is a gap in the body of knowledge in this regard. Thus, developing a model to assess the potential impacts of climate change on floral resources and their implications on future honey production.

The impact and scope of natural disasters can differ significantly across various geographical regions. However, it is crucial not to underestimate the significance of bushfires and floods, given their global occurrences (Xie & Peng, 2019) and potential effects on honeybee populations and their habitats (Agriculture Victoria, 2023). Australia, in particular, is highly vulnerable to bushfires, being one of the continents most affected by them (Russell-Smith et al., 2007). Apart from the substantial consequences on human lives, infrastructure, and agriculture, which incur an annual estimated cost of 8.5 billion dollars, bushfires have a profound influence on terrestrial ecosystems (Ashe et al., 2009; Sharples et al., 2016). Bushfires, by destroying significant portions of these natural landscapes for extended periods (Sharples et al., 2016), have a catastrophic impact on honey bees, depriving them of vital food sources. Additionally, bushfires weaken and destroy honey bee colonies (Agriculture Victoria, 2023). Similarly, flooding, another devastating event in Australia, can have detrimental effects on both bee hives and the crucial floral resources that honey bees depend on (Department of Primary Industries, 2023). In 2022, floods imposed a substantial financial burden of $7.7 billion on Queensland (Queensland Reconstruction Authority, 2020).

Accordingly, the need for endeavours to address these concerns faced by this vital species and the industry is of paramount importance. This understanding serves as a pivotal foundation for exploring the significance of this study in the following section.

1.3 Significance of the study

Despite the crucial role honey bees and the apiary industry play, Australia has not conducted comprehensive land suitability assessments to establish apiary sites. This glaring gap in research becomes even more apparent when considering that no previous study has ventured into utilising the fuzzy technique within the multi criteria decision analysis (MCDA) to assess land suitability for honey bees or apiary sites in the context of the apiary industry. The absence of such assessments represents a significant research void in the domain of apiculture and ecological conservation efforts in the country and in the world. This study undertook the task of addressing these critical gaps in knowledge and methodology. It not only identified the essential criteria necessary for conducting thorough land suitability assessments but also highlighted their profound significance in the broader context of honey bee ecology and the sustainability of the apiary industry. By delving into the complexities of these criteria and proposing more accurate assessment methods, this research aimed to fill the existing gap and provide insights into establishing robust, ecologically sound apiary sites.

One of the most noteworthy oversights in previous research has been the lack of attention given to a crucial aspect of honey bee ecology: predicting how their habitats might shift in response to the changing climate. This study pioneered a model that utilised high-resolution climate data, allowing for the anticipation of these habitat shifts. By focusing on two distinct future time frames, this research focused on unravelling the relationship between bioclimatic variables and honey bee habitat suitability, expanding the understanding of the dynamic nature of honey bee habitats while providing relevant stakeholders with essential knowledge to adapt and conserve these habitats in the face of climate change. Furthermore, this study recognised the pressing need to consider threat factors when assessing land suitability for honey bees and apiary sites. By incorporating this crucial element into the assessment framework, the research aimed to provide a holistic perspective that accounts for potential risks and challenges faced by honey bees and the apiary industry. This comprehensive approach lays a solid foundation for informed conservation and ecological sustainability efforts.

Aim and objectives were defined, as indicated in section 1.4, to bridge the existing gaps in knowledge and methodology related to honey bee habitat suitability assessments. By shedding light on the critical criteria, proposing innovative methodologies, and incorporating the complexities of climate change and threat factors, this research contributes significantly to the conservation and sustainable management of honey bee habitats and the apiary industry.

1.4 Aim and objectives

This study aimed to integrate Geographic Information Systems (GIS) and agricultural ecology, into a unified platform capable of generating a comprehensive habitat suitability map. This map facilitates the assessment of land suitability for apiaries by incorporating both spatial and temporal variations of influential factors. Furthermore, the research sought to predict future suitability for honey bees in response to climate change through the implementation of an ensemble modelling approach. This approach aimed to capture the complex interactions between diverse environmental and bioclimatic variables and their impact on honey bee habitats. Additionally, the study aimed to identify specific habitats that merit prioritised protection from natural hazards. By doing so, it aimed to contribute valuable insights for conservation efforts, ensuring the preservation of critical ecosystems supporting honey bee populations.

The overarching objective of this thesis is to develop an integrated GIS-based framework for assessing and predicting land suitability for apiaries, incorporating spatial and temporal variations, while identifying priority habitats for conservation to ensure the preservation of critical ecosystems supporting honey bee populations.

Chapter 2 critically reviews existing literature to establish theoretical frameworks, while Chapter 3 delineates the research methodologies employed for gathering, processing, and analysing data. Chapters 4, 5, and 6 are aimed at presenting the three objectives of the study.

More specifically, the study has the following objectives:

1. to develop a reliable methodology for mapping suitable areas for apiary sites, addressing the challenge of incorporating floral resources information and the temporal variations of the relevant criteria, and comparing the accuracy of fuzzy-based multi-criteria decision analysis (MCDA) approaches in land suitability assessment for apiary sites (Chapter 4).

2. to identify the key bioclimatic and environmental predictor variables influencing honey bee distribution, quantify their relative impact, evaluate the predictive performance of

an ensemble approach utilising these variables, and investigate the potential effects of climate change on honey bee distribution under 2030 and 2070 climate conditions (Chapter 5).

3. to comprehensively assess the threats posed by bushfire and flood to honey bee suitability areas, identify and map high-priority honey bee habitats requiring protection against these hazards, and propose effective management strategies for safeguarding honey bee habitats from bushfire and flood risks (Chapter 6).

1.5 Scope and limitations of the study

This study had a comprehensive scope, encompassing the assessment of land suitability for apiaries, the prediction of shifts in suitability under changing climate conditions, and the investigation of the convergence between suitability and natural hazards. The analysis considered the most influential criteria for apiary sites while utilising two fuzzy logic-based multi-criteria decision analysis methods (MCDA). Importantly, the study accounted for both spatial and temporal variations of the criteria. The distribution of honey bee habitats under changing climate conditions was forecasted using an ensemble modelling approach that leveraged the most significant bioclimatic variables. Subsequently, an overlay analysis was conducted, integrating a honey bee suitability map with two natural hazards, bushfire and flood, to identify areas requiring prioritised protection. Additionally, the study formulated management strategies based on underlying land cover and land use.

For validation, this study primarily relied on apiary site locations rather than direct honey bee observation data. This reliance was necessitated by the limited and insufficient availability of reliable natural honey bee occurrence records from credible sources. Furthermore, the study area under consideration is located within a specific part of Queensland, not encompassing the entire Australia. Therefore, the results of the biophysical and socio-economic criteria analysis are not transferable to other areas. In addition, spatial analysis and modelling were limited to variables for which maps were available. Any criterion lacking a corresponding map was excluded from the spatial analysis.

1.6 Conceptual framework

The conceptual framework of the study is presented in Figure 1.4.

The identification of suitable habitats for honey bees and the apiary industry was based on a thorough review of existing literature and expert opinions. Various factors, categorised as bioclimatic variables, environmental variables, and anthropogenic variables, were pinpointed as crucial criteria for assessing honey bee habitat suitability. To create a comprehensive honey bee habitat suitability map, two fuzzy-based Multi-Criteria Decision Analysis (MCDA) techniques were employed. These techniques were validated against the locations of existing apiary sites. Utilising bioclimatic and environmental variables, in conjunction with honey bee occurrence data and apiary site location data, honey bee habitat suitability maps were developed using an ensemble modelling approach. One map focused exclusively on environmental variables, another centred on bioclimatic variables, and a third combined both sets of variables. The models' accuracy and predictive power were assessed using metrics such as the area under the relative operating characteristic curve (ROC) (Hanley & McNeil, 1982), Cohen's Kappa (Monserud & Leemans, 1992), and the True Skills Statistics (TSS). The validated suitability map, generated through the integration of bioclimatic and environmental variables, was subsequently overlaid with bushfire and flood layers. This overlay facilitated the identification of areas requiring prioritised protection measures. Additionally, it served as the basis for developing management strategies tailored to the specific land cover and land use characteristics of these areas. This study aims to provide essential information for the planning, management, and policymaking related to the apiary industry, with a focus on protecting honey bee habitats for the sustainability of the apiary sector.

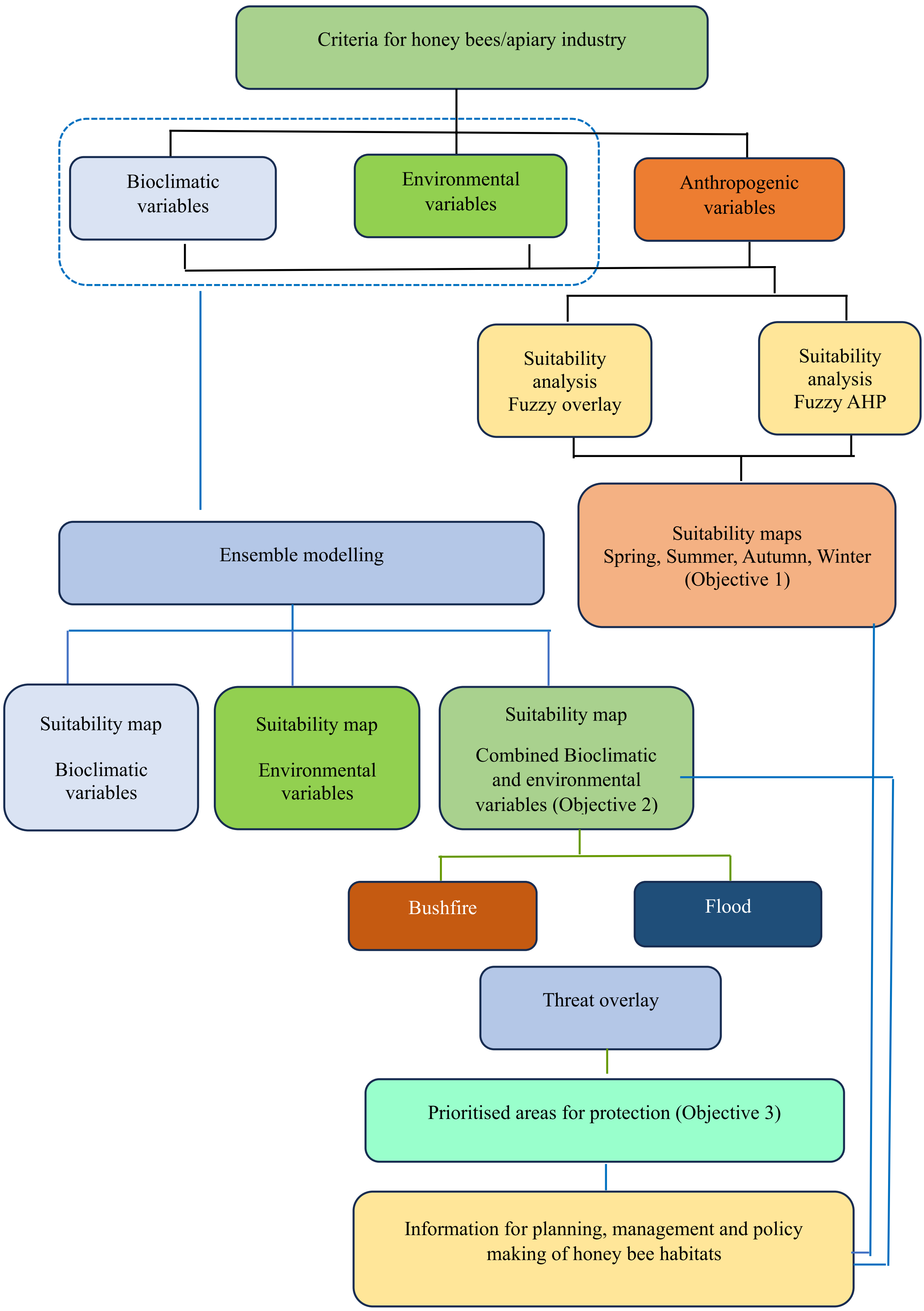


Figure 1. 4 Conceptual framework of the study

1.7 Organisation of the dissertation

This thesis is organised into seven chapters. **Chapter 1**, the introduction, presents the background of the study, identifies research gaps, enumerates the significance, outlines the broad aim and objectives of the present work, and defines its scope and limitations.

Chapter 2, Review of literature, examines the current knowledge sets relevant to the study. These include the following topics: Land suitability analysis in apiary management, predicting honey bee habitat shifts in response to climate change, and the confluence of natural hazards and honey bee habitat suitability.

In **Chapter 3**, the research methods adopted by the study are discussed. This includes the description of the study area, the general design of the study, as well as the processes of data acquisition, pre-processing, and analysis.

Chapter 4 discusses the analysis of land suitability for establishing apiary sites. This chapter delves into the process of selecting the most influential criteria, rating melliferous floral resources, and preparing and standardising criteria. The study goes on to assess the effectiveness of two fuzzy logic-based Multi-Criteria Decision Analysis Methods (MCDA), fuzzy AHP and fuzzy overlay in evaluating land suitability for apiaries. Furthermore, the research incorporates both spatial and temporal variations of the criteria for a comprehensive understanding of the suitability landscape.

Chapter 5 focuses on the application of an ensemble modelling approach to depict the distribution of honey bees, utilising environmental and bioclimatic variables. The chapter aims to predict the future distribution over two distinct periods (2020-2039 and 2060-2079) within the Australian context.

In **Chapter 6**, a comprehensive threat overlay analysis is undertaken, integrating the honey bee habitat suitability map with considerations of natural hazards such as bushfires and floods. This chapter strives to pinpoint areas necessitating prioritised protection against these threats.

Simultaneously, it introduces strategic management approaches aimed at mitigating the adverse impacts on honey bees and their habitats.

Finally, in the concluding chapter, **Chapter 7**, the study presents overall conclusions, implications, research contributions, and enumerates recommendations for future studies.

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction

In Chapter 1, the overall framework of the study was discussed, elaborating on the importance of conducting land suitability analysis to establish apiary sites, predicting the impact of climate change on honey bee habitats and examining the confluence of natural hazards on honey bee habitat suitability. In the second chapter, the current literature on land suitability assessment using GIS-based multi-criteria decision analysis (MCDA) methods, application of ensemble species distribution modelling in predicting future distribution of species under changing climate conditions and threat overlay in suitability analysis are reviewed. The specific and detailed reviews of literature for each technical chapter are presented in chapters 4-6.

The remaining part of the chapter is divided into five sections. Section 2.2 discusses GIS-based land suitability analysis in apiary management, while Section 2.3 focuses on the application of species distribution modelling to predict the future distribution of a species. In Section 2.3, the chapter explores the most influential and widespread natural hazards, namely floods and bushfires, and analyses threat overlay as a component of land suitability assessment. The chapter concludes in Section 2.4 with a summary.

2.2 Land suitability analysis in apiary management

Because of the importance of honey bees and the apiary industry, the analysis of land suitability for apiary sites has gained widespread attention. Certain studies related to honey bees and beekeeping have concentrated on creating suitability maps to mitigate adverse environmental conditions, such as heat and cold stress (Abou-Shaara, 2013; Abou-Shaara et al., 2013). Several studies have delved into understanding the effects of changes in land use and land cover on the suitability of sites for apiaries (Gallant et al., 2014; Otto et al., 2016; Smith et al., 2021). Some other studies have endeavoured to develop suitability maps for apiary sites across different geographic locations, taking into account pertinent factors that influence land suitability for apiculture (Ambarwulan et al., 2016; Sarı et al., 2020).

MCDA is a field within operational research focused on determining optimal outcomes in complex situations involving diverse indicators, objectives, and criteria. This approach is gaining more popularity in land suitability assessment because it empowers decision-makers to make choices while weighing all criteria and objectives simultaneously (Kumar et al., 2017). Assessments of land suitability involve defining both qualitative and quantitative criteria that determine suitability and utilising MCDA methods on the GIS platform to integrate layers of spatial data representing the model's criteria (Elaalem et al., 2011). The MCDA methodology is a multi-step, iterative process that includes: (i) criteria selection, (ii) criteria weighting and evaluation, and (iii) criteria aggregation (Wang et al., 2009). All the criteria utilised in prior studies related to land suitability assessment for beekeeping were examined to comprehensively grasp the essential factors necessary for successful apiculture. Table 1 illustrates the criteria employed in earlier studies.

In addition to MCDA, remote sensing and machine learning methods have been widely employed in land suitability analysis (Nurda et al., 2020; Zolekar & Bhagat, 2015). The advantages of remote sensing and machine learning methods lie in their capacity to provide high-resolution data (Wulder et al., 2004), automate analysis processes, handle large datasets efficiently, and recognise complex patterns within the data (L’heureux et al., 2017). However, these approaches also come with drawbacks. They often require substantial amounts of training data (Bhavsar & Ganatra, 2012), leading to complex models that may be difficult to interpret. Moreover, the implementation of these methods may demand significant computational resources.

Table 2. 1 Criteria used in the literature on suitability analysis for apiary site selection.

Criteria	Related criteria considered in literature
Floral resources	Nectar class/pollen class (Maris et al., 2008)
	Flora criterion (Sarı et al., 2020)
	Floral diversity (Donkersley et al., 2017)
	Floral abundance (Jachuła et al., 2021)
	Flowering period (Di Pasquale et al., 2016)
	Distance from plants (Abou-Shaara, 2015; Abou-Shaara, 2021)
	Vegetation composition (Amiri & Shariff, 2012)
	Land cover (Zoccali et al., 2017)
Topography	Elevation (Maris et al., 2008)
	Slope, Elevation, Aspect (Sarı et al., 2020)
	Altitude (Zoccali et al., 2017)
	Slope (Abou-Shaara, 2015)
	Elevation, sensitivity to erosion (Amiri & Shariff, 2012)
Distance to water	Distance to water (Amiri & Shariff, 2012; Maris et al., 2008)
	Hydrographic network (Zoccali et al., 2017)
Distance to roads	Distance to roads (Abou-Shaara, 2021; Ambarwulan et al., 2016; Amiri & Shariff, 2012; Maris et al., 2008; Zoccali et al., 2017)
	Distance to highways (Sarı et al., 2020)
Climatic factors	Precipitation (Abou-Shaara, 2015; Abou-Shaara, 2021; Ambarwulan et al., 2016; Amiri & Shariff, 2012; Maris et al., 2008; Quinlan et al., 2023; Sarı et al., 2020)
	Temperature (Abou-Shaara, 2015; Abou-Shaara, 2021; Ambarwulan et al., 2016; Amiri & Shariff, 2012; Zoccali et al., 2017)
	Solar radiation (Abou-Shaara, 2021)
	Wind speed (Abou-Shaara, 2021)
Geology	Soil and geology (Amiri & Shariff, 2012)
Social criteria	Distance from markets (Ambarwulan et al., 2016)
	Distance from settlements (Ambarwulan et al., 2016)
Land use	Land use (Ambarwulan et al., 2016; Quinlan et al., 2023)

Saaty's analytic hierarchy process (AHP) (Saaty, 1987) is an approach used for calculating the weights of criteria based on their relative importance derived from a pair-wise comparison matrix (Steele et al., 2009). AHP has been used extensively in multiple fields due to its ease of use and ability to calculate factor weights and prioritise alternatives systematically (Liu et al., 2020). Despite the popularity and convenience of use, the drawbacks associated with AHP include uncertainty and subjectivity of human judgements (Chan & Kumar, 2007; Kamvysi et al., 2014; Lootsma, 1990; Prakash, 2003); inability of the relative importance scale based on whole numbers to calculate intermediate values (for instance when a value lies between very strong importance to strong importance) (Sarkar et al., 2022); high inconsistency of the outcome resulted by group decision making (Escobar et al., 2004); and arbitrary ranking of alternatives (Dyer, 1990).

Other than AHP, there are several other MCDA approaches with many variations and hybrid methods. The common ones include simple additive weighting (SAW), weighted product model (WPM), technique for order of preference by similarity to ideal solution (TOPSIS), preference ranking organisation method for enrichment of evaluations (PROMETHEE) and analytic network process (ANP). Past assessments of land suitability for beekeeping have applied methods such as AHP (Estoque & Murayama, 2011), PROMETHEE (Sari et al., 2020), and TOPSIS (Sarı et al., 2020). Yet, the major drawback associated with these methods is the subjectivity of judgments made by decision-makers. Moreover, these methods do not address or assess the uncertainty involved with such human judgment, whereas the fuzzy concept is capable of incorporating the uncertainty in human decisions (Prakash, 2003). Even though the application of fuzzy logic is limited in land suitability assessment for apiary management, this has widely been used in land suitability assessment in many other fields.

2.2.1 Fuzzy logic

Zadeh (1988) introduced fuzzy logic with the premise that in situations characterised by uncertainty and imprecision, approximate reasoning outperforms precise reasoning. Therefore, fuzzy logic seeks to represent approximate forms of reasoning, commonly observed in human judgment. Limitations in suitability analysis arise from the subjectivity involved in experts assigning weights to criteria and the rigid boundaries of these weights (Mallik et al., 2022). Fuzzy logic is based on the rationale that in an environment of uncertainty and imprecision, approximate reasoning performs better than exact reasoning. Thus, fuzzy logic aims at modelling approximate modes of reasoning which is often an outcome of human judgment. The limitations associated with suitability analysis include subjectivity associated with allocating weights to criteria by the experts and the crisp boundaries of the allocated weights (Mallik et al., 2021).

GIS, coupled with Fuzzy AHP, has been used in land suitability assessment in agriculture including sugarcane cultivation in Bijnor district, India (Jamil et al., 2018), wheat and maize farming in semi-arid regions in Iran (Pilevar et al., 2020), rice production in Mazandaran province, Iran (Amini et al., 2020), wheat cultivation in Turkey (Kılıc et al., 2022) and sorghum crop production in Ethiopia (Kahsay et al., 2018). On the other hand, other studies have conducted weighted overlay analysis using GIS software. Weighted overlay applies a common scale of weights to all the input layers used in the analysis and thus can produce inconsistent results when the input layers are highly dissimilar (Baidya et al., 2014).

Conversely, fuzzy overlay analysis which is based on fuzzy logic can model nonlinear relationships in the GIS environment while preserving the continuous nature of certain input layers (Kirschbaum et al., 2016). Thus, fuzzy overlay is widely being selected over conventional weighted overlay to represent the uncertainty associated with spatial data. Moreover, fuzzy overlay in GIS-based land suitability assessment, provides the option of eight different operators (Nwazelibe et al., 2023) and different membership types. Fuzzy overlay analysis has been employed in a vast array of fields including land management (AbdelRahman et al., 2018; Akbari et al., 2019), environmental planning (Pahlavani et al., 2017; Weerasiri et al., 2014), and disaster risk assessment and management (Mohebbi Tafreshi et al., 2021). Zoccali et al. (2017), have applied GIS based fuzzy overlay as a novel approach to assess beekeeping suitability to avoid the high degree of uncertainty associated with human decisions when assigning weights to criteria.

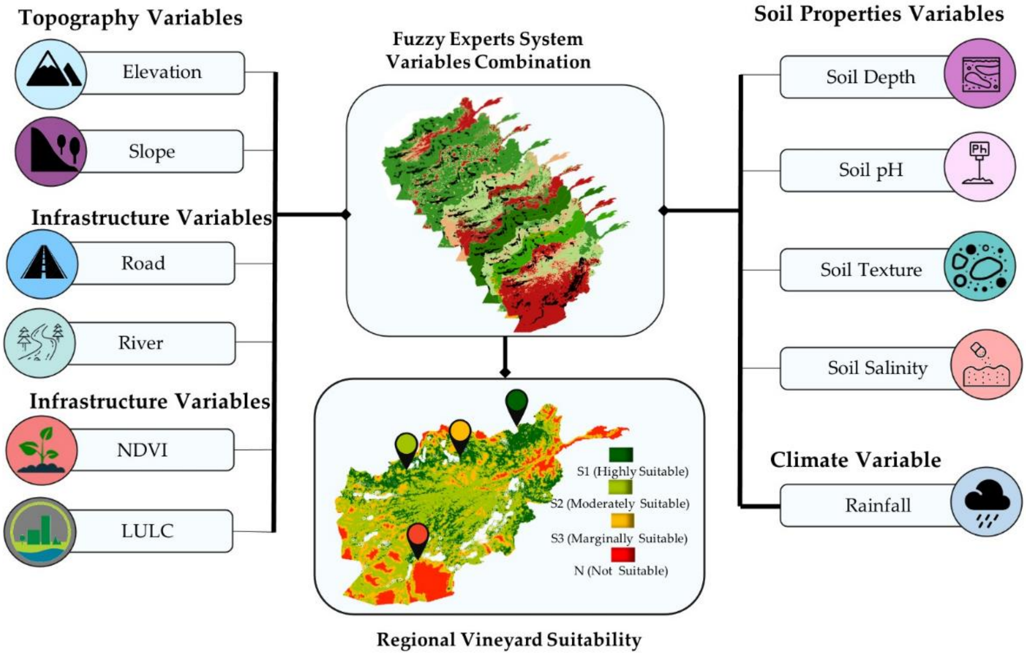


Figure 2. 1 Application of fuzzy overlay in land suitability assessment for vineyards (Arab & Ahamed, 2022)

In Australia, studies on land suitability assessment to establish apiary sites have not been conducted despite the increasing demand for commercial pollination, honey and other products. Most importantly, the Queensland government's decision to look for alternative sites to keep the apiary sites off the national parks stresses the importance of a methodology to assess land suitability for apiary sites. This thesis, particularly objective 1, will bridge this knowledge gap.

2.3 Predicting honey bee habitat shifts in response to climate change

2.3.1 Impacts of climate change on biodiversity

Climate plays a significant role in determining how a species is distributed across different geographic locations and time periods (Adhikari et al., 2023; Araújo, Pearson, et al., 2005; Pant et al., 2021). Climate change is referred to as a systematic and gradual change in average weather conditions (Weber, 2010). For instance, over the past century, the Earth's temperature has risen by approximately 0.74°C, and it is anticipated to increase further, reaching a global average temperature rise of 4.3 ± 0.7°C by the year 2100 (Almazroui et al., 2020; Pachauri et al., 2014; Pant et al., 2021). This increase in temperature is anticipated to cause changes in the intensity, duration, and pattern of precipitation, along with alterations in the duration and occurrence of extreme weather events (Borghi et al., 2019).

Such changes have serious implications on the distribution, physiology, and proliferation of a wide range of species including pollinators (Aryal et al., 2016; Vercelli et al., 2021). To endure changing climate conditions, a species must either cope, adapt, or relocate from their current geographic areas (Maggini et al., 2011). Adaptation in the face of climate change can manifest in diverse dimensions: in geographic space, a species can adjust its distribution to align with favourable climates and habitats; in environmental space, it can modify its phenotypes in response to new environmental conditions, potentially inheriting new traits through natural selection (Maggini et al., 2011). A species can adapt in the face of climate change through phenotypic plasticity, which includes physiological and behavioural flexibility, and/or evolutionary changes occurring over multiple generations (Visser, 2008; Williams et al., 2008). Additionally, in the temporal dimension, seasonal events like reproduction or migration might occur earlier or be delayed. However, when populations fail to cope or adapt in any of these dimensions or cannot do so swiftly enough (Devictor et al., 2008), a species may face extinction (Maggini et al., 2011).

2.3.2 Impacts of climate change on honey bees

The impact of climate change on honey bees can take different forms, with direct influences on behaviour and physiology. Furthermore, it can alter the geographical distribution of honey bees and create new competitive interactions among different species, races, and their parasites and pathogens (Le Conte & Navajas, 2008). Most importantly, climate change can significantly impact the quality of essential floral resources for honey bees, including flower development, as well as the quantity of nectar and pollen produced, upon which they rely entirely. Plants and animals exhibit diverse responses to climate change, resulting in mismatches in phenology. These mismatches carry significant consequences for species engaged in mutual relationships, such as honey bees and flowering plants (Borghi et al., 2019). Numerous studies have explored the influence of climate change on honey bee populations, behaviour and physiology (Abou-Shaara, 2016; Flores et al., 2019; Le Conte & Navajas, 2008). However, only a limited number of studies have endeavoured to predict the habitat shifts that may occur in response to climate change. In addressing this knowledge gap, Objective 2 of this thesis will focus specifically on this aspect.

Figure 2. 2 A honey bee drone that died during a heat wave (Huxter, 2021)

2.3.3 Species distribution modelling (SDM)

Predictive models forecasting species distributions are extensively utilised to address issues related to ecology, biogeography, and species conservation (Jiménez-Valverde et al., 2008; Kosicki, 2020; Peterson, 2006). The theorem upon which these modelling approaches are based involves the characterisation and quantification of a species' distribution in relation to its ecological and environmental space. This information is then utilised to predict their potential distribution (Guisan & Zimmermann, 2000; Pearson & Dawson, 2003; Peterson, 2006). These models are static and probabilistic in nature, investigating statistical relationships between species presence data and associated environmental and climatic variables (Guisan & Zimmermann, 2000).

A variety of models are available, spanning different categories such as regression models (e.g. generalised linear model, generalised additive model, multivariate adaptive regression splines model, and hierarchical modelling), classification models (e.g., mixture discriminant analysis, generalized boosting model, and classification and regression tree analysis), and complex models (e.g., artificial neural networks, random forest, genetic algorithm for rule set production, and maximum entropy approaches) (Li & Wang, 2013). The selection of a modelling technique can profoundly impact the accuracy of predictions. Nevertheless, there is no single method that consistently outperforms others across diverse species, geographic areas, and applications (Elith et al., 2006; Pearson et al., 2006; Segurado & Araujo, 2004). This variability makes it challenging to determine the most suitable method, leading to the concept of combining predictions from various models into what is known as an ensemble, as proposed by Araújo and New (2007).

2.4 Confluence of natural hazards and honey bee habitat suitability

2.4.1 Natural hazards and their impacts on honey bees

Natural hazards stand out as distinct biophysical occurrences, having the potential to cause harm to both the physical environment and the social structures within their impact zones (Nicholson & Egan, 2020). Gill and Malamud (2014) have categorised natural hazards into five distinct groups as follows:

1) geophysical (e.g., earthquake, tsunami, volcanic eruption, landslide, and snow avalanche).
2) hydrological (flood and drought).
3) shallow Earth processes (regional subsidence and uplift, local subsidence and heave, and ground collapse).
4) atmospheric (tropical cyclone, tornado, hail, snow, lightning and thunderstorm, long-term climatic change, and short-term climatic change).
5) biophysical (bushfire)

The impacts of natural hazards are not limited only to the time of occurrence but can also have continuing effects. This is much more significant when exposure to such disasters is repeated (Alcántara-Ayala, 2002). Natural hazards such as droughts, hurricanes, and earthquakes continuously reshape the Earth's biosphere (Nicholson & Egan, 2020). Natural hazards are defined as extreme with respect to the effect of the hazard (e.g. unusual rainfall pattern) and the response to that hazard by the ecosystem (unusual productivity), which are outside the bounds of normal variability (Smith, 2011). As climate change advances, the intensity and frequency of extreme hazardous events such as droughts, floods, and heatwaves have escalated (IPCC, 2007). As a result, species extinctions and shifts in phenology and geographical distribution have become more prominent. Most of these gradual biological changes are attributed to responses to natural hazards and climate change (Easterling et al., 2000). Thus, species existence and ecosystem stability are under threat, and this is exacerbated, especially when species-ecosystem interactions are disturbed (Aslan et al., 2013; Hegland et al., 2009; Memmott et al., 2007).

The relationship between honey bees and plants is a crucial interaction, where honey bees pollinate plants and depend on floral resources for their food. Natural disasters have the potential to disrupt the mutual relationships between honey bees and plants (Nicholson & Egan, 2020). These effects on honey bees and plants can be observed at various biological levels, including individual physiological reactions (Scaven & Rafferty, 2013) and changes in the taxonomic, functional, and phylogenetic composition (Gámez-Virués et al., 2015; Ponisio et al., 2016). One of the most severe consequences of natural hazards for honey bees is the potential for significant population reductions or even the complete loss of entire colonies (Sari & Kandemir, 2022). Furthermore, honey bee habitats can be rendered unsuitable for extended periods due to exposure to natural hazards (Sharples et al., 2016). However, only a limited number of studies so far has attempted to quantify the threat imposed by loss of habitats for honey bees due to natural disasters. The nature of natural disasters and the extent of their effect can vary across different geographic locations. Nevertheless, the significance of bushfire and flood incidents cannot be underestimated, given their occurrences across the globe (Xie & Peng, 2019) and potential effects they might impose on both honeybee populations and their habitats (Agriculture Victoria, 2023).

2.4.2 Bushfire

Bushfires are induced by anthropogenic, climatic and ecological factors (Suryabhagavan et al., 2016). Bushfires have severe consequences on human lives, infrastructure, and the environment, while also playing a crucial role in shaping the natural environment and its ecological dynamics (Sharples et al., 2016). Australia stands as one of the continents, most susceptible to bushfire incidents (Russell-Smith et al., 2007). In addition to the significant repercussions that bushfires have had on human lives, infrastructure, and agriculture throughout the years, with an annual estimated cost of 8.5 billion dollars, they have also exerted a substantial influence on terrestrial ecosystems (Ashe et al., 2009; Sharples et al., 2016). Honey bees rely on the floral resources to meet their nutritional requirements (Donkersley et al., 2014). The Australian honey bee industry primarily relies on the native flora that extends across ecosystems, encompassing forests, woodlands, and shrublands (Tennakoon, Apan, Maraseni, et al., 2023) thereby contributing to 70% of the total nation's honey production (Spicer & McGaw, 2020). Thus, bushfires that result in the loss of significant portions of natural landscapes for an extended period of time (Sharples et al., 2016) have a catastrophic impact on honey bees, which lose access to vital food sources. Moreover, bushfires lead to the destruction and weakening of honey bee colonies (Agriculture Victoria, 2023).

Figure 2. 3 Bushfire in Australia (Moir, 2019)

Figure 2. 4 Bushfire affected beehives in Australia (Briggs, 2020)

2.4.3 Flood

Floods represent a significant natural hazard, affecting both natural resources and ecological systems. Climate change, characterised by increased global rainfall, stands as the primary catalyst for these floods (Kain et al., 2018; Toosi et al., 2019). Floods not only ravage the environment but also disrupt plant life and pollen sources by altering the landscape (Sari & Kandemir, 2022). A flash flood occurs as a result of intense and rapid rainfall over a brief period, typically less than six hours (Abunassar, 2009), leading to swift and forceful water flow in urban areas, riverbeds, or mountain valleys after heavy rain (Rufat et al., 2015). Flash floods are responsible for numerous flood-related fatalities in developed nations (Jonkman, 2005). These flash floods often render it impossible to relocate apiaries to safer ground. Moreover, floods demolish plant varieties and pollen/nectar sources in a single season, as soils and trees shift due to the force of the water (Sari & Kandemir, 2022). Floods affecting Australia can result in detrimental impacts on both bee hives and the essential floral resources that honey bees rely upon (Department of Primary Industries, 2023). According to the 2022 figures, floods incurred a comprehensive financial burden of $7.7 billion on Queensland (Queensland Reconstruction Authority, 2020).

Figure 2. 5 A flood affected apiary site in Australia (Sunderland, 2021)

2.4.4 Threat overlay analysis

Earlier studies have employed weighted overlay analysis on GIS platforms to assess land suitability by overlaying various threats or hazards (Basharat et al., 2016; Shit et al., 2016). An integral component of disaster mitigation planning involves hazard mapping, which offers essential spatial data regarding areas susceptible to potential disasters. Through hazard mapping, valuable insights are gained into the distribution of locations at risk, enabling informed and strategic mitigation efforts (Nugraha et al., 2018). However, a notable gap exists in the literature concerning honey bee habitat suitability, as these studies have not accounted for the impact of threats on their habitats. Objective 3 of this thesis aims to bridge this existing gap by conducting a comprehensive overlay analysis. This analysis involves integrating the honey bee suitability map with two of the most significant natural hazards: floods and bushfires.

2.5 Summary

From the preceding review of previous studies, the following research gaps related to investigating the honey bee habitat suitability, predicting future distribution and assessing the connections with natural hazards are summarised below:

- The assessment of suitable land for apiary sites has so far focused on spatial factors, neglecting the crucial aspect of temporal variability in these factors.

- Up to this point, there has been no effort to devise a standardised methodology for scoring floral resources specifically for honey bees. Previous studies have mainly focused on floral and land cover composition or proximity to floral resources, without assigning any weight to these factors. Considering the pivotal role of floral resources in the sustenance and productivity of honey bees, this represents a significant limitation in current research.

- Most of the studies have failed to encompass all the pertinent criteria related to beekeeping in their research.

- None of the existing studies on land suitability assessment for apiary sites have integrated fuzzy logic, particularly fuzzy AHP, which is proposed as a superior alternative to the conventional AHP methodology.

- There is a notable gap in the literature regarding a comparative analysis of conventional AHP and fuzzy AHP.

- Moreover, the existing literature lacks comprehensive studies that assess the combined application of fuzzy logic with various MCDA methods.

- Despite the literature indicating the significant impact of climate change on honey bees, there has been no attempt in any study to predict their future distribution amidst the changing climate.

- Although the economic impact of bushfires and floods on honey bees has been estimated, no study has endeavoured to conduct a comprehensive threat overlay analysis or propose potential remedies to mitigate these challenges.

In the upcoming chapter, the methodology employed in this study to achieve the objectives outlined in Chapter 1 will be discussed.

CHAPTER 3 - RESEARCH METHODS

3.1 Introduction

In the preceding two chapters, a comprehensive exploration was conducted on the pivotal role played by honey bees and the apiary industry. Special emphasis was placed on assessments of land suitability to optimise outcomes, along with the far-reaching impact of climate change and natural hazards on biodiversity, particularly concerning honey bees. These chapters delved into prior research, specifically focusing on land suitability assessment within the apiary industry, studies related to climate change, and prediction of species distribution under changing climatic conditions, as well as analyses of natural hazards and threats. Chapter 2 also presents the current research gaps on the topic that need to be addressed, and these gaps served as the basis for developing the aim and the objectives of the study. The current chapter elaborates on the common methods employed in the study, including the descriptions of the study areas, to accomplish the objectives of this research. More detailed explanations of the methods can be found in Chapters 4 to 6, corresponding to the three specific objectives of this thesis. This chapter delineates the subsections: a) Study area overview, b) Data acquisition, and c) Data processing and analysis.

3.2 The study area

The agricultural area in Queensland is the largest of any Australian state and the annual contribution to the economy by agriculture sector accounts for more than ten billion dollars (Business Queensland, 2022). The honey bee industry is a prominent component of agriculture and according to the 2018–2019 statistics published by the State Department of Primary Industries, Queensland is the third largest state in terms of honey production with 9.7% of the 20,000–25,000 tonnes of annual production. Moreover, the state has 17% of the total number of registered apiarists in Australia and 16% of total amount of hives (Michael & Feuvre, 2021).

The study area covers part of the southern Queensland, Australia with an area of 37,689 km^2 encompassing 265 localities under four Local Government Areas, namely Toowoomba Regional, Southern Downs Regional, Goondiwindi Regional, and Western Downs Regional

The major honey producing region in Queensland has 4,491 apiary sites while the study area chosen contains 1,591 sites (approximately 35%). (Figure 3.1). It is geographically located between latitude $27^{0}77'$ - $27^{0}68'$ S and longitude $150^{0}12'$ - $151^{0}97'$ E. The study area is predominantly rural consisting of large agricultural areas, rangelands, and regional ecosystems mostly consisting of remnant and non-remnant forests, woodlands, and shrub lands. Figure 3.2 illustrates images depicting woodlands and cropping areas within the study area. The agricultural area accounts for 11,712 km^2 rangelands expand over 11,899 km^2, while the regional ecosystems cover the largest extent of 13,488 km^2. Figure 3.2 illustrates different regional ecosystems in the study area.

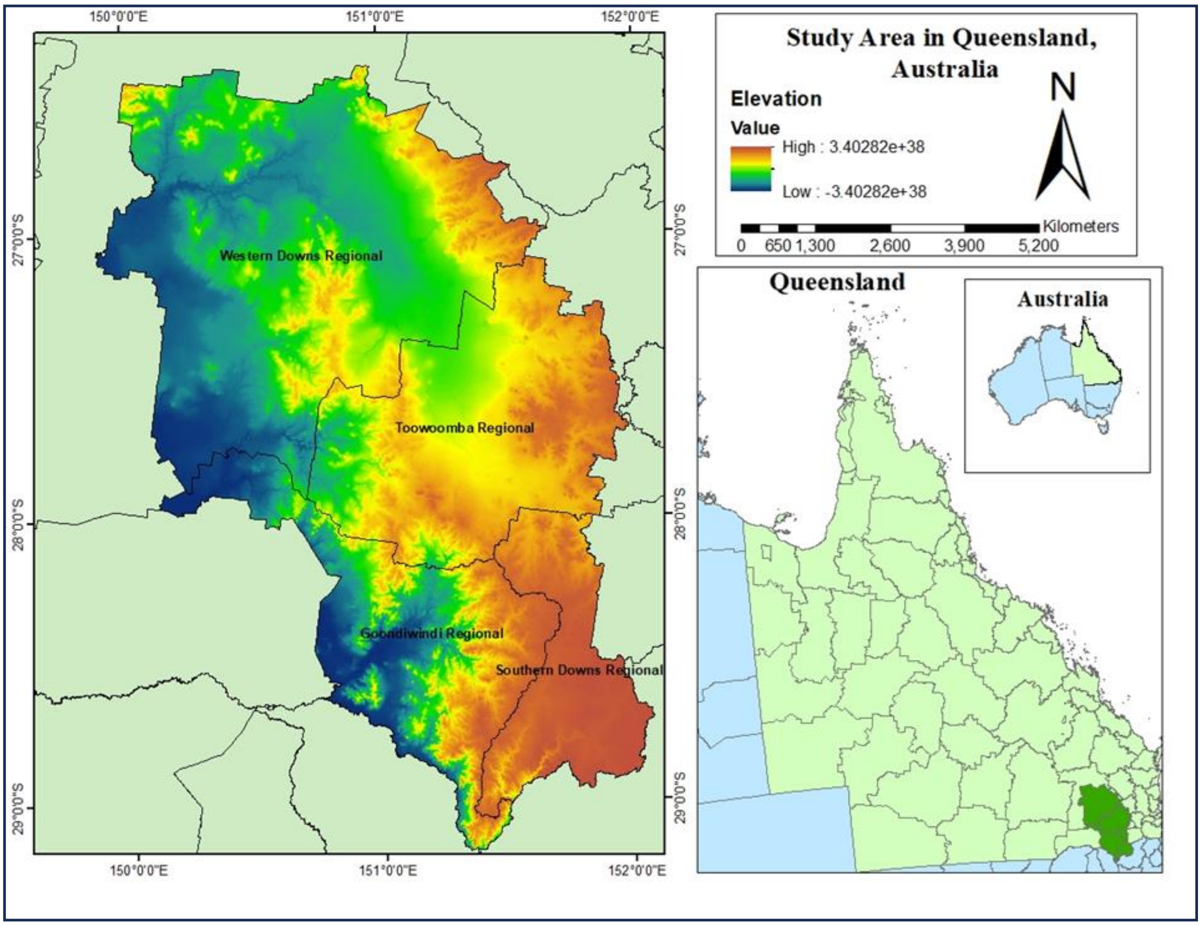
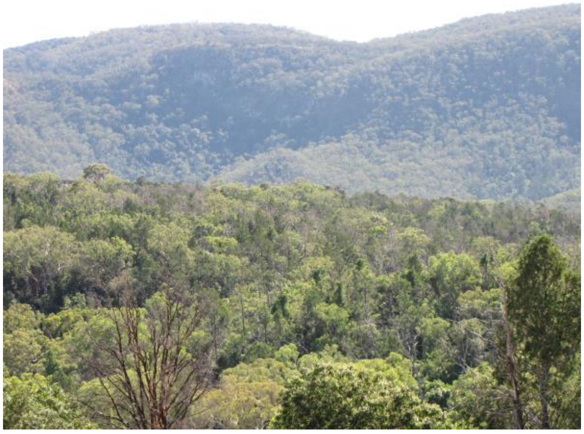


Figure 3. 1 The study area and the elevation map

There are four distinct seasons in Australia i.e., spring (from September to October), summer (from December to February), autumn (from March to May), and winter (from June to August). Queensland has a varied climate across different parts of the state and is divided into four climate zones as tropical, sub-tropical, hot arid and warm temperate. The study area represents some variations in terms of climate. Toowoomba and Southern Downs belong to a warm temperate climate zone where there are four distinct seasons. The winters are cool with low humidity, whereas the summers are warm with a moderate humidity For instance, the mean minimum temperature in Stanthorpe, Southern Downs during winter can be as low as 1.1 ˚C with a maximum temperature of 27.4 ˚C during summer. On the other hand, the mean annual rainfall of the same area is 764.2 mm. Western Downs and Goondiwindi have a hot arid climate which is characterised by hot and dry summers, cold winter nights, low rainfall and low humidity. In Miles, western Downs, the mean minimum temperature in winter is 3.6 ˚C whereas the mean maximum temperature is 33.3 ˚C. The mean annual rainfall is 643.4 mm (Australian Bureau of Statistics, 2022).

In the 2021 statistics, Toowoomba stood out as the most densely populated area within the study scope, with a population of 173,204. In contrast, Southern Downs and Western Downs housed 48,822 and 33,843 residents respectively. Notably, Stanthorpe had the smallest population, with 5,290 inhabitants, making it the least densely populated region in the study area (Australian Bureau of Statistics, 2021).

(a) (b)



(c) (d)

(e)

Figure 3. 2 Woodlands and a cropping field in the study area. (a -d) woddlands; (e) cropping area

3.2.1 Basis in selecting the study area

The selection of study area adhered to the following criteria:

1. The study area, situated within Queensland's primary honey-producing region and encompassing 35% of the apiary sites, also benefits from the ready availability of high-resolution climate data (250m).

2. The study area possesses data available in raster or vector formats, encompassing all the criteria utilised in the study.

3. The presence of a regional ecosystem database for the study area serves as the foundation for developing a methodology to assess floral resources for honey bees.

3.3 Data acquisition

Figure 3.3 gives an overview of the study showing the data inputs, data analyses and the outputs to achieve its three objectives. In Objective 1, environmental, topographic, climatic, and anthropogenic variables were utilised to generate suitability maps for each season using ArcMap. These generated suitability maps underwent validation against honey bee presence data, which served both as the benchmark for presence and as a basis for generating pseudo-absence data for species distribution modelling using *biomod2*. For Objective 2, the non-correlated, most-influential environmental and bioclimatic variables were employed as input variables. Three distinct suitability maps, namely climate-only, environment-only, and combined climate and environment, were generated in addition to the projected maps.

The combined climate and environment map was subsequently overlaid with natural hazard layers to delineate areas prioritised for protection and to develop management strategies.

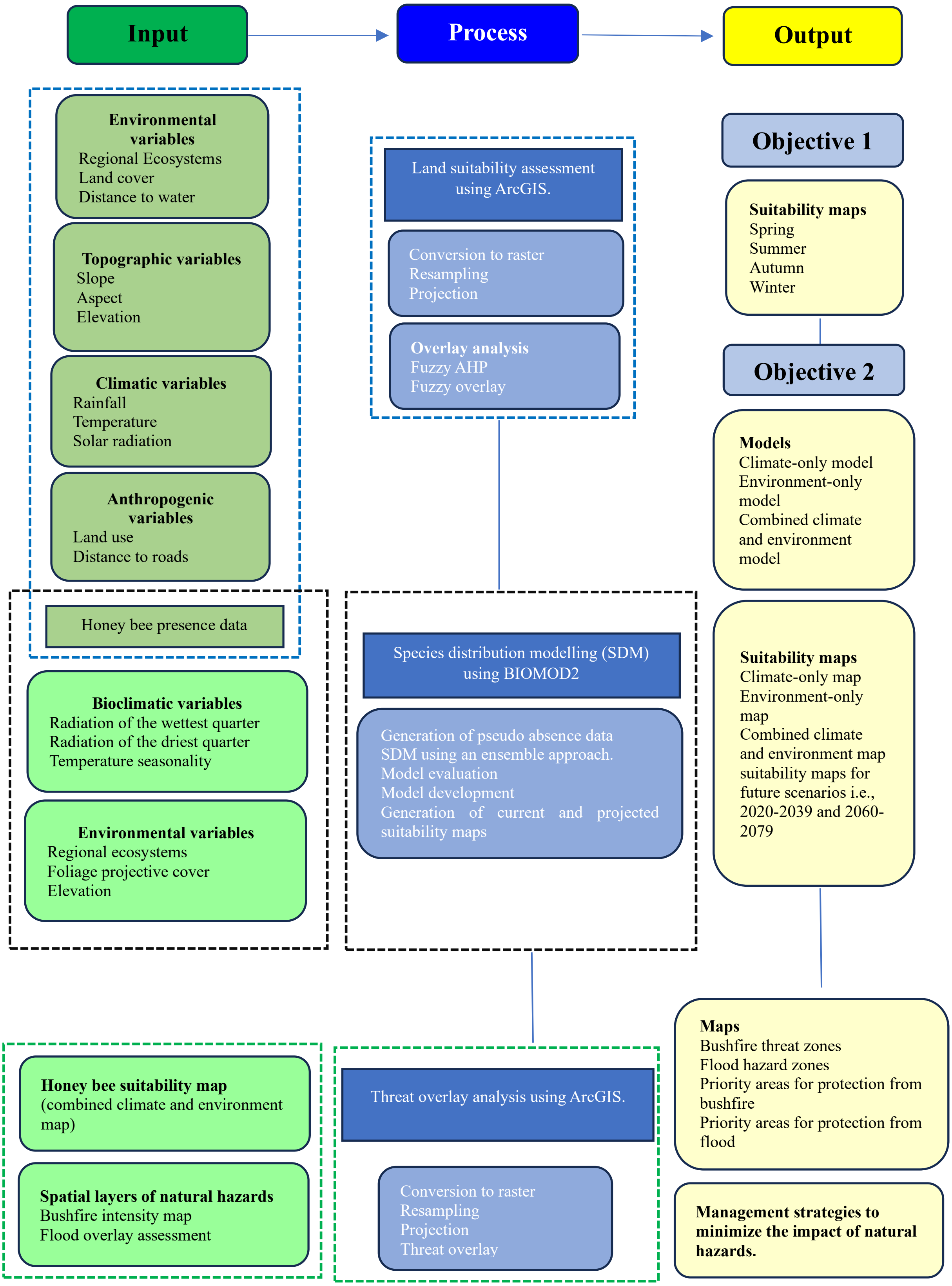


Figure 3. 3 Input-Process-Output model of the study

Table 3. 1 Input data and sources

Input data	Source	Spaial resolution	Data application objective
Regional ecosystems	Regional Ecosystems Maps – Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2021)	100m	Objectives 1 and 2
Land cover	Esri Land Cover – ArcGIS Living Atlas of the World (https://livingatlas.arcgis.com/landcover/) (ESRI Land Cover, 2022)	10m	Objectives 1 and 3
Distance to water	Drainage, GEODATA TOPO2.5M from the Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)	100m	Objective 1
Slope	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)	250m	Objective 1
Aspect	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)	250m	Objective 1
Elevation	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)	250m	Objectives 1 and 2
Bioclimatic variables	New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling	250m	Objectives 1 and 2

	(NARCliM) (Hutchinson & Xu, 2014)		
Land use	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2023)	Not available (A vector layer)	Objectives 1 and 3
Distance to roads	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Resources, 2021)	Nat available (A vector layer)	Objective 1
Foliage projective cover	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2014)	30m	Objective 2
Bushfire intensity map	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Commonwealth Scientific and Industrial Research Organisation (CSIRO) et al., 2015)	Not available (A vector layer)	Objective 3
Flood overlay assessment	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Resources, 2013)	Not available (A vector layer)	Objective 3
Honeybee presence data (apiary site locations)	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Agriculture and Fisheries, 2019)	Not available (A vector layer)	Objectives 1 and 2
Observations of honey bee occurrences	Atlas of Living Australia (https://www.ala.org.au/) (Atlas of Living Australia, 2020)	Not available (A vector layer)	Objective 2

3.4 Data processing and analysis

Figure 3.3 illustrates the data processing and analyses conducted to achieve the study's objectives. The specific methods for each data processing and analysis are elaborated in the subsequent technical chapters. Since these chapters entail distinct data processing and analysis procedures, this section provides only a brief overview.

For Objective 1 (i.e., to assess land suitability for beekeeping, considering spatial and temporal variations in criteria, using GIS-based multi-criteria decision analysis (MCDA)), 11 criteria were selected for apiary site suitability analysis based on literature and expert opinion. These criteria were categorised into four different groups: environmental variables (floral resources, land cover, distance to water), topographic variables (slope, aspect, elevation), climatic variables (rainfall, temperature, solar radiation), and anthropogenic variables (land use, distance to roads). All vector layers were converted to raster maps and resampled to a 25m×25m grid cell size with GDA2020 projection, while regional ecosystem, land cover, and land use layers were reclassified using assigned ratings. Suitability maps were generated separately for each season using GIS based fuzzy AHP and fuzzy overlay techniques. ArcMap 10.8.1 was used in criteria preparation and overlay analysis. The accuracy of these maps was validated against existing apiary site locations, and the results obtained from the two methods were compared using one-way ANOVA to determine the best technique. In Chapter 4, a comprehensive explanation of the methodology employed in this study will be provided, including a detailed presentation of the novel method used to assess floral resources for honey bees.

For Objective 2 (i.e., predicting honeybee distribution using bioclimatic and environmental variables for two future time spans: 2020-2039 and 2060-2079), the honey bee presence data were rarefied using the SpThin package in R version 4.2.2 to ensure that no more than one occurrence record was present in a cell with the size of 250m x 250m. The biomod2 package in R software was utilised to conduct species distribution modelling. Due to the unavailability of absence data, pseudo absence data were generated using biomod2. Both bioclimatic and environmental variables were assessed for multicollinearity using the USDM package. The three most influential variables from each category were selected for the final model development: bioclimatic variables included radiation in the wettest and driest quarters, and temperature seasonality, while environmental variables encompassed regional ecosystems, foliage projective cover, and elevation. Based on the True Skills Statistics (TSS) threshold, ensemble models were developed for climate variables, environmental variables, and a combination of both. The climate model, based on data from 1990-2009, was projected for the time periods 2020-2039 and 2060-2079. More details about the methods are provided in Chapter 5.

For Objective 3 (to pinpoint high-priority areas for protection from bushfires and floods, implementing effective mitigation strategies), the honey bee suitability map (combined climate and environment map derived from objective 2) was combined with a bushfire intensity map and a floodplain assessment overlay to create the bushfire threat zone map, the flood hazard zone map, and a combined map of both bushfire and flood. The priority areas for protection were delineated from the bushfire threat zone and flood hazard zone maps, taking into consideration the suitability of habitats, the intensity of bushfires, and the presence of flood hazards. These priority areas were then integrated with land cover and land use maps to develop management strategies aimed at minimising the impacts of natural hazards. ArcMap 10.8.1 was utilised for the combination of raster layers with 250m resolution and GDA2020 projection. Chapter 6 furnishes additional details regarding the methodologies employed.

3.5 Summary

In this chapter, the overall approach and the general methods employed to accomplish the three objectives of the study are outlined. While the specific methods will be discussed in detail in the preceding technical chapters, a brief overview of the methods used is provided here.

The study conducted a comprehensive assessment of land suitability for beekeeping, employing two advanced GIS-based multi-criteria decision analysis (MCDA) techniques: fuzzy AHP and fuzzy overlay. This analysis involved a diverse set of criteria, introducing innovative methods to evaluate floral resources for honey bees and considering both spatial and temporal variations in these criteria. A rigorous comparison of the two fuzzy-based MCDA methods was carried out to identify the most accurate approach for assessing land suitability for beekeeping.

Additionally, the research utilised an ensemble species distribution modeling approach to predict the future habitats of honey bees amidst changing climate conditions. To enhance the practical applications of the findings, the current honey bee suitability map was overlaid with natural hazards, specifically floods and bushfires. This overlay facilitated the identification of priority areas requiring protection. Subsequently, effective management strategies were determined based on these priority zones, ensuring a proactive approach to safeguarding beekeeping habitats from environmental risks.

In Chapter 4, the thesis delves into the technical aspects, initiating with a detailed exploration of land suitability assessment to establish apiary sites by taking into account spatial and temporal variations in the relevant criteria. Additionally, the chapter introduces an innovative method for evaluating floral resources for honey bees. Furthermore, it includes a comparison of contemporary techniques in multi-criteria decision analysis applied to land suitability assessment, such as fuzzy AHP and fuzzy overlay.

CHAPTER 4 - GIS BASED FUZZY AHP AND FUZZY OVERLAY TO ASSESS LAND SUITABILITY FOR APIARY SITES

4.1 Introduction

Chapter 2 highlighted a critical knowledge gap through a comprehensive literature review on land suitability assessment in beekeeping. No previous study has addressed the complexities arising from both spatial and temporal variations in the criteria affecting beekeeping, nor have they effectively incorporated floral resource information—widely recognised as a pivotal criterion for bees. The chapter, focusing on objective 2 of the thesis, also underscored the importance of evaluating the effectiveness of fuzzy-based MCDA methods, addressing a significant knowledge gap identified within the context. This study conducts species distribution modelling to predict the future distribution of honey bees under changing climates that is critical for understanding how environmental shifts may impact their habitats and for devising proactive conservation strategies. This chapter has the following objectives: 1) to develop a reliable methodology for mapping suitable areas for apiary sites, particularly the challenge of incorporating floral resources information; b) to evaluate the differences in suitable areas for apiary sites during the spring, summer, autumn, and winter seasons; and c) to compare the accuracy of different approaches used in this study.

This chapter is organised into five sections. The Background section presents and discusses information on previous studies undertaken about the topic and the knowledge gaps in land suitability assessment for beekeeping. These gaps serve as the foundation for the chapter's objectives. These knowledge gaps were used as the basis to form the objectives of the chapter. The chapter then proceeds with the Methods section, in which the approaches and methodologies used to achieve the objectives are discussed. The Results, as well as the Discussion sections, follow. The chapter concludes by highlighting the new knowledge and insights generated from this study.

This study offers the following innovations and contributions: a) it used a regional ecosystem map to extract floral information of each season; b) it utilised a relatively high-resolution

(250m) climate data; c) it considered the temporal variability of criteria in suitability analysis; and d) it compared fuzzy AHP and fuzzy overlay in suitability analysis for apiary sites.

4.2 The need for land suitability analysis in beekeeping

Honey bees are widely recognised for their essential role in pollinating a diverse range of agricultural crops (Calderone, 2012) and hold the distinction of being the most prevalent single species of pollinator for crops globally (Garibaldi et al., 2013). Honey bees also play a crucial role in natural environments, where they serve as the predominant pollinators, accounting for an average of 13% of floral visits. Additionally, 5% of plant species exclusively depend on honey bees for pollination (Hung et al., 2018). This observation underscores the meaningful contribution of honey bees to preserving biodiversity within native communities of flowering plants. Honey, propolis, royal jelly, bee pollen, bee bread, venom, and wax constitute a range of products generated by bees. These products possess a range of biological attributes, including antimicrobial, anti-inflammatory, anticancer, and antioxidant properties (Nainu et al., 2021; Ranneh et al., 2021). Throughout history, bee products have served as beneficial nutritional supplements for promoting health (Thakur & Nanda, 2020). Accordingly, honey bees and the beekeeping industry play a crucial role in the global economy, particularly in the context of agricultural production (Stanhope et al., 2017).

Beekeeping, also known as apiculture, is the refined practice that encompasses the art and science of collecting and managing honeybee colonies of preferred species. This involves placing them in carefully designated and standardised containers, situating them at suitable locations, maintaining an optimal number of colonies through scientifically informed management, and leveraging both the direct and indirect benefits derived from these activities (Sain & Nain, 2017). Land suitability analysis offers geospatial data on the optimal locations for agricultural activities including beekeeping, serving as a vital tool in addressing modern challenges such as meeting global demand for food, adapting to climate change, and facilitating sustainable production (Akpoti et al., 2019; Hartemink & McBratney, 2008; Sharma et al., 2018). However, as suggested by the literature, there are limitations in the land suitability assessments conducted on beekeeping. These limitations include the unavailability of a proper mechanism to rate floral resources for honey bees, the non-inclusion of contemporary fuzzy techniques, and a limited number of criteria used. A comprehensive literature review on land suitability assessment for apiaries has been presented in Chapter 2.

4.3 Methods

4.3.1 Study area

The study was conducted in a sub-section of southern Queensland, spanning 37,689 km^2 and encompassing 265 localities across four Local Government Areas: Toowoomba Regional, Southern Downs Regional, Goondiwindi Regional, and Western Downs Regional. This expansive study area is primarily rural, characterised by vast agricultural expanses, extensive rangelands, and diverse regional ecosystems comprising both remnant and non-remnant forests, woodlands, and shrublands. Specifically, the agricultural sector covers 11,712 km^2, rangelands extend over 11,899 km^2, and regional ecosystems dominate the landscape, spanning a significant 13,488 km^2. The primary honey-producing region in Queensland houses a total of 4,491 apiary sites. Within the selected study area, there are 1,591 sites, constituting approximately 35% of the total apiary sites in the broader region.

Queensland experiences diverse climatic conditions, with the state divided into four climate zones: tropical, sub-tropical, hot arid, and warm temperate. The study area displays variations in climate. Toowoomba and Southern Downs fall within a warm temperate zone, exhibiting four distinct seasons. Winters are cool with low humidity, while summers are warm with moderate humidity. For example, in Stanthorpe, Southern Downs, winter temperatures can drop as low as 1.1°C, while summer temperatures reach a maximum of 27.4°C. The area receives an average annual rainfall of 764.2 mm. In contrast, Western Downs and Goondiwindi experience a hot arid climate characterised by hot and dry summers, cold winter nights, minimal rainfall, and low humidity. In Miles, Western Downs, winter temperatures average 3.6°C for minimum and 33.3°C for maximum, with an annual rainfall of 643.4 mm. (Australian Bureau of Statistics, 2022). Chapter 3 presents more information on the study area, accompanied by a map.

4.3.2 Overview of the methodology

The overall flow of objective 2 is presented in figure 4.1. Criteria were selected for suitability analysis based on literature and expert opinion. All the vector layers were converted to raster and resampled to a 25m × 25m grid cell size. The regional ecosystem, land cover and land use layers were reclassified using the ratings assigned. Using fuzzy AHP and fuzzy overlay techniques, the output suitability maps were derived for each season separately. The output maps were validated for accuracy and the results of two methods were compared to determine the best technique.

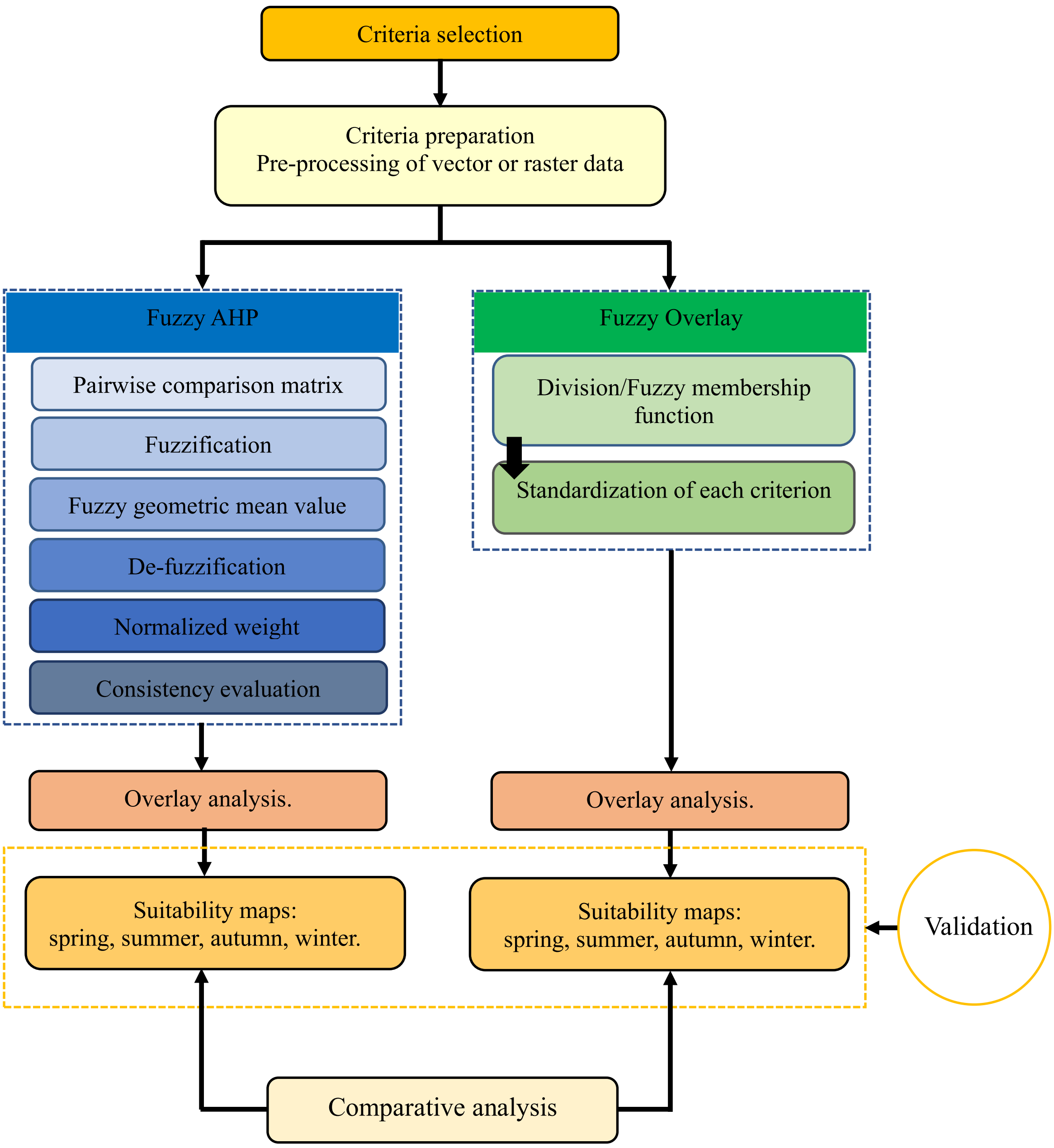


Figure 4. 1 Overview of the research methodology

4.3.3 Criteria selection

Table 2.1 in Chapter 2 indicates the different criteria used in the literature on suitability analysis in apiary site selection. Eleven criteria, including biotic needs of the bees, factors required for migratory beekeeping, and constraints that impose barriers on beekeeping, were selected for the present study. These criteria, along with their relative importance and the source of the data, are all shown in Table 4.1.

Table 4. 1 Criteria used in the study, their importance, and the sources.

Criteria	Importance	Source
Floral resources	Honey bees forage on different flowering species and gather nectar and pollen which are vital not only for their existence but also for honey production. Therefore, when selecting a location to establish an apiary site, one of the major factors to be considered is the availability of food (nectar/pollen) sources for honey bees. The Queensland regional ecosystems database provides data on vegetation communities in a bioregion. Regional ecosystems are defined as "vegetation communities in a bioregion that are consistently associated with a particular combination of geology, landform and soil" (Sattler & Williams, 1999). Thus, this data base acts as an ideal source that can be used to identify the floral species for honey bees in a particular ecosystem.	Regional Ecosystems Maps – Queensland Spatial Catalogue: Department of Environment and Science (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2021)
Land Cover	A land cover map is essential to differentiate the potential areas from unsuitable areas for beekeeping (Estoque & Murayama, 2011). The land cover raster layer downloaded from ESRI Land Cover – Living Atlas provides high resolution maps (10 m) based on Sentinel- 2 data.	Esri Land Cover – ArcGIS Living Atlas of the World (https://livingatlas.arcgis.com/landcover/) (ESRI Land Cover, 2022)
Land Use	While Queensland regional ecosystem map and database are good resources to identify vegetation composition in natural ecosystems, land use maps can be used to identify potential areas for beekeeping outside the natural environment.	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2023)
Slope	Slope is associated with the floral resources, meteorological conditions, and aspect of an area (Sarı et al., 2020). A flat land is preferred to establish an apiary site. Flat or low slope lands have a low risk of water accumulation (Abou-Shaara, 2021) with easy access for the apiarists.	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)
Aspect	The importance of this factor tends to vary depending on the season of the year and climatic conditions. According to (Somerville, 2020), in Queensland when bee hives are oriented towards North-East aspect bees can fly early in the morning being warmed up by the first radiant heat emitted from the sun.	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)
Elevation	Elevation is closely correlated with floral resources and climatic factors that affect beekeeping.	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)

Criteria	Importance	Source
Climate (Rainfall, Temperature, Solar Radiation)	Rainfall: According to (Adjare, 1990), annual rainfall amount should not exceed 1250mm for a site to be considered as suitable. Since this study is conducted season wise, as the maximum permissible rainfall per quarter, 312.5mm (1250 mm / 4), was used instead of the annual figure. Temperature: The optimum temperature range for honey bee foraging is 10^0C - 40^0C (Abou-Shaara, 2014). Below 10^0C honey bee foraging starts to decline (Joshi & Joshi, 2010). Moreover, low temperatures can lead to colony losses, which make temperature a critical factor to be considered especially when choosing honey bee wintering sites and thus the areas with a minimum temperature of 8^0C or below were considered unsuitable (Abou-Shaara, 2021). Solar Radiation: High solar radiation is a desired factor especially during winter since bee egress rate (i.e., moving out of the hive) is associated with temperature and radiation. A low bee egress rate had been examined under low temperature and solar radiation (Clarke & Robert, 2018).	New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling (NARCliM) (Hutchinson & Xu, 2014)
Distance to Water	Just as pollen and nectar, water is an essential requirement of bees and it is been used for honey production and cooling the colonies (Amiri et al., 2011). Therefore, good accessibility to a water source is critical (Estoque & Murayama, 2010).	Drainage, GEODATA TOPO2.5M from the Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Stein, et al., 2008)
Distance to Roads	This is an important criterion to be considered since access to roads is essential for establishment and management of apiary sites (Amiri & Shariff, 2012; Estoque & Murayama, 2010).	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Resources, 2021)

4.3.4 Data processing and analysis

Fuzzy logic – The base concept of fuzzy AHP and fuzzy overlay

The fuzzy logic introduced by Zadeh (Zadeh, 2008) is based on the rationale that in an environment of uncertainty and imprecision, approximate reasoning performs better than exact reasoning. Thus, fuzzy logic aims at modelling approximate modes of reasoning which is often an outcome of human judgment. The limitations associated with suitability analysis include subjectivity associated with allocating weights to criteria by the experts and the crisp boundaries of the allocated weights (Mallik et al., 2021). The two methods fuzzy AHP and fuzzy overlay which are based on fuzzy logic were applied in generating suitability maps in the present study.

Fuzzy AHP

The steps of AHP involve selection and arrangement of factors into a hierarchy followed by pair-wise comparison to determine the relative importance of each factor (Saaty, 1994). AHP has been used extensively in multiple fields due to its ease of use and ability to calculate factor weights and prioritise alternatives systematically (Liu et al., 2020). Despite the popularity and convenience of use, the drawbacks associated with AHP include uncertainty and subjectivity of human judgements (Chan & Kumar, 2007; Kamvysi et al., 2014; Lootsma, 1990; Prakash, 2003); inability of the relative importance scale based on whole numbers to calculate intermediate values (for instance when a value lies between very strong importance to strong importance) (Sarkar et al., 2021); high inconsistency of the outcome resulted by group decision making (Escobar et al., 2004); and arbitrary ranking of alternatives (Dyer, 1990). This research employs fuzzy AHP that integrates fuzzy logic with basic AHP (Nuhu et al., 2022). The Fuzzy AHP can handle the imprecision linked with the conventional AHP especially when judgments are made under uncertainty (Liu et al., 2020). This integrated method has the advantages of both AHP and fuzzy logic. The steps of fuzzy AHP are the following:

Step 1: preparing a pair-wise comparison matrix to indicate the relative importance of each criterion.

The pair-wise comparison matrix is prepared using the verbal judgments (in the form of nine linguistic terms as indicated in table 4.2) of experts regarding a relevant importance of a criterion with respect to another.

Step 2: Conversion of linguistic terms used in pair-wise comparison into triangular fuzzy membership function (fuzzification).

Fuzzy AHP can translate the linguistic terms into Triangular Fuzzy Numbers (TFN) (Chang, 1996; Sarkar et al., 2021; Zamani-Sabzi et al., 2016) instead of the crisp numbers used in AHP (table 4.3). This is known as fuzzification. A TFN consists of three integers including the smallest possible value, the most probable value and the largest possible value (Sarkar et al., 2021). A TFN is used to represent an expert's judgment on relative importance of criterion *'i'* over criterion *'j'* (Liu et al., 2020). The inverse of a TFN is used when the relative importance of criterion *'j'* over criterion *'i'* is expressed.

A TFN A is denoted as, A = (l,m,u),

Where, l is the lower bound of the TFN while u represents the upper bound of the TFN.

The inverse of that TFN or the reciprocal is $(A)^{-1} = (l,m,u)^{-1} = (1/u, 1/m, 1/l)$ (Wang & Chen, 2008).

Table 4. 2 Linguistic terms, triangular Fuzzy Numbers (TFN), inverse and crisp values

Linguistic Term	TFN	Inverse of TFN	Crisp Value
1. Equal	(1,1,1)	(1,1,1)	1
2. Moderate	(2,3,4)	(1/4,1/3,1/2)	3
3. Strong	(4,5,6)	(1/6,1/5,1/4)	5
4. Very Strong	(6,7,8)	(1/8,1/7,1/6)	7
5. Extremely Strong	(9,9,9)	(1/9,1/9,1/9)	9
6. Intermediate Value	(1,2,3)	(1/3,1/2,1)	2
7. Intermediate Value	(3,4,5)	(1/5,1/4,1/3)	4
8. Intermediate Value	(5,6,7)	(1/7,1/6,1/5)	6
9. Intermediate Value	(7,8,9)	(1/9,1/8,1/7)	8

Step 3: Calculation of weight for each criterion considering the overall matrix based on geometric mean method.

In this step a single fuzzy weight is calculated for a criterion by aggregating multiple fuzzy sets (TFNs) allocated to the same criterion during pair-wise comparison. Several aggregation methods have been used in previous studies including arithmetic mean, geometric mean, logarithmic least squares, lambda-max method, eigenvector method, and fuzzy programming methods (Liu et al., 2020). In the present study, geometric mean method introduced by Buckley (1985) was used to calculate fuzzy weight of each criterion. This method has been widely applied due to the relatively less complicated computation that produces valid results (Liu et al., 2020). Equation 1 (Helmy et al., 2021) was used to calculate fuzzy geometric mean of criteria.

Equation 1: $$\begin{aligned} Fuzzy\ geometric\ mean\ value\ (ri)&: A1 \otimes A2 \otimes An \\ &= (l1, m1, u1) \otimes (l2, m2, u2) \otimes (ln, mn, un) \\ &= (l1 * l2 * \ldots\ldots ln, ml * m2 \ldots\ldots * mn, u1 * u2 \ldots\ldots un)^\wedge 1/n \end{aligned}$$

Where: An is the fuzzy number of n^{th} criterion; $ln, mn, and\ un$ are the smallest possible value, the most probable value and the largest possible value of n^{th} criterion respectively; and, n is the number of criteria.

Then fuzzy weight of each criterion is calculated using geometric mean of criteria using the equation 2.

Equation 2: $Fuzzy\ weight(wi) = ri \otimes (r1 \oplus r2 \oplus rn)\hat{} - 1$

Where, ri is the fuzzy geometric mean value of ith criterion.

Step 4: De-fuzzification to obtain crisp numeric values

De-fuzzification converts the fuzzy weight calculated from equation 2 for each criterion into a crisp numerical value based on Centre of Area (COA) method shown in equation 3.

Equation 3: $Weight\ of\ a\ criterion\ as\ a\ crisp\ numerical\ value = \frac{(l + m + u)}{3}$

Step 5: Normalisation

Weight of every criterion is normalized by dividing each weight by the summation of weights.

Step 6: Consistency evaluation of the judgments

The allocation of weights in the pair-wise comparison matrix is tested for consistency using the Consistency Ratio (CR). For calculating the consistency in this study, the respective crisp values of the fuzzy numbers were used. A CR less than 0.1 is considered as adequate (Saaty, 1987). For this study an online software (Goepel, 2018) was used to calculate CI. After calculation of normalised weights of criteria, sub-criteria were defined for every criterion. The same procedure used to calculate normalized weights for criteria was followed to calculate normalised weight of each sub-criterion. The weights of sub-criteria are known as ‘local weights’ and converted to ‘global weights’ by multiplying with the weight of the respective parent criterion (Liu et al., 2020).

Fuzzy overlay

Fuzzy logic is applied to convert crisp boundaries of input criteria into a fuzzy set consisting of values from 0 to 1, where 0 indicates no membership of the set while 1 indicates full membership of the set (Mallik et al., 2021). Accordingly, the larger the number means the greater the possibility of being a member of the set. This can be achieved through the application of an appropriate fuzzy membership function to each input criterion in the GIS environment. A fuzzy membership function can reclassify the input values to a 0-1 scale.

Thus, the application of a fuzzy membership function acts as the standardization of criteria as well. The fuzzy membership functions used in the study accompanied by corresponding graphical representations (figures 4.2 – 4.5) are outlined below.

Linear fuzzy membership

The minimum and maximum values can be chosen as per user discretion and a value of 0 is assigned for the minimum and values below minimum whereas a value of 1 is assigned to the maximum and above maximum values. If the minimum value is smaller than the maximum, the linear function will possess a positive slope. Conversely, if the minimum value is greater than the maximum, the linear function will exhibit a negative slope (ESRI Land Cover, 2022).

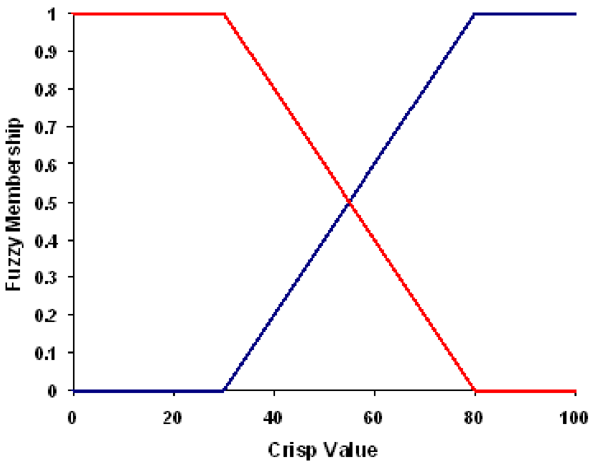


Figure 4. 2 Fuzzy Linear membership function (ESRI, 2023)

Small fuzzy membership

The smaller values are more likely to have membership values close to 1. Spread and midpoint are important aspects in this membership type and can be defined by the user. The Small function proves beneficial when smaller input values exhibit a higher degree of membership. The input values may consist of either positive integers or floating-point numbers (ESRI Land Cover, 2022).

The equation for the fuzzy small function is:

$$\mu(x) = \frac{1}{1 + \left[\frac{x}{f2}\right]^{f1}}$$

Where f1 is the spread and f2 is the midpoint.

Accordingly, making the spread wider makes the fuzzy membership curve steeper.

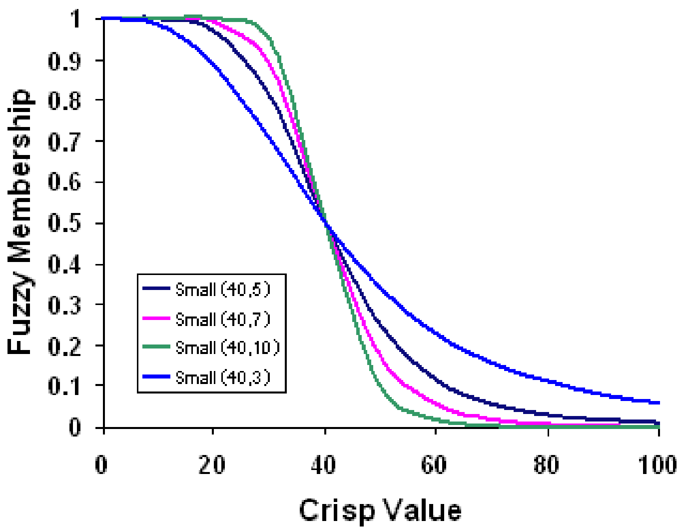


Figure 4. 3 Small fuzzy membership function (ESRI, 2023)

Large fuzzy membership

The larger values which are above the midpoint are more likely to be a member of the set (Jayarathna et al., 2022). The function is characterised by a user-defined midpoint, given a membership of 0.5, along with a defined spread. The Large function proves valuable when greater input values exhibit a higher degree of membership. The input values can be either positive integers or floating-point numbers (ESRI Land Cover, 2022).

The equation for the fuzzy large function is:

$$\mu(x) = \frac{1}{1 + \left[\frac{x}{f2}\right]^{f-1}}$$

Where f1 is the spread and f2 is the midpoint.

Making the spread wider makes the fuzzy membership curve steeper.

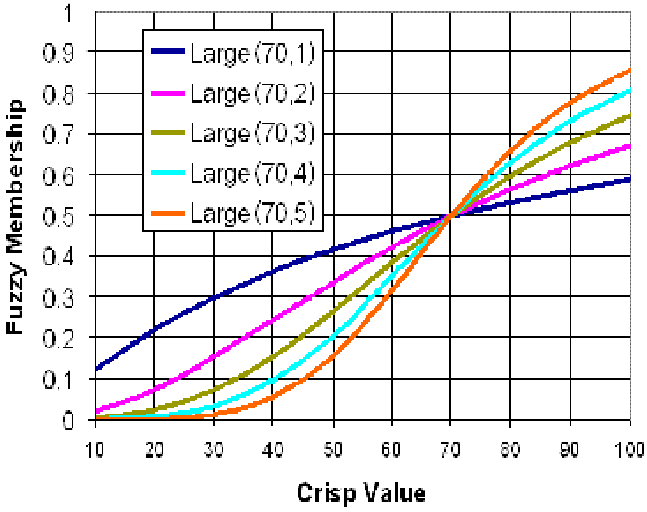


Figure 4. 4 Large fuzzy membership function (ESRI, 2023)

Near fuzzy membership

The midpoint defines the centre of the set, and the values fall on midpoint have a membership value of 1 whereas the membership gradually decreases as values move from midpoint. The Near function is effective when the membership is near a specific value. The input values may consist of either positive integers or floating-point numbers (ESRI, 2022).

The equation for the fuzzy near function is:

$$\mu(x) = \frac{1}{1 + f1 * (x - f2)^2}$$

Where f1 is the spread and f2 is the midpoint.

Increasing the spread leads to a steeper fuzzy membership curve.

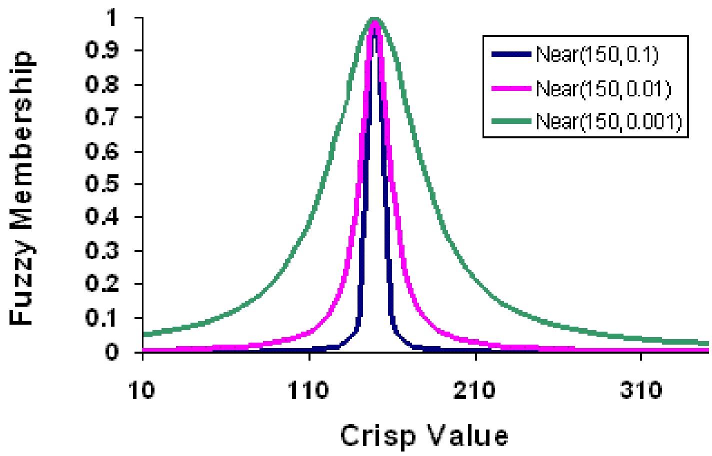


Figure 4. 5 Near fuzzy membership function (ESRI, 2023)

Suitability analysis using fuzzy overlay was conducted using ‘Fuzzy Membership’ and ‘Fuzzy Overlay’ tools available in ArcGIS Desktop. Fuzzy overlay aggregates all the fuzzified input criteria layers. In aggregation of input raster layers five different fuzzy combination operator options including fuzzy OR, fuzzy AND, fuzzy Product, fuzzy Sum, and fuzzy Gamma are available. The fuzzy OR and fuzzy AND generate the output based on the maximum and minimum membership values of the input layers while fuzzy Product uses the product of membership values of input layers to create the output (Mallik et al., 2021). Fuzzy Sum adds the values of each fuzzy set pertaining to a particular cell (ESRI, 2022). In this study, fuzzy Gamma combination operator was applied which is the algebraic product of fuzzy Product and fuzzy Sum raised to the power of GAMMA (Tangestani, 2004) offering a more balanced way to represent suitability when compared with other operators. Accordingly, fuzzy Gamma operator can generate an output with a gradient of suitability rather than an output with discrete boundaries of classes (Lewis et al., 2014).

4.3.5 Criteria preparation and standardisation

For criteria preparation and standardization, ArcGIS 10.8.1 software was used. All the vector layers were converted to raster using ‘feature to raster’ conversion tool in ArcToolbox and projected to GDA2020 MGA Zone 56 projection system.

Each regional ecosystem in the study area was allocated a rating considering the floral species available for honey bees in that ecosystem. Two important aspects of a floral species, namely value to honey bees (either as a pollen source or a nectar source) and the duration of flowering (in months) were taken into consideration for rating. The reference guide "Honey and Pollen Flora of South-eastern Australia" was used as the reference material to rate floral species (Somerville, 2020). The rating varies from one to five where five is assigned for the best species. The most suitable site in a season should consist of a floral species that flower during the whole three months of a season and has a rating of 5. Both value of a floral species to honey bees and the duration of flowering are assumed as equally important. Thus, the ratings and number of months are counted as equal units. The ecosystem with the highest rating is assigned a value of 100 which is equal to 8 units. Therefore, one unit was calculated as 12.5 (i.e., 100/8 = 12.5). The number of units in terms of the rating and flowering period are calculated for each regional ecosystem and a score out of 100 was obtained by multiplying by 12.5. When an ecosystem has more than one species that flower during a considered season, an average rating was calculated based on the ratings of those species. The number of months was calculated by adding the flowering months together, yet with the limitation of maximum number of months as three, as there are three months per season. The rates included values from 0-100. The vector layer of regional ecosystem was converted to a raster map. The regional ecosystem raster layer was standardized by dividing it by 100 to assign values from 0-1 (figure 4.6). Figure 4.7 visualizes the maps of regional ecosystems for each season along with the assigned ratings.

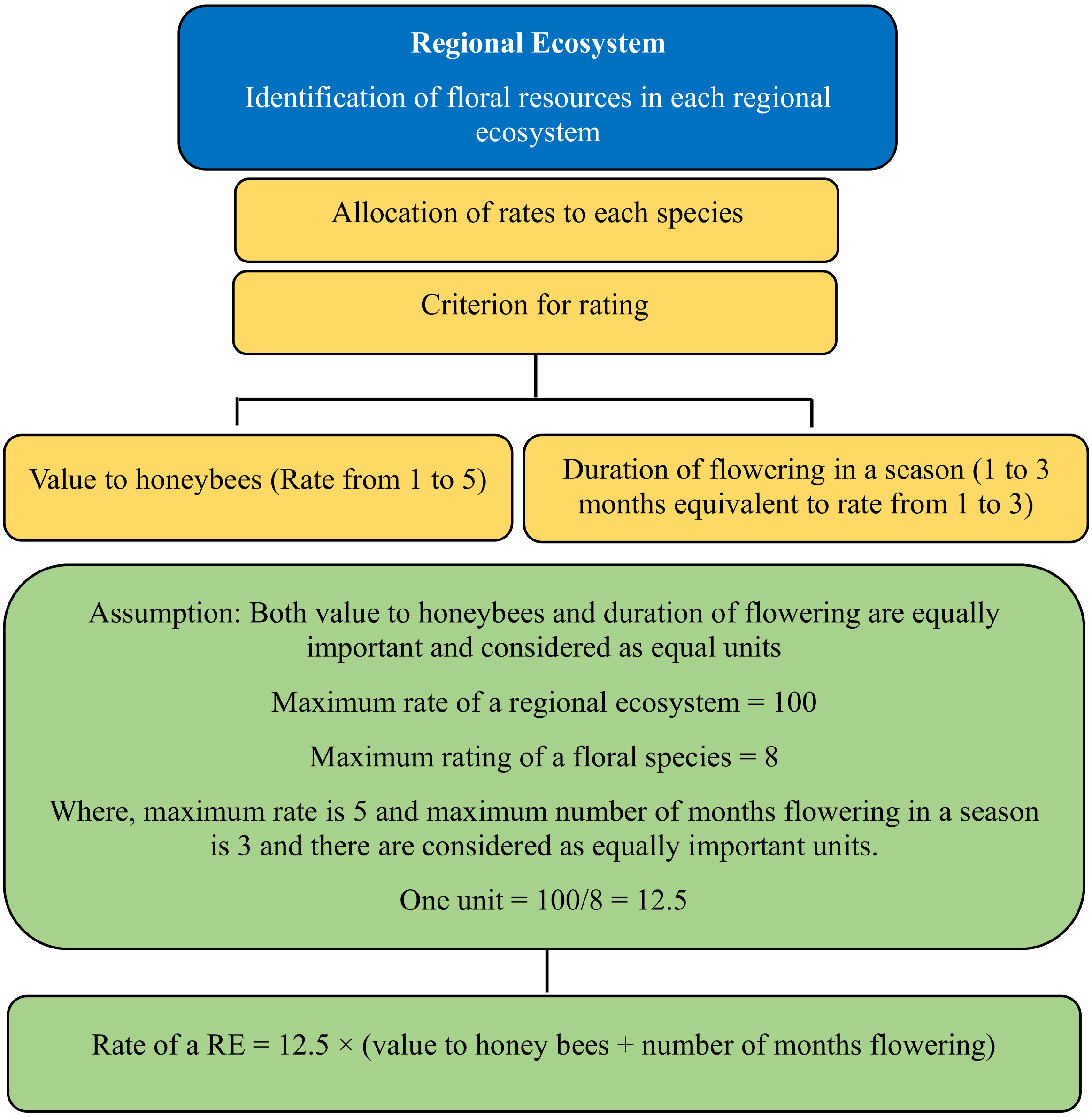


Figure 4. 6 Allocation of rates to regional ecosystems

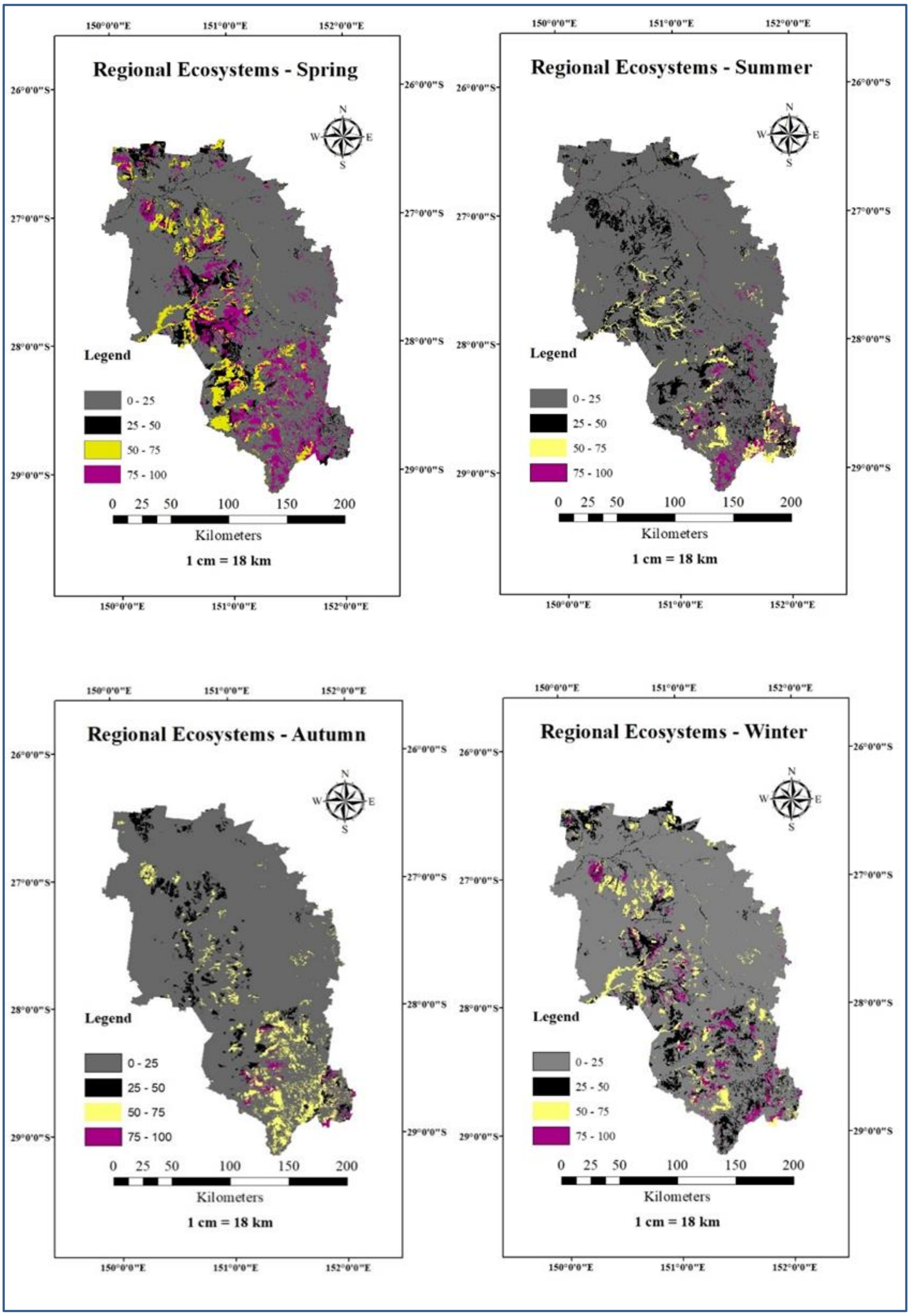


Figure 4. 7 Regional ecosystem maps with assigned ratings

The original land cover map consisted of nine classes: trees, flooded vegetation, crops, built area, bare ground, snow/ice, clouds, rangeland, and water. The study area of concern included eight land cover types except snow/ice. The scores were allocated based on literature and expert opinion. The highest rating of 10 (out of 10) was assigned to the class ‘trees’. The class ‘water’ was assigned a value of zero. Since land cover is a categorical variable, the raster layer was standardized by dividing it by 10 to allocate weights from 0-1. The land use map was reclassified based on the tertiary use in which scores were assigned taking into consideration the potential of each category to establish apiary sites. The categorical variable, ‘land use’ was standardized by dividing the raster layer by 10.

Slope was standardized using the small fuzzy membership function. In the aspect layer, flat lands were rated as the best followed by northeast and north aspects (Somerville, 2019). The near fuzzy membership function was used to standardize aspect raster layer. The DEM layer was used in the analysis and an inverse linear fuzzy membership function was applied since the minimum temperature required for active honey bee foraging can drop as the elevation increases (Estoque & Murayama, 2010).

The temperature raster of winter was standardized using the large fuzzy membership function and as the midpoint 8^0C was considered while 0.1 was chosen as the spread. The mean temperature range of the study area during winter is 7.2^0C to 13.2^0C. For the other three seasons, a linear fuzzy membership was used considering the correlation between temperature (within the suitable range for honey bees) and honey bee foraging. The maximum rainfall received by the study area over each season does not exceed the maximum threshold suggested for beekeeping. An inverse linear membership function was selected due to the negative correlation between rainfall and bee foraging. When applying the membership function, 312.5 (the maximum permissible rainfall per quarter) was defined as the maximum value. Similarly, the criterion solar radiation was standardized using the linear fuzzy membership function for every season. Bee foraging and solar radiation have a positive relationship up to a certain threshold (460W/m^2) (Clarke & Robert, 2018). Any part of the study area does not exceed this maximum threshold in any season.

According to beekeeping practices in Australia, water is provided on the property where hives are being placed if there is no water source in proximity (Rural Industries Research and Development Corporation, 2015). For the standardization of this criterion, the small fuzzy membership function was used with a spread of 100m and a mid-point of 2km. The maximum distance between a road and an apiary site is not specified in the literature. Due to practical difficulties in transporting beehives farther away from roads, a buffer was created. The buffer of 9km was chosen to avoid the occurrence of no data points in the final output when a smaller distance is chosen. The small fuzzy membership function was applied with a spread of 100m and a mid-point of 2km.

4.3.6 Generation of suitability maps using fuzzy AHP and fuzzy overlay

Fuzzy AHP was performed using the weighted overlay function in ArcMap. Regional ecosystem, rainfall, temperature, and solar radiation layers were different for each season while same layers of land use, land cover, distance to water, distance to roads, slope, aspect, and elevation were used due to no seasonal variations in these layers. The allocation of weights to criteria and sub-criteria during weighted overlay standardizes the criteria to the common scale of weights. Table 5 displays the fuzzy weights calculated for each criterion and sub-criterion. The criteria layers which were converted to a 0-1 scale based on a membership function (standardised) were used for fuzzy overlay. The value range of the outputs of fuzzy overlay was 0-1 equivalent to the input layers. Then, suitability maps generated from fuzzy AHP and fuzzy overlay analysis were further classified into four different suitability classes to better explain the variability in suitability rather than classifying as a binary output (suitable and not suitable). The intervals were defined based on geometric interval method which ensures that each class has approximately the same number of values and the change between classes is consistent (Alder et al., 2015). Furthermore, this classification method works well on continuous data (Ozdemir, 2016) which is the case in suitability values of suitability maps.

4.3.7 Validation of results

The predicted results must be validated against the actual data to ensure the adequacy of the model in representing the reality (Cheng & Sun, 2015). Thus, the results of the present study derived from fuzzy AHP and fuzzy overlay for each season separately were used to determine the accuracy of the two methods in mapping suitability for apiary sites. All the eight maps generated were used for validation against the existing map of apiary site locations on public lands retrieved form Department of Environment and Science (2023). By applying ‘Sample’ tool of ArcMap 10.8.1, the coordinates of existing apiary site locations in each suitability class and the coordinates of all the pixels (cell size 25mx25m) within each suitability class in the resultant map were extracted for comparison. The percentage values of predicted apiary locations in each suitability class that tally with the existing apiary locations were calculated using Microsoft Excel. The validation process was further extended creating a buffer of 200m for each existing location of apiary site.

4.3.8 Comparison of results

One-way ANOVA has been used widely to test for the difference among group means. Accordingly, this method was employed in the present study to explore whether there are statistically significant differences available across different seasons with respect to the area. The seasonal differences pertaining to the two methods i.e., fuzzy AHP and fuzzy overlay, were tested separately. T-test was used to test for the variance of the suitability area of a particular season resulted by the two methods.

4.4 Results

4.4.1 Fuzzy AHP

The weights assigned for the main criteria and sub-criteria were tested for consistency. A Consistency Ratio (CR) of 0.047 was obtained for the main criteria while the CR calculated for each sub-criterion was less than 0.1 (Table 4.3). These values indicate that the allocation process of weights is consistent or acceptable. Additionally, it was shown that the regional ecosystem (with the highest weight of 27.4%) is the most important criterion in this study. Other significant criteria are land cover (14.4%), land use (14.4%), distance to roads (14%), slope (5.4%), aspect (5.4%), and elevation (5.4%). The lack of reliance on natural water resources by Queensland apiarists explains why the distance to water criterion was given the lowest rating of 2.2%.

Table 4. 3 Weights of criteria and sub-criteria

Main Criteria	Weight (%)	Sub-criteria	Local Weight (%)	Consistency Ratio – sub-criteria
Regional Ecosystem (Floral resources)	27.4	High (75-100)	58	0.057
		Moderate (50-75)	30	
		Marginal (25-50)	9	
		Low (0-25)	3	
Land Cover	14.4	High (trees)	58	0.057
		Moderate (rangelands, clouds)	30	
		Marginal (flooded vegetation, bare grounds, crops)	9	
		Low (water)	3	
Land Use	14.4	High (80-100)	58	0.057
		Moderate (40-60)	30	
		Marginal (10-30)	9	
		Low (0)	3	
Slope	5.4	High (0-25.6^{0})	56	
		Moderate (25.6^{0}-51.1^{0})	27	
		Marginal (51.1^{0}-76.7^{0})	13	
		Low (76.7^{0}-102.2^{0})	4	
Aspect	5.4	High (flat, north, northeast)	52	0.063
		Moderate (east)	20	
		Marginal (southeast, southwest, west, northwest)	18	
		Low (south)	9	
Elevation	5.4	High (499.1-761.4)	46	0.019
		Moderate (761.4-1023.7)	29	
		Marginal (236.8-499.1)	18	
		Low (1023.7-1286)	7	
Distance to Water	2.2	High (200m)	53	
		Moderate (200m-1000m)	32	
		Marginal (1000m-2000m)	10	
		Low (>2000m)	5	
Distance to Roads	14	High (200m)	62	0.011
		Moderate (200m-1000m)	28	
		Marginal (1000m-2000m)	6	
		Low (>2000m)	4	

Main Criteria	Weight (%)	Sub-criteria	Local Weight (%)	Consistency Ratio – sub-criteria
Rainfall	6.4	High (215.5mm-254mm)	40	0.026
		Moderate (254mm-292.6mm)	27	
		Marginal (292.6mm-331.1mm)	20	
		Low (331.1mm-369.6mm)	13	
Temperature	2.5	High (18.7^0C – 20.5^0C)	40	0.026
		Moderate (16.8^0C-18.7^0C)	27	
		Marginal (14.9^0C-16.8^0C)	20	
		Low (13.1^0C-14.9^0C)	13	
Solar Radiation	2.5	High (19.3-19.7)	42	0.026
		Moderate (18.9-19.3)	31	
		Marginal (18.6-18.9)	18	
		Low (18.2-18.6)	9	

According to a comparison of seasonal suitability, only 5853.8 km2 or 15.56% of the total area is highly suitable during the spring season. It is revealed that the area moderately suitable for apiary sites is 67.78% in spring, 76.53% in summer, 80.38% in autumn, and 64.69% in winter. In winter, the areas identified as marginally suitable and not suitable, which is 11,417 km2 (30.33%), is higher than in other season (16.66% in spring, 18.11% in summer, and 13.88% in autumn) (Table 4.4). But the highly suitable extent is second only to spring which is characterized by the availability of some flowering species in winter. Figure 4.8 shows the suitability maps generated for each season by fuzzy AHP. Anyhow, no significant difference was found on the values derived from the Fuzzy AHP per season using one-way ANOVA (p value = 0.999 > a = 0.05). This means that there is essentially no variation in the seasonal patterns of suitability for the apiary sites (figure 4.10).

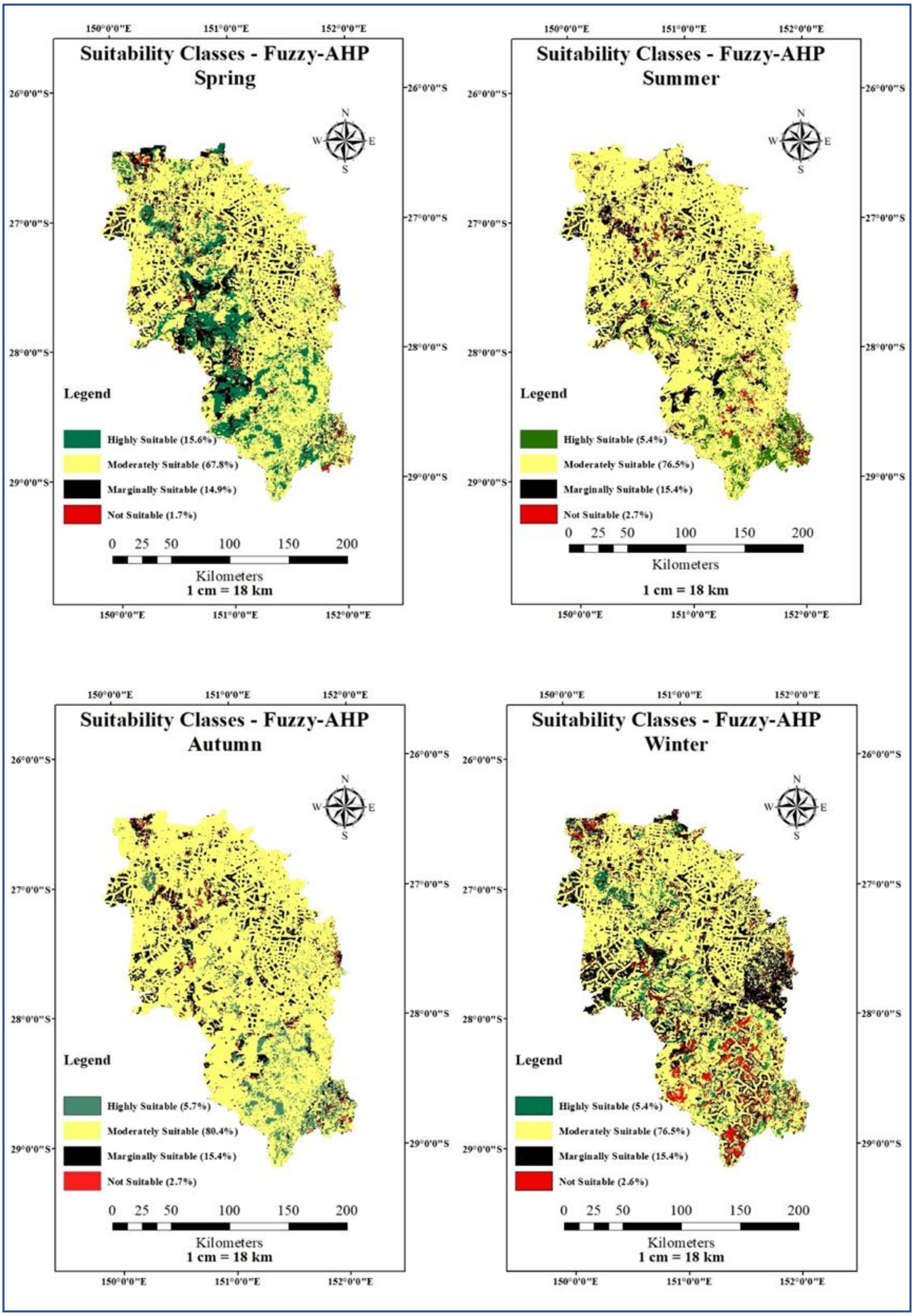


Figure 4. 8 Fuzzy-AHP output of suitability maps for four different seasons

Table 4. 4 Suitability of area (km^2) for apiaries under four varying seasons using fuzzy AHP

Classification	Spring		Summer		Autumn		Winter	
	Area	Percent	Area	Percent	Area	Percent	Area	Percent
Highly Suitable	5,853.8	15.6	2,015.9	5.4	2,160.4	5.7	2,247.7	5.9
Moderately Suitable	25,494.4	67.8	28,788.9	76.5	30,234.1	80.4	23,957.0	63.7
Marginally suitable	5,612.6	14.9	5,798.6	15.4	4,696.9	12.5	9,094.5	24.2
Not suitable	654.6	1.7	1,012	2.7	524	1.4	2,316.2	6.2
Total	**37,615.4**	**100**	**37,615.4**	**100**	**37,615.4**	**100**	**37,615.4**	**100**

4.4.2 Fuzzy overlay

In fuzzy overlay output maps, the extent of highly suitable and moderately suitable areas pertaining to each season is smaller than the result obtained in fuzzy AHP output maps. In contrast, the marginally suitable and not suitable areas in fuzzy overlay output maps are larger than those of fuzzy AHP maps. Consistent with the results of fuzzy AHP, the spring season has the largest extent of highly suitable area of 1,587.3 (4.2% of the total area). The percent value of the moderately suitable area in spring is 36.5% while it is 36% is summer, 36.8% in autumn, and 36.3% in winter (Table 4.5). According to fuzzy overlay output maps (Figure 4.9), the largest extent of marginally suitable and not suitable areas is found in summer that is 60.6% of the total area. This value is 59.8% in winter, 59.5% in autumn, and 59.3% in spring. The extent values of each suitability class across four different seasons indicate that highly suitable, moderately suitable, marginally suitable, and not suitable areas remain steady throughout the year. However, places classified as highly suitable had the lowest score when compared to the other categories of suitability. It is also interesting to discover that the number of locations that are not suitable is considerably more than the number of highly suitable sites. Nevertheless, it is still lower than the number of marginal to moderately suitable areas (Figure 4.9). Further, using one-way ANOVA, it was found that the values derived from the Fuzzy overlay in every season has no significant difference (P-value = 1 > a= 0.025). This implies that irrespective of the season, apiary locations are likely to exhibit consistent suitability patterns.

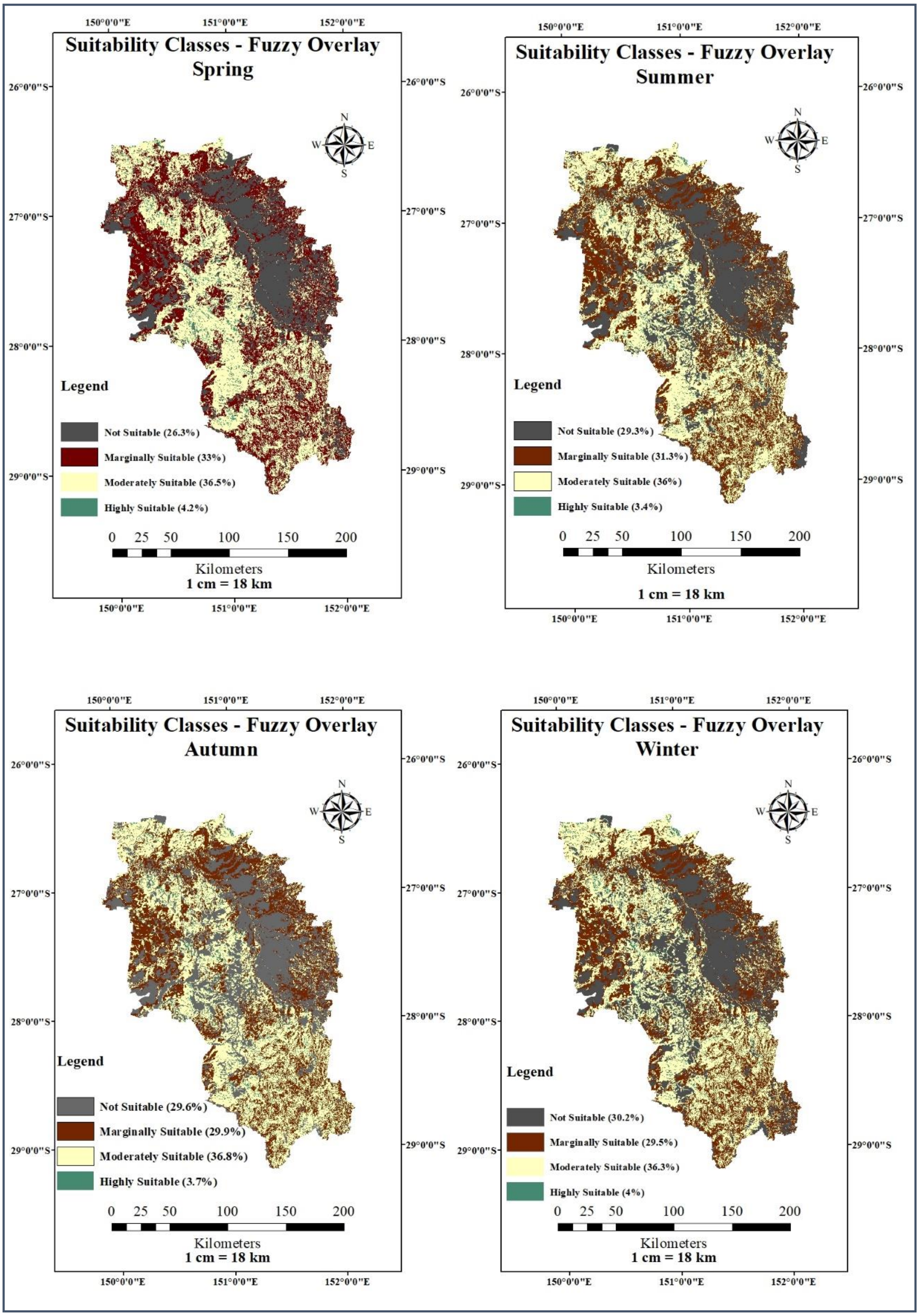


Figure 4. 9 Fuzzy overlay output of suitability maps for four different seasons

Table 4. 5 Suitability of area (km^2) for apiaries under four varying seasons using fuzzy overlay.

Classification	Spring		Summer		Autumn		Winter	
	Area	Percent	Area	Percent	Area	Percent	Area	Percent
Highly Suitable	1,587.3	4.2	1,304.8	3.5	1,401.5	3.7	1,490.5	3.9
Moderately Suitable	13,718.4	36.5	13,533.0	35.9	13,832.7	36.8	13,639.7	36.3
Marginally suitable	12,401.0	33.0	11,757.3	31.3	11,242.8	29.9	11,084.5	29.5
Not suitable	9,908.6	26.3	11,020	29.3	11,138.3	29.6	11,400.7	30.3
Total	**37,615.3**	**100**	**37,615.1**	**100**	**37,615.3**	**100**	**37,615.4**	**100**

4.4.3 Accuracy of fuzzy AHP and overlay

Validation results (Table 4.6) indicate that according to fuzzy overlay, 82.09% of highly and moderate suitable locations identified in the present study tally with the existing apiary locations while that value is 70.16% as per fuzzy AHP. Conversely, the validation values pertaining to fuzzy AHP in other three seasons (summer, autumn, and winter) are higher than those of fuzzy overlay. Significant differences between the values indicate that fuzzy AHP is a more reliable method than fuzzy overlay in suitability analysis in summer, autumn, and winter.

Table 4. 6 Validation results - percentage of apiary sites that fit in each suitability class of each season.

Season	Fuzzy Overlay			Fuzzy-AHP		
	High to Moderate (%)	Marginal (%)	Not Suitable (%)	High to Moderate (%)	Marginal (%)	Not suitable (%)
Spring	**82.1**	2.2	4.3	70.2	18.2	0.2
Summer	58.7	1.5	28.4	**63.5**	24.9	0.1
Autumn	58.5	1.0	29.1	**75.3**	13.2	0.1
Winter	56.4	0.9	31.2	**67.0**	12.4	9.1

Validation results were obtained by creating a buffer of 200m for the existing apiary locations (Table 4.7). The distance allowed between two apiary sites is 0.8km in Australia (Queensland Biosecurity Act, 2014) allowing an area with 1.6km diameter for bee foraging. Accordingly, we were required to create a buffer less than this value to avoid possible overlapping with the adjacent sites. A buffer of 200m was considered reasonable for validation of results.

This method improved the results emphasising the importance of exploring the suitability of an area that circumferences the identified specific locations.

Table 4. 7 Validation results (when a buffer of 200 m is created for apiary site locations) - Percentage of apiary sites that fit in each suitability class of each season.

Season	Fuzzy Overlay			Fuzzy-AHP		
	High to Moderate (%)	**Marginal (%)**	**Not Suitable (%)**	**High to Moderate (%)**	**Marginal (%)**	**Not suitable (%)**
Spring	**82.9**	2.9	4.8	71.9	18.6	0.1
Summer	59.5	1.9	29.5	**65.4**	25.1	0.1
Autumn	59.1	1.3	31.0	**77.1**	13.5	0.1
Winter	56.8	1.4	32.8	**68.3**	12.5	9.9

4.4.4 Comparison of fuzzy AHP and fuzzy overlay

The results of fuzzy AHP and fuzzy overlay were compared (table 4.8) to determine the best performing method in suitability analysis for apiary sites.

Table 4. 8 Area resulted from Fuzzy AHP and fuzzy overlay under each suitability class (km^2)

Season	Highly Suitable		Moderately Suitable		Marginally Suitable		Not Suitable	
	Fuzzy AHP km^2 (%)	**Fuzzy Overlay km^2 (%)**	**Fuzzy AHP km^2 (%)**	**Fuzzy Overlay km^2 (%)**	**Fuzzy AHP km^2 (%)**	**Fuzzy Overlay km^2 (%)**	**Fuzzy AHP km^2 (%)**	**Fuzzy Overlay km^2 (%)**
Spring	5,853.8 (15.6%)	1,587.3 (4.2%)	25,494.4 (67.8%)	13,718.4 (36.4%)	5,612.6 (14.9%)	12,401.0 (32.9%)	654.6 (1.8%)	9,908.6 (26.3%)
Summer	2,015.9 (5.4%)	1,304.8 (3.5%)	28,788.9 (76.5%)	13,533.0 (36.0%)	5,798.6 (15.4%)	11,757.3 (31.3%)	1,012 (2.7%)	11,020.3 (29.3%)
Autumn	2,160.4 (5.7%)	1,401.5 (3.7%)	30,234.1 (80.4%)	13,832.7 (36.8%)	4,696.9 (12.5%)	11,242.8 (29.8%)	524.0 (1.4%)	11,138.3 (29.6%)
Winter	2,247.7 (6.0%)	1,490.5 (4.0%)	23,957.0 (63.7%)	13,639.7 (36.3%)	9,094.5 (24.2%)	11,084.5 (29.5%)	2,316.2 (6.2%)	11,400.7 (30.3%)

According to the results of the T-test, the values produced from fuzzy AHP and fuzzy overlay do not indicate a significant difference during the springtime; however, results from other seasons demonstrate otherwise (Table 4.9).

Table 4. 9 Comparative analysis of Fuzzy AHP and overlay for each season using T-test: Two sample assuming unequal variances.

Season	**Fuzzy-AHP Mean**	**Fuzzy Overlay Mean**	**T computed**	**a**	**p-Value (two tail)**
Spring	3069.45	1446.025	1.74	0.05	0.18
Summer	27118.6	13680.95	9.28		0.003 s
Autumn	6300.65	11621.4	-5.29		0.006 s
Winter	1,126.7	10866.98	-18.53		1.59E-06 s

Box plots of each technique for each season were generated to differentiate the two approaches more clearly from one another. It is easy to see that the medians of the box plots do not all sit on the same level. This median line differences illustrate the clear disparity in the values that are produced by the various MCDA methods. The box plots for spring, autumn, and winter of the fuzzy AHP have sizes that are inconsistent with one another. This pattern indicates that the results are not consistent. Only the summertime boxplot of fuzzy AHP suggests a regularly distributed data. The results of fuzzy AHP boxplots strongly suggest that the method produced a generally varied result for the apiary site suitability analysis with regard to seasonal variation. On the other hand, it has been observed that the length of the box plots for the spring, summer, and autumn for the fuzzy overlay are noticeably shorter than those generated for fuzzy AHP. This demonstrates that the values obtained using such a method have a high degree of agreement with one another and are highly consistent with one another. Nevertheless, the height of the Fuzzy overlay boxplot increases during the winter, and it becomes skewed towards the lower whisker. This behaviour suggests that the values derived for such a season are not normally distributed and do not follow a normal distribution. When it comes to the values derived using the two MCDA techniques for apiary site suitability assessment with regard to seasonal variation, it is generally safe to conclude that the fuzzy overlay has a better outcome than that of the fuzzy AHP (Figure 4.9).

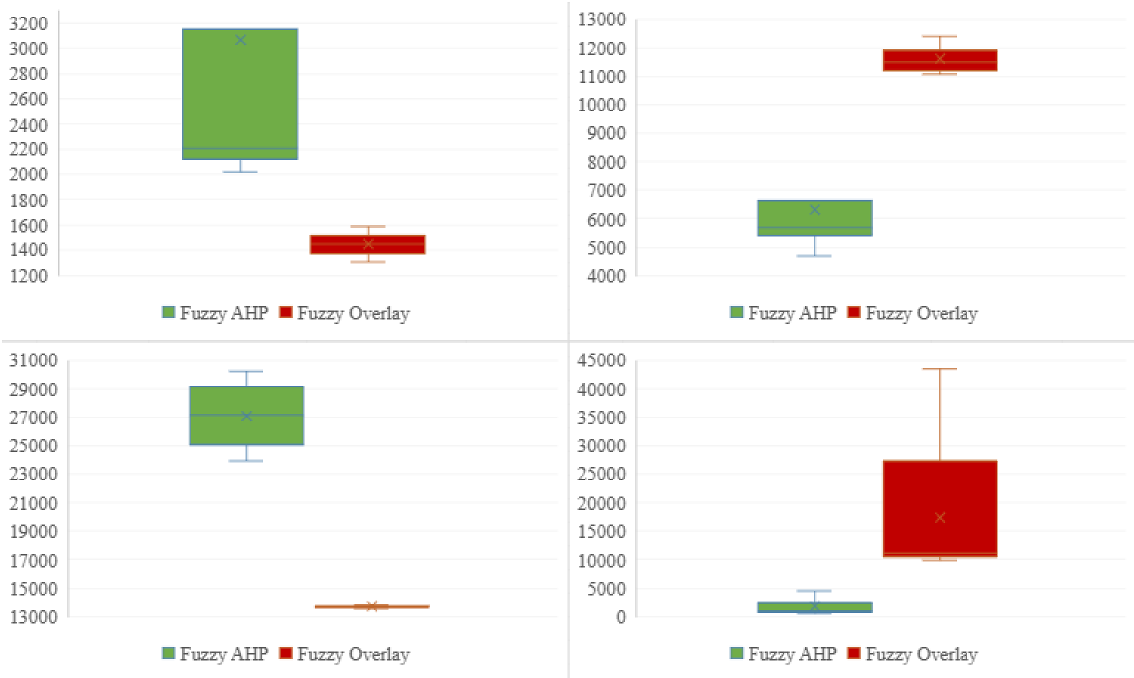


Figure 4. 10 Box plot of the Fuzzy AHP and fuzzy overlay for the apiary suitability sites for the following season: A. Spring; B. Summer; C: Autumn, D: Winter

4.5 Discussion

4.5.1 The approaches or methodology applied in apiary site suitability assessment

Land suitability analysis for apiary sites involves overlaying multiple criteria that are diverse such as those pertaining to ecological, topographical, climatic, social, infrastructure related and other factors. In addition, these criteria come in different units. Such characteristics make suitability analysis an unfeasible task without the use of MCDA techniques. Accordingly, several MCDA techniques had been employed in literature while AHP is the most popular method but associated with drawbacks such as uncertainty of decisions made by experts (Prakash, 2003). Fuzzy logic is an excellent alternative that can address the shortcoming associated with conventional methods by converting the criteria into grades or membership functions (Zhang et al., 2015). Therefore, by employing fuzzy AHP and fuzzy overlay, this study developed suitability maps based on the spatial and temporal variations of eleven criteria. In line with the initial hypothesis, according to both methods, the spring season has the highest extent under 'highly suitable' class. For each season, the highly suitable area is positively correlated with the regional ecosystem ratings. This implies the huge dependency of suitability on the occurrence of flowering species for honey bees throughout a considerable period. Regional ecosystems that represent the flora criterion has been assigned the highest weight under fuzzy AHP which is consistent with the previous studies (Sarı et al., 2020). Thus, when developing a methodology to map suitable locations for apiary sites, the inclusion of floral resource information is the most important aspect. Based on the evidence, the rated regional ecosystem maps have produced accurate results proving the methodology followed in this study to incorporate flora criterion is valid.

4.5.2 Apiary site suitability in terms of temporal variability

The changes of weather conditions due to seasonal shifts affect the forage availability that influence the success of bees (Schweiger et al., 2010). A review on honey bee survival based on temperature in Netherlands is found to be positively affected by forest and grassland presence, and negatively affected by increased temperature. When temperature drops below 10°C, the bees form a thermoregulation cluster that helps them maintain an optimal temperature for their survival (Calovi et al., 2021). A study confirmed that warmer and drier weather conditions in the preceding year were accompanied by increased winter mortality (Switanek et al., 2017). Therefore, according to the evidence provided in the literature, weather conditions associated with seasonal variations affect the performance of bees in both direct and indirect manner. Unfortunately, there is very little to no literature available that takes into account seasonal variation when determining how suitable a given location in Australia for an apiary. This study however attempts to include the seasonal shifts condition in selecting the suitable apiary locations.

Both approaches that were taken to find suitable locations for apiaries produce results that are very consistent with one another. Regardless of the method (whether fuzzy AHP or fuzzy overlay), the pattern of suitability is likely the same. The extent under each suitability class tend to differ across seasons. Yet statistically, there is no significant difference among the seasons with respect to the area of each suitability class. This behaviour of results can be explained by the nature of seasonal variation prevalent in Queensland. The study area under consideration has no extremes in temperature, solar radiation, or rainfall. Thus, statistically insignificant variations among season do not indicate that the temporal factor should be ignored. In fact, the methodology introduced in this study can be applied for regions where seasonal variations are prominent or extreme climatic conditions prevail.

4.5.3 The effectiveness of Fuzzy AHP and fuzzy overlay in apiary site suitability assessment

The validation results suggest that both fuzzy AHP and fuzzy overlay can be used for suitability analysis for apiary sites in spring while fuzzy AHP produces more accurate results in other three seasons (i.e., summer, autumn and winter). The highly suitable areas identified under fuzzy AHP for each season are larger than the same derived from fuzzy overlay. Conversely, the not suitable areas resulted by fuzzy AHP are smaller than those of fuzzy overlay. This can be explained by the way the criteria are combined to generate a final suitability map. Fuzzy AHP explicitly depends on relative importance of criteria whereas fuzzy overlay does not consider the relative importance but the contribution of values of a criterion towards the suitability. For instance, during weight allocation in fuzzy AHP, higher ratings are given to certain criteria while lower rates are allocated to less contributing criteria. But in fuzzy overlay, each criterion is standardized to a scale of 0 to 1 using a fuzzy membership function selected considering the impact of values of a criterion on suitability. Both methods are widely used in suitability assessment yet can produce different outcomes depending on the data and problem being solved.

Fuzzy AHP is a more complicated and a time-consuming technique than fuzzy overlay. This is due to the incorporation of expert opinion to rank criteria and unavailability of a free and a reliable software to calculate criteria weights. Therefore, fuzzy overlay had been used in several studies on suitability analysis (Baidya et al., 2014; Lewis et al., 2014; Maddahi et al., 2017; Mallik et al., 2021) and produced accurate results. Yet, the two methods fuzzy AHP and fuzzy overlay have never been compared in terms of accuracy. Even though fuzzy overlay generates a highly consistent results from one another, the validity it possesses is far lesser than that of the fuzzy AHP. According to the results of the reliability assessment, the fuzzy AHP method can be regarded as a more trustworthy approach to land suitability evaluation for apiary site selection overall. However, since this method inherently has more bias than the fuzzy overlay, its use needs to be carefully considered.

4.5.4 Limitations of the present study and recommendations

Irrespective of the popularity of Fuzzy AHP, the method is criticized for certain drawbacks including violation of basic axioms of AHP and logic of fuzzy set theory (Mukherjee, 2017;

Zhu, 2014). As proven by Dubois (2011), Zhu (2014) and Mukherjee (2017), Fuzzy AHP violates the classical AHP anti-reciprocity axiom. Fuzzy AHP violates this axiom when the lower bound is the reciprocal of the upper bound and the modal is equal to 1 (Zhu, 2014). The pair-wise comparison matrix used in this study has only one TFN of which the modal value is equal to 1, i.e. (1,1,1). Thus, we believe that the violation of anti-reciprocity axiom is minimized. Furthermore, we conducted consistency evaluation to ensure that the expert judgments are consistent. The results we obtained from consistency evaluation indicate that this axiom is not violated. Further, fuzzy AHP does not have a generally accepted method for ranking fuzzy numbers and validation (Zhu, 2014). This can be perceived as a limitation associated with fuzzy AHP and thus use of same must be carefully considered. Further, in future studies, it is recommended to compare fuzzy AHP with AHP in site suitability for apiary sites. This can be used to test whether use of a crisp number from the beginning like in AHP instead of defuzzification is effective. This could potentially contribute to the argument that the AHP scale is already fuzzy (Saaty, 2006; Saaty & Tran, 2007, 2010). The validation method employed in this study produced an accurate and consistent output. Yet, a limitation associated with the validation process in this study is that only the apiary sites on public lands have been considered. Validation against apiary sites on public lands, private lands and agricultural areas will improve the assessment outcome. Moreover, this is the first study that takes into consideration the temporal variability of criteria in suitability analysis for apiary sites and compares the accuracy of two methods (fuzzy AHP and fuzzy overlay) in assessing land suitability for apiary sites. One of the potential applications is to conduct suitability analysis for agricultural crops where seasonality impacts the production and land transition would be a method to overcome the barriers imposed due to seasonal changes. A possible extension of this study is to compare other MCDA methods coupled with fuzzy logic. Furthermore, this study can be extended considering the monthly variations of relevant criteria instead of seasonal variations to enhance the accuracy.

4.5.5 Implications for optimal land use for beekeeping

The research findings on land suitability for beekeeping reveal notable insights into the dynamic nature of seasonal variations and overall distribution of suitable areas. The study identifies spring as the season with the highest proportion (15.56%) of highly suitable land for beekeeping, showcasing optimal conditions. However, challenges emerge during winter, where

30.33% of the total area is classified as marginally suitable or not suitable, although it still ranks second in highly suitable areas. Interestingly, the study finds consistent moderate suitability across all seasons, ranging from 64.69% in winter to 80.38% in autumn, with summer standing out as the season with the highest percentage of moderately suitable areas (76.53%). Fuzzy AHP and Fuzzy Overlay Output maps highlight distinctions in the distribution of suitability classes, with larger areas classified as marginally suitable or not suitable in Fuzzy Overlay maps. The number of locations classified as not suitable exceeds highly suitable sites but remains lower than marginal to moderately suitable areas.

4.6 Conclusion

Analysing an area's suitability for apiary sites in terms of spatial and temporal parameters are essential for facilitating sustainable apiary management. In the process of developing a system for determining apiary site suitability, the incorporation of floral resources data is considered to be the most essential aspect, apart from other biophysical parameters. The present study developed land suitability maps for southern Queensland, Australia using fuzzy AHP and fuzzy overlay for the four seasons separately. It was observed that both methodologies used in this study (fuzzy AHP and fuzzy overlay) to find suitable sites for apiaries have generated results that are quite comparable with one another's findings. Further, the pattern of suitability is likely the same regardless of season. Overall, the fuzzy AHP method is deemed more appropriate for suitability analyses. In instances where it can be assumed that the contribution of each criterion towards suitability is equal, fuzzy overlay can be used since the implementation of fuzzy overlay is relatively easier when compared with Fuzzy AHP. Fuzzy AHP can be more time-consuming and complicated due to the unavailability of an open-source software to calculate fuzzy weights. Further, this technique is slightly subjective than the fuzzy overlay and is argued to have some flaws including violation of basic axioms of AHP. Therefore, its use should be thoroughly considered. However, it is suggested to conduct suitability assessment for apiary sites using several MCDA methods based on fuzzy logic to identify the most robust method that can best explain the spatial and temporal variations of criteria. Moreover, land suitability under future land use and climatic changes can be conducted. Another important extension to this study is the incorporation of vulnerability factors including floods and drought to develop a risk-based management strategy for the industry.

Land suitability maps to establish apiary sites with respect to spatial and temporal variations in floral resources and related biophysical factors provide valuable information to the Queensland apiarists and government authorities. One of the major challenges faced by the Queensland apiary industry is the identification of alternative sites for beekeeping due to government's proposed decision to relocate the existing apiary sites off the national parks. The suitability maps generated through this study can be used to identify suitable locations for apiary sites outside the national parks. Furthermore, the methodology used in this study can be adopted to generate suitability maps for bigger area for each season whereby enabling the key stakeholders to identify potential areas for beekeeping. Particularly, the novel methodology developed in the present study based on fuzzy logic to capture the temporal variation in floral resources and biophysical factors related to apiary management can be utilised not only by other Australian states but also by other countries where migratory beekeeping takes place.

CHAPTER 5 - AN ENSEMBLE MODELLING APPROACH TO PREDICT SHIFTS IN HONEY BEE HABITAT SUITABILITY UNDER CHANGING CLIMATE

5.1 Introduction

In Chapter 4, a comprehensive assessment of land suitability for apiary sites was conducted, employing two GIS-based methods, fuzzy AHP and fuzzy overlay. This evaluation considered spatial and temporal variations across eleven criteria, generating crucial insights into the suitability of land for sustainable apiary management. This information serves as a practical tool for mapping suitable areas across all four seasons. Notably, this study indicates that climatic factors play a significant role in influencing land suitability for honey bees. In the current landscape of ongoing debates surrounding climate change, there is a pressing need to anticipate future changes in land suitability. Anyhow, existing literature reveals a gap, as no study has systematically addressed the impact of climate change on honey bee habitat suitability. This chapter aims to bridge this gap and contribute valuable insights to the intersection of climate change and apiary site suitability.

This study employed an ensemble modelling approach to model the distribution of honey bees based on environmental and bioclimatic variables and to predict the future distribution over two distinct periods (2020-2039 and 2060-2079) within the Australian context. This chapter, centred on the second objective of the thesis, outlines the following specific objectives: 1) to identify the bioclimatic and environmental predictor variables that contribute the most to the distribution of honey bees, and to quantify their relative impact on honey bee distribution; 2) to assess the predictive performance of an ensemble approach in modelling the distribution of honey bees using bioclimatic and environmental variables; and 3) to investigate the potential impact of climate change on honey bee distribution under 2020-2039 (referred to as 2030) and 2060-2079 (referred to as 2070) climate conditions. This chapter pioneered several innovations: 1) it employed an ensemble approach to assess the distribution of *Apis mellifera* in relation to bioclimatic and environmental variables; 2) it utilised relatively high-resolution climate data (250m); and 3) it evaluated the distribution of *Apis mellifera* under changing climate conditions, considering two future time spans.

This chapter is organised into six sections. Section 1 enumerates the objectives of the chapter, while Section 2 discusses the background literature, previous works, and research gaps related to predicting the impacts of climate change on honey bee habitats. Section 3 describes the methods used to achieve the chapter's objectives. Section 4 presents the results of the ensemble modelling approach, along with the evaluation and validation of the models generated by the study. Section 5 discusses and interprets the results considering the objectives and research gaps identified in Section 2. The chapter concludes in Section 6 with implications of the results and recommendations for future studies.

This study is the first to investigate the future distribution of honey bee habitats under a changing climate.

5.2 Prediction of honey bee habitat distribution under changing climate

Honey bees are recognised as the foremost economically valuable pollinators for agricultural crops worldwide (Johnson et al., 2007). Additionally, they play a vital role in sustaining biodiversity through the pollination of various plant species (Allen-Wardell et al., 1998; Le Conte & Navajas, 2008). The impacts of climate change on honey bees are diverse, affecting their behaviour, physiology, distribution, and the evolution of interactions with diseases. Additionally, climate change brings about changes in the floral environment crucial for honey bees as a source of food. In the context of climate change, alterations are expected in plant phenology, particularly in the flowering period. This shift is likely to influence the bioclimatic and economic equilibrium, shaping the types and distribution of both agricultural crops and natural vegetation (Thuiller et al., 2005). Climate change may disrupt the established relationships between flowers and pollinators, necessitating protective measures to ensure the preservation of their vital pollination function. This function holds immense significance for both the economy and ecological balance (Le Conte & Navajas, 2008). This study centres on predicting the shifts in honey bee distribution in response to a changing climate.

Chapter 2 provides an extensive literature review, examining the broader implications of climate change on biodiversity and delving into the specific impact on honey bees. Moreover, it explores the application of species distribution modelling to anticipate future distribution patterns. This section delves deeper into the literature concerning ensemble species distribution modelling and its application in forecasting the distribution of a species. Species distribution modelling (SDM), also known as ecological niche modelling or habitat suitability modelling has become a progressively vital instrument in ecology, biogeography, and conservation sciences (Hao et al., 2019). SDM is gaining more popularity over the other tools of analysis available for ecologists to predict the distribution of species (Tikhonov et al., 2020). The aim of SDM is to provide an insight on the spatio-temporal assembly of a species and the anticipated future distribution against the climatic and environmental changes (Guisan & Rahbek, 2011). Most importantly, SDM can be used not only for natural ecosystems but also for human managed ecosystems (Woodin et al., 2013).

Given the variability in predictions from different species distribution models, a prevailing recommendation is to employ multiple methods, such as ensemble modelling (Araújo & New, 2007; Araújo, Whittaker, et al., 2005), within a consensus modelling framework (Marmion, Luoto, et al., 2009; Thuiller, 2004). This modelling framework is more assuring, as it has been proven to reduce the predictive uncertainty of individual models by amalgamating their predictions. Existing studies consistently show that the accuracy of species distribution predictions can be markedly enhanced through the application of consensus methods (Araújo, Whittaker, et al., 2005; Crossman & Bass, 2008; Marmion, Luoto, et al., 2009). Moreover, it has been stressed that outcomes derived from SDMs are not universally reliable for all species (Luoto et al., 2005), and the best-performing models may vary across different species (Barbet-Massin et al., 2009; Segurado & Araujo, 2004).

The biomod2 package (Thuiller et al., 2016) is widely utilised for species distribution modelling, serving as an ensemble software on the open-source R platform (R Core Team, 2013). This tool provides a diverse set of methods and tools for modelling species distribution, allowing the computation of species distribution models with up to 10 distinct modelling methods. Table 5.1 provides a comprehensive list, including abbreviated names of the models available on biomod2 platform for species distribution modelling. Biomod2 facilitates the integration of these individual models into ensembles using various approaches, including weighted mean, mean, median, and committee averaging (Hao et al., 2019).

Table 5. 1 An overview of the different modelling algorithms available in biomod2

Model	Overview
Artificial Neural Networks (ANN)	ANNs are non-linear models with several parameters (Marmion, Luoto, et al., 2009) and are based on the function of the human brain (Lek & Guégan, 1999). This is an effective rule-based, machine learning algorithm gaining more popularity in SDM (Marmion, Luoto, et al., 2009).
Classification Tree Analysis (CTA)	CTA being an alternative machine learning algorithm to regression techniques uses a tree-based analysis system (Franklin, 2002; Venables & Ripley, 2013). This offers the benefit of capturing non-additive behaviour and intricate interactions. Nonetheless, CTA tends to generate excessively intricate models, which can result in misleading interpretations (Breiman, 2017).
Generalized Additive Model (GAM)	GAM is a non-parametric extension to GLM (Hastie & Tibshirani, 1987). GAMs are better suited for more complex non-linear relationships between species and predictor variables that cannot be addressed by GLM (Yee & Mitchell, 1991).
Generalized Boosting Method (GBM)	GBM, a machine learning algorithm, exhibits high efficiency in data fitting, possess non-parametric characteristics, and leverages the strengths of various contemporary statistical techniques (Ridgeway, 1999).
Generalized Linear Model (GLM)	GLMs are mathematical expansions of linear models (McCullagh, 2019). GLMs can accommodate non-linear relationships and various statistical distributions that characterize spatial data and are closely connected to conventional techniques employed in linear modelling (Marmion, Luoto, et al., 2009).
Multivariate Adaptive Regression Spines (MARS)	MARS is an extension to linear regression models and important when there are large number of explanatory variables with low-order interactions (Thuiller et al., 2009).
Flexible Discriminant Analysis (FDA)	FDA is a classification method and important in performing classification among multiple groups (Hastie et al., 1994).
MAXENT.Phillips.2	This is a specific implementation of the MaxEnt algorithm with additional features and improvements. Maxent is a machine learning algorithm that offers a precise mathematical framework, making it highly suitable for modelling species distributions (Phillips et al., 2006).

Model	Overview
Random Forest (RF)	RF is capable of effectively managing correlated variables, accommodating larger datasets, processing a vast number of input variables, and handling missing data (Breiman, 2017). RF is regarded as one of the most precise algorithm in SDM (Iverson et al., 2008).
Surface Range Envelope (SRE)	Widely employed in SDM, yet has shortcomings such as the inability to achieve the same level of performance as certain alternative modelling techniques (Elith et al., 2006). Anyway, it continues to be favoured due to its simplicity and comprehensibility (Pecchi et al., 2019).

Biomod2 offers the flexibility to select the specific individual models to be incorporated into the ensemble. This might involve utilising all available models or opting for models that surpassed a predefined threshold on a chosen metric (Hao et al., 2019).

5.3 Methods

5.2.1 Study area

As the study area, a sub-section of Southern Queensland, Australia that covers an extent of 37,650km^2 encompassing the four Local Government Areas of Toowoomba, Southern Downs, Goondiwindi, and Western Downs (Figure 1) was selected. More information on the study area is presented in Chapter 3.

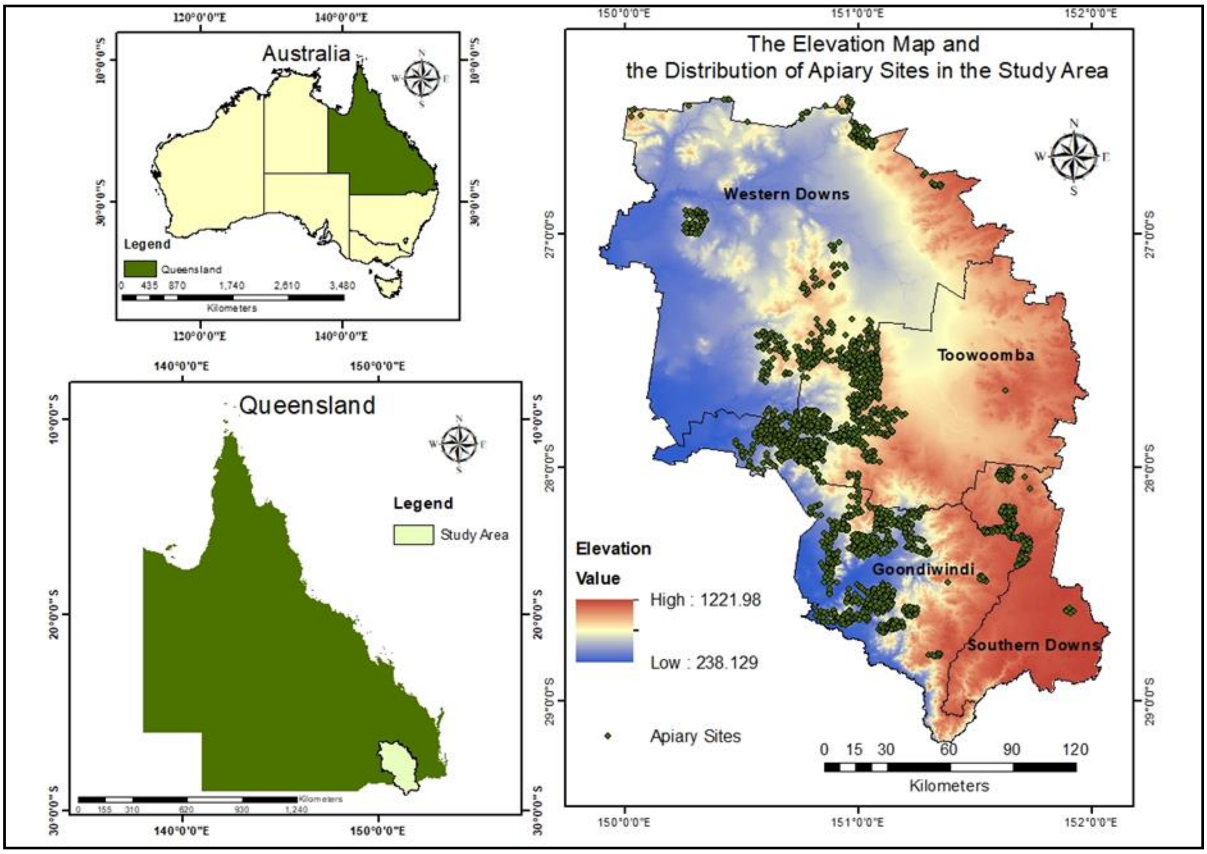


Figure 5. 1 Elevation map and the apiary site locations in the study area

The overview of the research methods used in this study is shown in Figure 5.2. The modelling procedure of this study followed the overview, data, model, assessment, and prediction (ODMAP) protocol introduced by (Zurell et al., 2020). The ODMAP protocol followed in this study is detailed in Appendix Table 2. The initial occurrence data were rarefied using the SpThin package in R 4.2.2. Both bioclimatic variables and environmental variables were tested for multicollinearity using the USDM package, and three variables from each category were chosen for final model development. Based on the True Skills Statistics (TSS) threshold, ensemble models were developed for climate variables, environmental variables, and a combination of climate and environmental variables. The climate model, based on climate data from 1990-2009, was projected for the time periods 2020-2039 and 2060-2079.

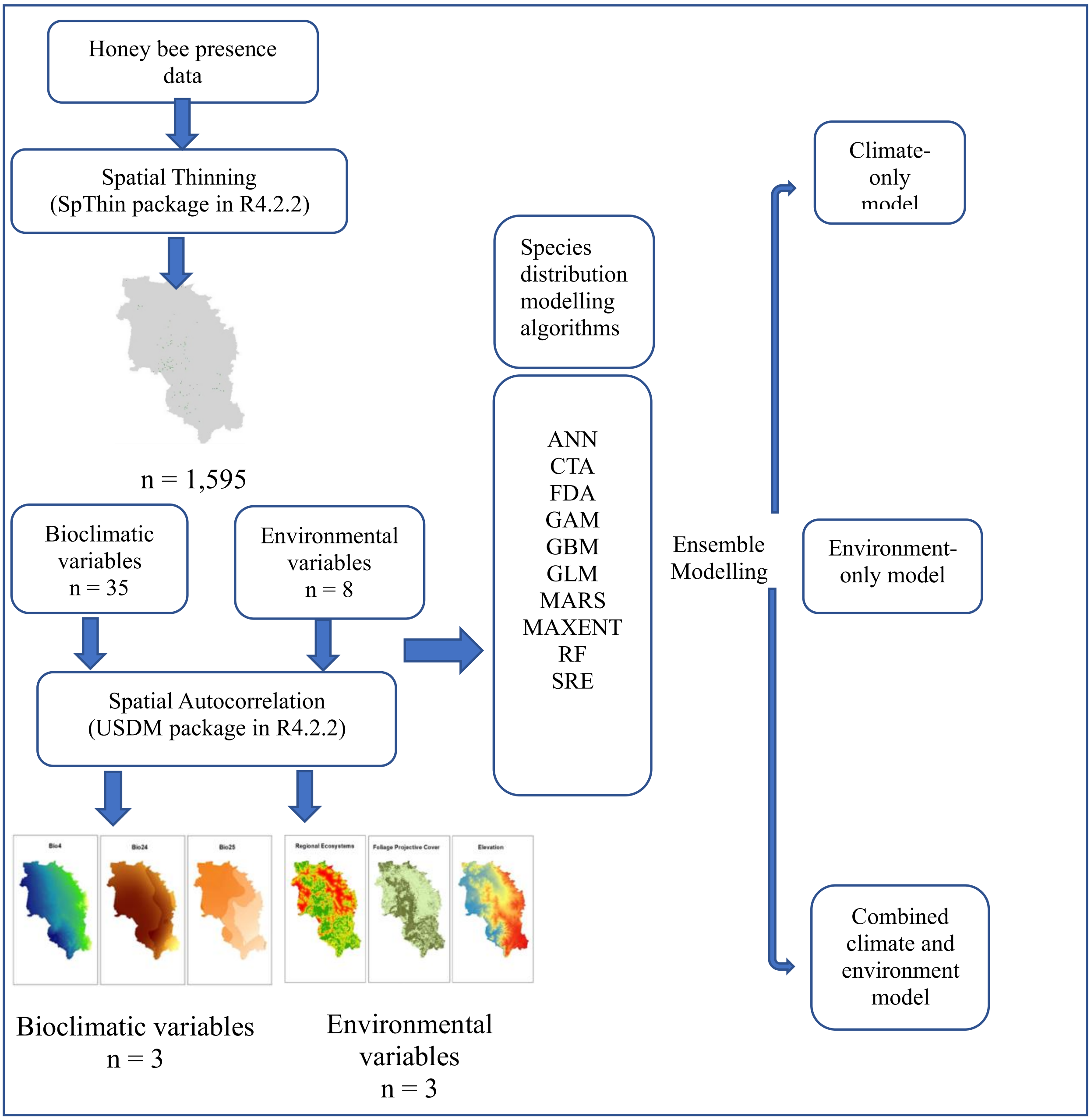


Figure 5. 2 Overview of the research methods

5.2.3 Honey bee presence data

This study aimed to utilise two disparate categories of presence data, including managed apiary site locations and records of observations derived from different sources such as the Atlas of Living Australia (ALA) and the Global Biodiversity Information Facility (GBIF). The selection of apiary sites is based on various factors, primarily including the availability of food sources for honey bees, and consideration of climatic and topographic conditions. Consequently, the locations of managed apiary sites can be regarded as reliable indicators of geographic suitability for honey bees, akin to natural occurrences. The apiary site locations on public lands were retrieved from the Queensland Spatial catalogue, and the database contains 1,592 records. Occurrence data from 1990 to the present year were obtained using ALA and GBIF. The study period was selected to encompass the available climate data from 1990 onwards. Only human and machine observations were included, excluding preserved specimens or museum records, as these do not accurately represent the true geographic distribution of a species (Araujo & Guisan, 2006). GBIF did not have any presence or absence records of *Apis mellifera* for the study area during the specified time, while ALA had only six records of occurrences. Thus, the bulk of the presence data was acquired from the Queensland Spatial Catalogue.

The spatial resolution of the environment and climate raster layers used in this study was 250m×250m. Occurrence of multiple presence data within this resolution can lead to spatial sampling bias (Aiello-Lammens et al., 2015), spatial autocorrelation (Pant et al., 2021) and overestimated measures of prediction accuracy (Veloz, 2009). Therefore, the SpThin package in R 4.2.2 was utilised to perform spatial thinning of the presence records (Aiello-Lammens et al., 2015), resulting in a total of 1,595 records after removing only three records from the initial dataset. This can be attributed to the fact that the managed apiary site locations, which serve as the primary occurrence data in this study, are established while maintaining a reasonable distance between two sites in accordance with government regulations (Biosecurity Act, 2014).

5.2.4 Bioclimatic and environmental variables

As suggested by the literature, honey bee activity (Jiang et al., 2016), honey bee colony losses and population (Hristov et al., 2020; Le Conte & Navajas, 2008), and productivity (Otto et al., 2016) are significantly influenced by environmental and climatic factors. For this study, initially, eight environmental variables that impact honey bees and the apiary industry were selected based on existing literature. These variables included regional ecosystems/flora criterion (Sarı & Ceylan, 2017; Sarı et al., 2020), Foliage Projective Cover (FPC), land use (Ambarwulan et al., 2016), land cover, topographical features (slope, aspect, elevation), and distance to water bodies (Zoccali et al., 2017). Bioclimatic variables derived from temperature and rainfall values are often used in SDM, representing annual trends, seasonality, and extremes in these climate factors. Thirty-five bioclimatic variables at a finer scale (250m×250m) were sourced from the New South Wales (NSW) and Australian Capital

Territory (ACT) Regional Climate Modelling (NARCliM) database (Hutchinson & Xu, 2015) (Appendix Table 1). IPCC SRES A2 emission scenario, which corresponds to the relative forcing and mean temperature trajectories of the RCP8.5 scenario, has been applied to derive these future projections (Hutchinson & Xu, 2014).

All the variables selected for modelling were tested for multicollinearity using the USDM (Uncertainty Analysis for Species Distribution Models) package on the R platform. Two indicators, namely the correlation coefficient and variance inflation factor (VIF), were employed as measures of multicollinearity. Multicollinearity can increase uncertainty in model parameters and decrease the predictive performance of the model (De Marco & Nóbrega, 2018). Variables with a correlation coefficient greater than 0.8 and a VIF higher than 5 were excluded from further analysis, following previous studies on SDM (Diao & Wang, 2014; Fois et al., 2018). All eight environmental variables were retained, while only four bioclimatic variables (i.e., Bio4, Bio15, Bio24, Bio25) remained after conducting multicollinearity testing. To mitigate overfitting, the number of predictor variables was reduced (Breiner et al., 2015) by iteratively removing the least contributing variables during the model formation process (Zeng et al., 2016). The variables used for the final model formation, along with their sources, are listed in Table 5.2 whilst figures 5.3-5.6 visualize these variables. ArcMap 10.8.2 was used to create raster layers with a cell size of 250m × 250m and the WGS84 projection.

Table 5. 2 Bioclimatic and environmental variables finally utilised for the ensemble modelling.

Predictor Variable	Rationale	Source
Bioclimatic variables		
Bio4 (Temperature seasonality)	Temperature has a huge impact on honey bee mortality (Switanek et al., 2017), activity (Abou-Shaara et al., 2017; Huang & Robinson, 1995), and reproduction (Rangel & Fisher, 2019)	New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling (NARCliM) (Hutchinson & Xu, 2015)
Bio24 (Radiation of wettest quarter (Wm-2) Bio25 (Radiation of driest quarter (Wm-2)	Having a significant amount of solar radiation is particularly desirable during winter because the rate at which bees leave the hive (bee egress rate) is influenced by temperature and radiation. Previous studies have observed a reduced bee egress rate when exposed to low temperatures and limited solar radiation (Clarke & Robert, 2018). Solar radiation is also associated with defensive behaviour of honey bees (Southwick & Moritz, 1987)	
Environmental Variables		
Regional Ecosystems (Floral resources)	Honey bees gather nectar and pollen from various flowering species, which are crucial for their survival and honey production. Hence, honey bees are present in areas where they have access to floral resources. Furthermore, when choosing a location for an apiary, it is essential to consider the availability of food sources (nectar/pollen) for honey bees. The Queensland regional ecosystems database contains information about vegetation communities in a specific bioregion. Regional ecosystems refer to vegetation communities in a bioregion that consistently correspond to specific combinations of geology, landform, and soil (Sattler and Williams 1999, Vegetation Management Act 1999). This database, therefore, serves as an excellent resource to identify the floral species suitable for honey bees in a particular ecosystem. The same methodology used to rate regional ecosystems by Tennakoon, Apan, Maraseni, et al. (2023) was used in the present study.	Regional Ecosystems Maps – Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2021)
Foliage Projective Cover (FPC)	FPC refers to the proportion of the ground surface taken up by the vertical projection of foliage (Queensland Spatial Catalogue, 2014). Foliage is an important factor related with honey bee foraging being an indicator of food sources available for honey bees and the incoming solar (Specht, 1981; Steven et al., 1986).	Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) (Department of Environment and Science, 2014)

Predictor Variable	Rationale	Source
Elevation	Elevation is closely correlated with floral resources and climatic factors that affect honey bees.	GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) (Hutchinson, Stein, Anderson, et al., 2008)

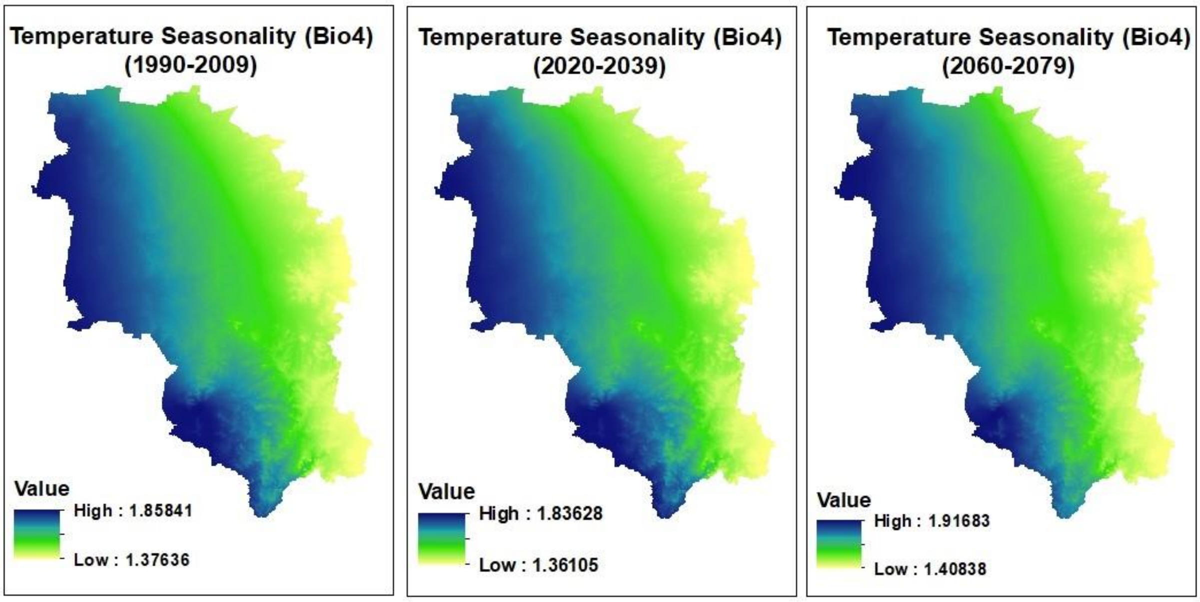


Figure 5. 3 Temperature seasonality maps of 1990-2009, 2020-2039 and 2060-2079

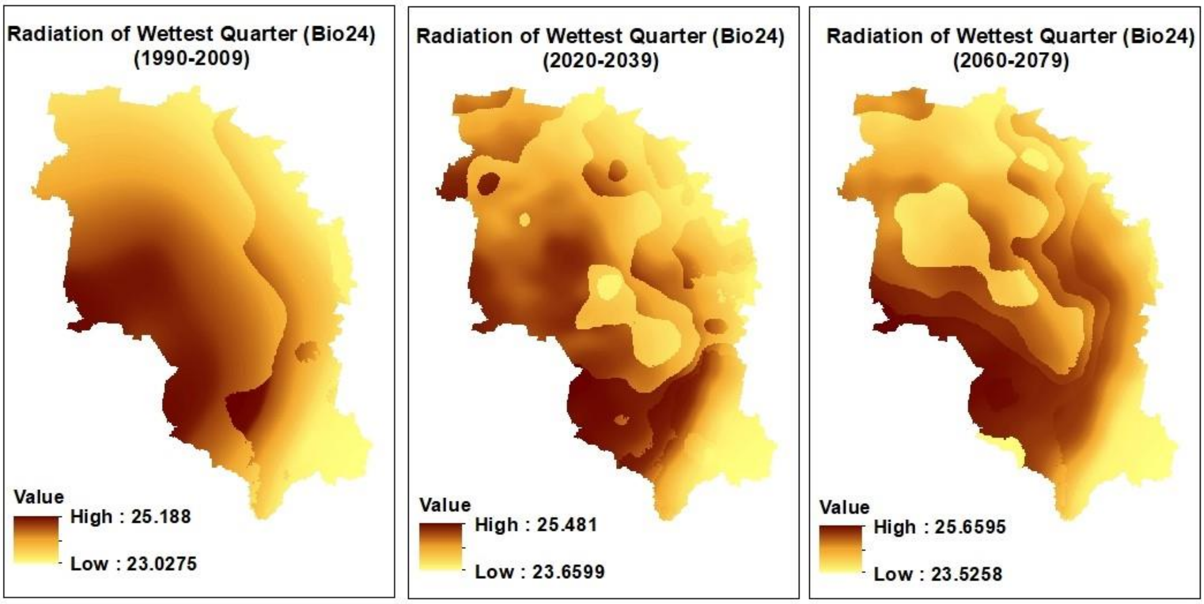


Figure 5. 4 Radiation of wettest quarter (Bio24) maps of 1990-2009, 2020-2039 and 2060-2079

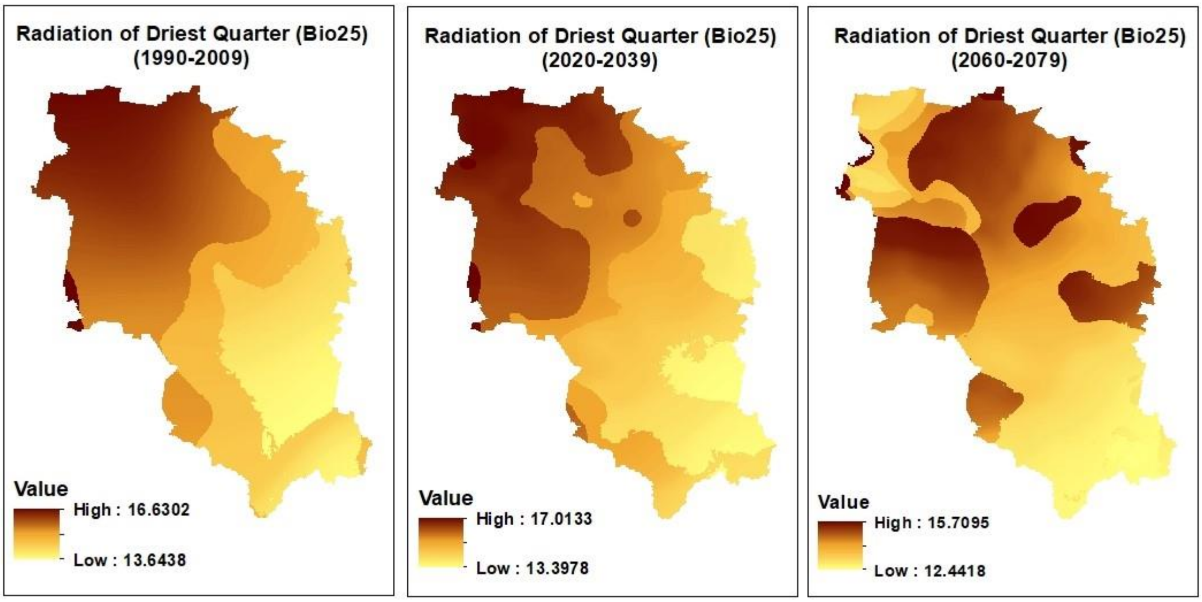


Figure 5. 5 Radiation of driest quarter (Bio25) maps of 1990-2009, 2020-2039 and 2060-2079

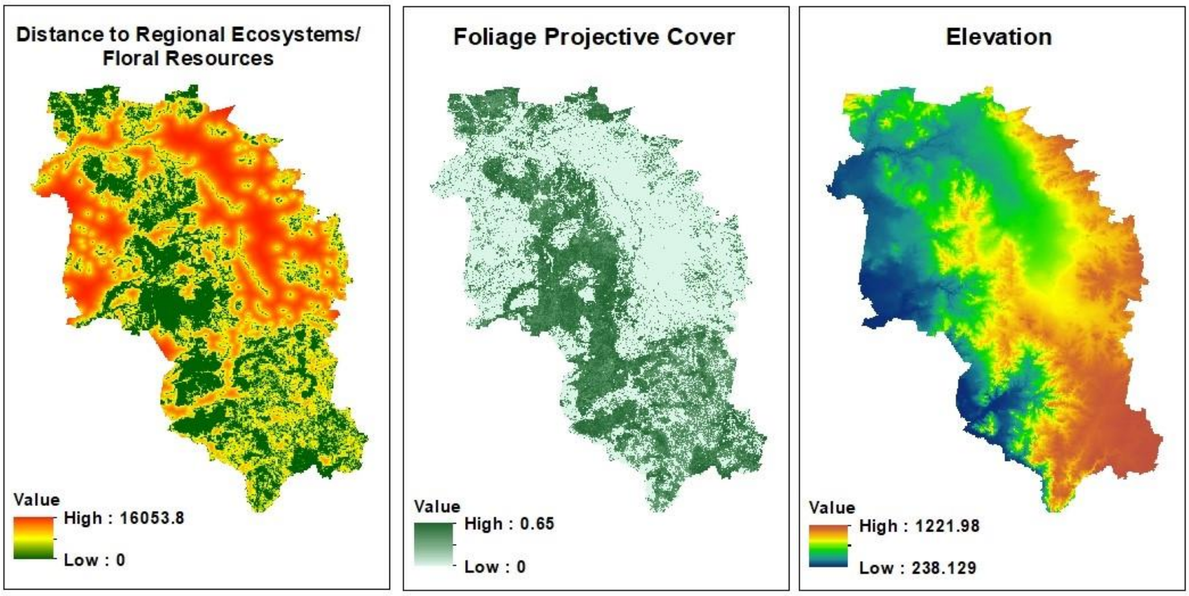


Figure 5. 6 Environmental variables (Distance to regional ecosystems (floral resources), Foliage projective Cover (FPC) and elevation)

5.2.5 Species distribution modelling: Ensemble approach using biomod2

Biomod2 is extensively used across different locations around the world in distribution modelling of a wide range of taxa mostly using presence only data and environment and climate factors (Hallgren et al., 2019). Biomod2 permits running ten different modelling algorithms, model calibration, evaluation, building ensembles, ensemble forecasting and visualisation of data and results (Thuiller et al., 2016). Even though, some algorithms used in modelling such as rectilinear envelope and distance-based envelope can handle presence-only data, most of the modelling algorithms utilise both presence and absence data. Moreover, it is proven that the presence-absence models perform better than presence-only models (Elith et al., 2006). However, collecting absence data, particularly for mobile species, and ensuring its accuracy when compared with presence data, can be a challenging task (MacKenzie & Royle, 2005). In this case, researchers rely on pseudo absence or background data to enhance the predictive performance of the model. In this study, 5,000 pseudo-absence points were generated, taking into consideration the varying number of pseudo-absence points required for each algorithm (Barbet-Massin et al., 2012). Equal weight was assigned to the presence and absence points, and the process of generating pseudo-absences was repeated three times to alleviate random bias.

To estimate the predictive power of the model, a training dataset is used, ensuring that the training data are not spatially autocorrelated with test data (Allouche et al., 2006). In cases where independent data is unavailable for training the models, the original dataset is divided into two parts: training data and testing data. The honey bee presence and pseudo-absence data were divided randomly into training (80%) and testing (20%) sets, following the approach recommended by previous studies (Chapman et al., 2019; Hopkins, 2009; Laman et al., 2018; Senay & Worner, 2019; Waldock et al., 2022). The modelling process consists of a total of 90 model runs, which includes ten modelling algorithms, three pseudo absence generation runs, and three evaluation runs. Using the ensemble modelling option available in biomod2, an ensemble species distribution model was constructed by applying multiple algorithms above a selected threshold.

5.2.6 Model evaluation

Model evaluation in biomod2 consists of an assessment of the explanatory power using a standard approach associated with each algorithm and evaluating the predictive power of the model using AUC i.e., area under the relative operating characteristic curve (ROC) (Hanley & McNeil, 1982), Cohen's Kappa (Monserud & Leemans, 1992) and the True Skills Statistics (TSS) (Allouche et al., 2006). AUC considers two aspects: sensitivity, which is the proportion of presences correctly predicted as presence, and specificity, which is the proportion of absences correctly predicted as absences. AUC can range from 0 to 1, with a practical range of 0.5 to 1. A value of 0.5 indicates a random model, while a value of 1 indicates a perfect model (Hallgren et al., 2019). The Kappa statistic evaluates the degree to which models predict occurrence at a level that exceeds what would be expected by chance (Monserud & Leemans, 1992). The Kappa statistic can have values ranging from -1 to +1. Values of 0 or below indicate random performance, while a value of +1 indicates perfect agreement (Allouche et al., 2006). The TSS considers both omission (proportion of presences identified as absences) and commission errors (proportion of absences identified as presences), and has a range of -1 to +1, where a value of +1 indicates perfect agreement, and values of zero or less indicate performance no better than random. Unlike Kappa, TSS is not influenced by prevalence. Additionally, TSS is unaffected by the size of the validation set, and two methods with equal performance will have equal TSS scores (Allouche et al., 2006).

5.2.7 Model development

In this study, three models namely the climate-only model, the environment-only model, and the combined climate (1990-2009) and environment model were developed. The climate-only model was developed using the three most influential bioclimatic variables for honey bees, namely Bio4 (temperature seasonality), Bio24 (radiation of the wettest quarter), and Bio25 (radiation of the driest quarter). Only individual models with a TSS greater than 0.7 were utilised for ensemble model building. The three environmental variables with the highest contribution to the model i.e., proximity to regional ecosystems (floral resources), foliage projective cover, and elevation were used in building the environment-only model. Unlike the TSS values of individual algorithms pertaining to the climate-only model, the TSS values of algorithms in environment-only model were less than 0.7. Thus, a cut-off TSS of 0.6 was selected when building the ensemble environment-only model. The combined climate and environment model was developed by incorporating the environmental and bioclimatic variables from both environment-only and climate-only models. These variables included foliage projective cover, proximity to regional ecosystems, elevation, bio4, bio24, and bio25.

5.2.8 Generation of suitability maps for current and projected climate change

Suitability maps were generated using biomod2 for each scenario under consideration, namely: climate-only (1990-2009), environment-only, and the combined climate and environment model. Using ensemble forecasting, suitability maps for the two future scenarios i.e., 2020-2039 and 2060-2079 were generated. Each output map was divided into four suitability classes, based on the criterion namely: highly suitable (with a probability of occurrence exceeding 75%), moderately suitable (with a probability of occurrence ranging from 50% to 75%), marginally suitable (with a probability of occurrence between 25% and 50%), and not suitable (with a probability of occurrence less than 25%). For this manual method of reclassification, the reclassify tool in ArcMap 10.8.2 was utilised. A manual method of reclassification presents both advantages and disadvantages. For instance, manual classification holds significance in specific contexts where human expertise is indispensable. It allows experts to exert full control over the classification process, leveraging their in-depth knowledge and understanding of the dataset. Conversely, manual reclassification carries certain drawbacks, including subjectivity in interpretation and the potential for human errors. Manual reclassification method relies heavily on the nature of the data set making it less reproducible and consistent.

5.3 Results

5.3.1 Model performance

Climate-only model

Among the algorithms used in ensemble modelling, RF had the highest average TSS value of 0.77, followed by CTA with a value of 0.72, while SRE had the lowest TSS of 0.27. Algorithms such as ANN, GAM, GBM, GLM, MARS, and MAXENT also had average TSS values less than 0.7 (Figure 5.7). Consequently, these algorithms were excluded from ensemble modelling. Radiation variables including Bio24 and Bio25, had the highest contribution to the model, each accounting for 35.57% and 37.73% respectively. Bio4 or the temperature seasonality contributed to the model by 26.70%. According to the response curve pertaining to probability of honey bee occurrences and radiation in the wettest quarter, the optimum radiation for honey bees is $25Wm^{-2}$. Based on the response curve for radiation in the driest quarter, honey bee occurrences display a fluctuating pattern as the radiation increases, with sudden increases and declines but an overall increasing trend. However, the optimum radiation value for honey bees in the driest quarter or winter is observed as 16Wm^{-2}. It is apparent that honey bee occurrences are limited when the temperature seasonality or Bio4 ranges between 1.6 and 1.7. Otherwise, the pattern remains relatively stable (Figure 5.8). The ensemble climate-only model exhibited strong predictive performance, achieving a TSS of 0.85, an AUC of 0.98, and a Kappa value of 0.72. The same bioclimatic variables were used to project the model's predictions into the 2020-2039 (2030) and 2060-2079 (2070) periods.

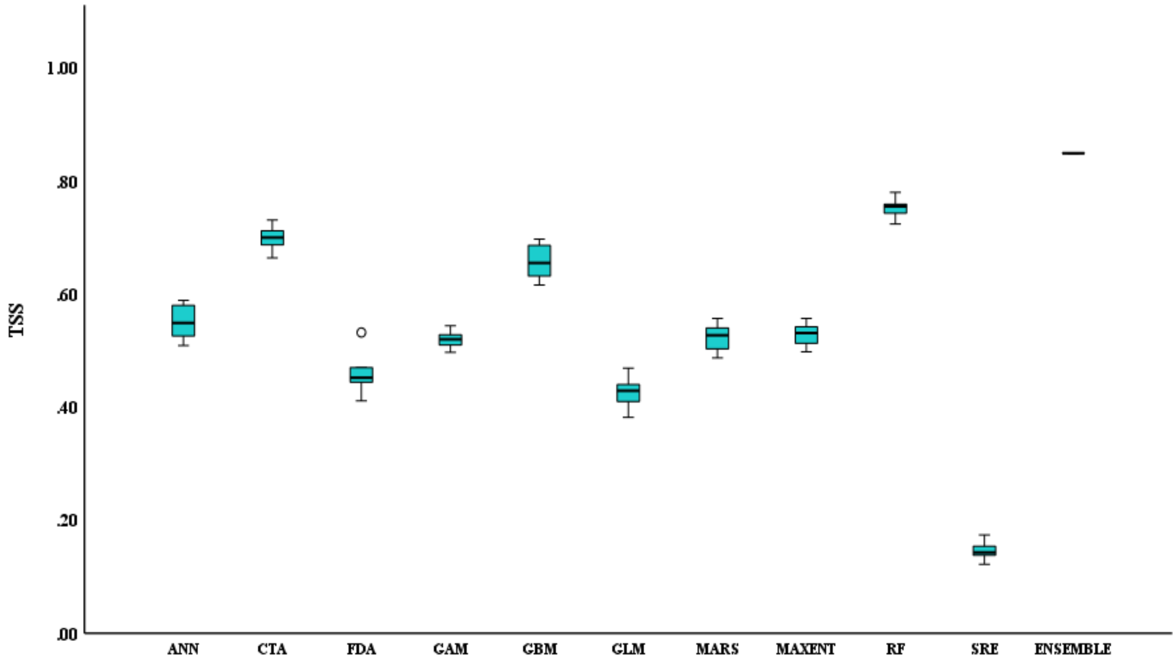


Figure 5. 7 TSS scores of individual algorithms and the ensemble model (climate-only)

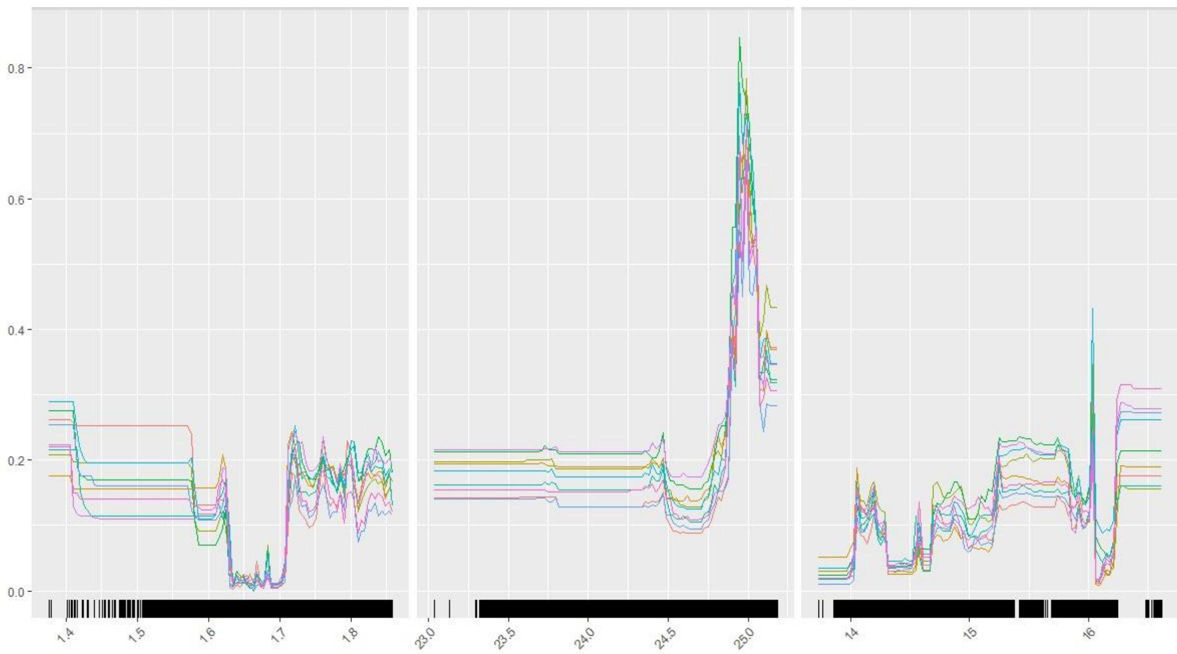


Figure 5. 8 Response curves of bioclimatic variables in the climate-only model

Environment-only model

GBM had the highest average TSS value of 0.63, while RF and ANN also performed comparatively well in modelling honey bee presence data against environmental variables, achieving an average TSS of 0.62. MARS demonstrated good performance as well, with a TSS of 0.61, slightly lower than that of GBM, RF, and ANN. On the other hand, MAXENT had a TSS of 0.6. SRE, similar to the climate-only model, demonstrated the least predictive performance, achieving a TSS of 0.31 (Figure 5.9). The Foliage Projective Cover made the most significant contribution to the model, accounting for 57.36% of the total. Following was the distance to regional ecosystem or floral resources, which contributed 34.10%. The elevation had the least impact on the model, contributing only 8.54% to the model. According to the response curve for regional ecosystems, honey bee occurrences are optimized near the regional ecosystems with floral resources for honey bees. There is a sharp decline as the distance from regional ecosystems increases. The probability of honey bee occurrences increases with FPC and reaches its peak when FPC is 0.3. Beyond this point, the curve remains stable. Elevation displays a rather constant pattern but with a spike between 375m and 425m (Figure 5.10). The ensemble environmental-only model showed strong predictive performance similar to the climate-only model, with a TSS of 0.88, an AUC of 0.98, and a Kappa value of 0.75.

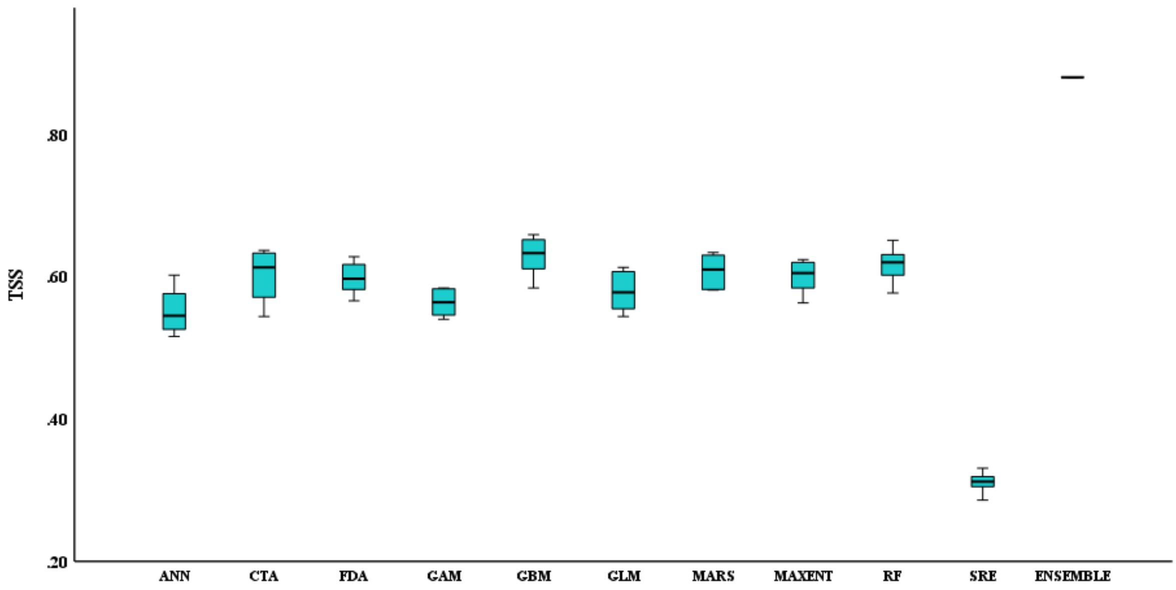


Figure 5. 9 TSS scores of individual algorithms and the ensemble model (environment-only)

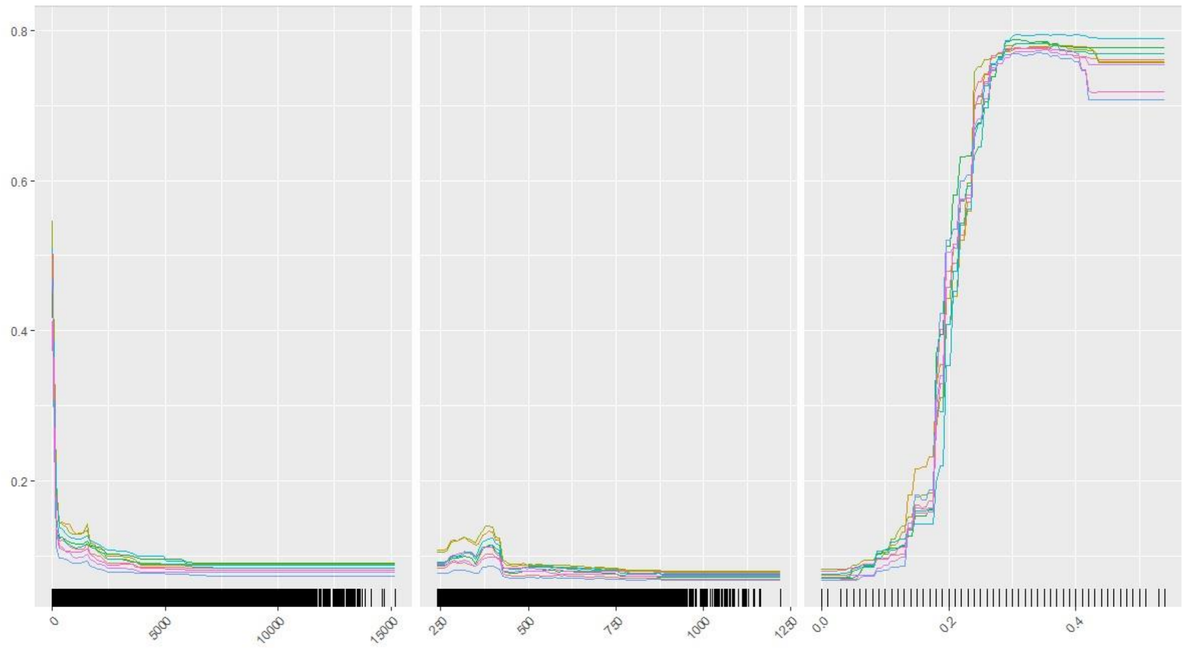


Figure 5. 10 Response curves of environmental variables in the environment-only model

Combined climate and environment model

Just like in the climate-only model, in the combined model, RF was the best-performing algorithm with an average TSS score of 0.76. CTA and GBM also had average TSS values of

0.72 and 0.71, respectively. Comparable to the other two models, SRE displayed the lowest TSS of 0.38 (Figure 5.11). To construct the combined model, a TSS threshold of above 0.7 was chosen. The greatest contribution to the model came from bio24 (radiation in wettest quarter), accounting for 27.74%, followed by distance to regional ecosystems (floral resources) and Foliage Projective Cover (FPC) with approximately equal percentages of 21.25 and 21.63 correspondingly. The contribution of Bio25 (radiation in driest quarter) accounted for 18.36%. On the other hand, bio4 (temperature seasonality) and elevation, which were the least influential variables in the model, had values of 5.44% and 5.58%, respectively. As per the combined model, the predictor variables behave similarly to the individual models. The combined climate and environment model demonstrated strong predictive performance, with a high TSS score of 0.96, a near-perfect ROC score of 0.99, and a Kappa value of 0.92. Therefore, it is evident that the prediction of honey bee occurrences can be enhanced by using both environmental and climate variables together in the same model as the predictor variables.

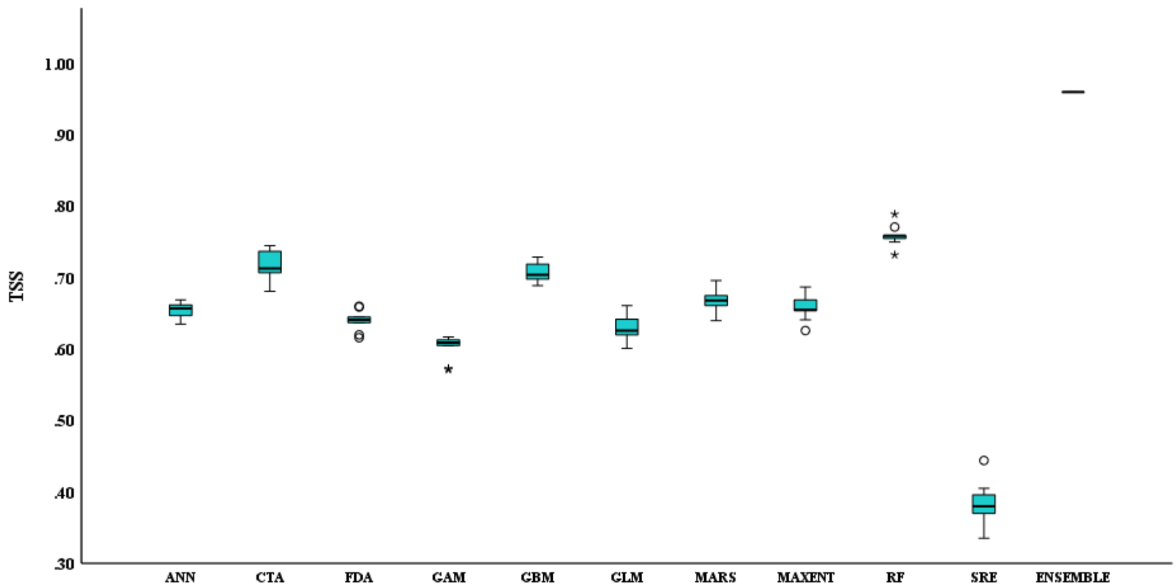


Figure 5. 11 TSS scores of individual algorithms and the ensemble model (combined)

5.3.2 Land suitability for honey bees

Based on the climate-only model, the area classified as highly suitable (in Toowoomba, Western Downs, and Goondiwindi regions) experiences a drastic decline of approximately 88% from the initial period of 2000 to the projected period of 2030 (Table 5.3). These areas were relegated into the moderately suitable and marginally suitable categories. Furthermore, this highly suitable area is completely lost from 2030 to 2070. Conversely, the moderately suitable area demonstrates an increase of 58% from 2000 to 2030 but experiences a significant loss of 96% from 2030 to 2070, suggesting a potential future loss of areas with high and moderate suitability. The area classified as marginally suitable has more than doubled between 2030 and 2070. However, there is a decrease in the area classified as not suitable from 2000 to 2030 by 9%, followed by an increase of 15% from 2030 to 2070. It is worth noting that the not suitable area is significantly large when compared to other suitability categories (Figure 5.12)

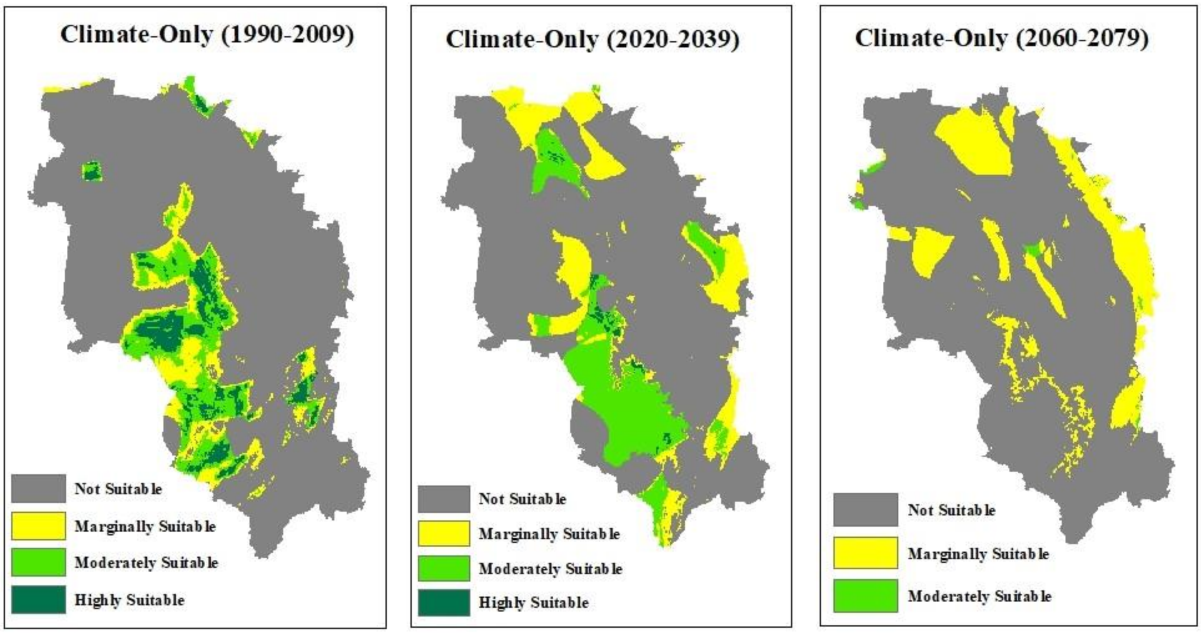


Figure 5. 12 Suitability maps for honey bees: Climate-only scenario in 1990-2009, 2020-2039 and 2060-2079

In the context of the environment-only model, the highly and moderately suitable area, which accounts for 24% of the total extent, surpasses the same area pertaining to any other climate scenario or the combined model in size. The climate-only model for 2030 indicates a significantly lower value of only 15% for the highly and moderately suitable area, making it the second-largest value. On the other hand, the marginally and not suitable area resulted by environment-only model is comparatively smaller, representing 76% of the total extent. In comparison, this value increases to approximately 85% for the 2000 and 2030 climate scenarios as well as the combined model, with a remarkably high value of 99% projected for 2070. This indicates that the study area offers more favourable environmental conditions for honey bees compared to suitability based on climatic factors alone. When compared with the combined climate and environment model, the highly and moderately suitable areas are larger in the environment-only model, while they are smaller in the climate-only model (Figure 5.13).

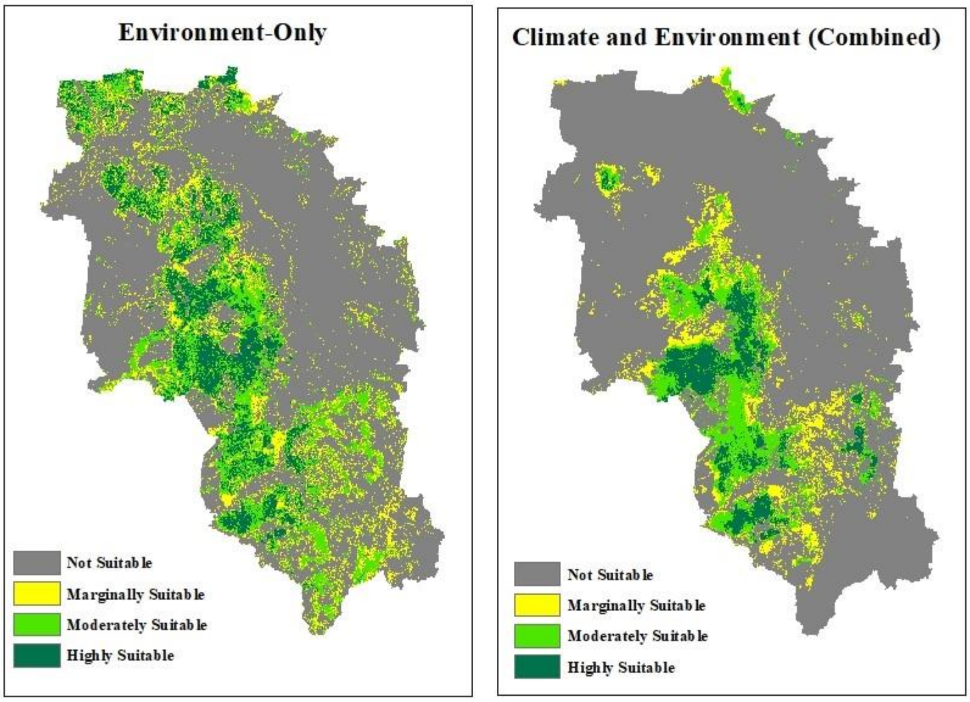


Figure 5. 13 Suitability maps for honey bee habitat: environment-only and combined (Climate and Environment) scenarios

Table 5. 3 Suitable area (km^2) for honey bees based on climate-only (2000, 2030, 2070), environment-only, and combined environment and climate model.

Classification	**Climate-only**						**Environment-only**		**Combined (Environment and Climate)**	
	1990-2009 (2000)		**2020-2039 (2030)**		**2060-2079 (2070)**					
	Area (km2)	**Percent (%)**	**Area (km2)**	**Percent (%)**	**Area (km2)**	**Percent (%)**	**Area (km^2)**	**Percent (%)**	**Area (km2)**	**Percent (%)**
Highly Suitable	1,832	4.9	227	0.6	0	0	3,748	10.0	2,056	5.5
Moderately Suitable	3,546	9.4	5,588	14.8	207	0.5	5,159	13.7	3,476	9.2
Marginally suitable	2,936	7.8	5,068	13.5	6,611	17.6	4,486	11.9	2,980	7.9
Not suitable	29,336	77.9	26,767	71.1	30,832	81.9	24,220	64.4	29,101	77.4
Total	**37,650**	**100**	**37,650**	**100**	**37,650**	**100**	**37,613**	**100**	**37,613**	**100**

The number of honey bee occurrences was recorded for each suitability class using the sample tool in ArcMap. The results show that the highest number of honey bee locations, accounting for approximately 72%, was found in the highly suitable class of the current climate-only model (2000). However, this number experiences a significant decline over the timeline from 2000 to 2070, indicating a complete loss of highly suitable areas by 2070. In contrast to the area distribution within each suitability class between the environment-only and combined models, the number of occurrences in the highly suitable area is higher in the combined model compared to the environment-only model. Only 8 honey bee occurrences were found in the not suitable area under the climate-only scenario. However, this number increases by approximately 89% in 2070, indicating a significant loss of highly and moderately suitable areas for honey bees in terms of climate (Table 5.4).

Table 5. 4 Number of honey bee occurrences by suitability class under each modelling scenario

Classification	**Climate-only**						**Environment-only**		**Combined (Environment and Climate)**	
	1990-2009 (2000)		**2020-2039 (2030)**		**2060-2079 (2070)**					
	No	**Percent (%)**	**No**	**Percent (%)**	**No**	**Percent (%)**	**No**	**Percent (%)**	**No**	**Percent (%)**
Highly Suitable	1,140	71.9	18	1.1	0	0	745	47.1	1,054	66.5
Moderately Suitable	395	24.9	547	34.5	1	0.0	618	39.0	413	26.1
Marginally suitable	42	2.7	206	13.0	173	10.9	170	10.7	79	5.0
Not suitable	8	0.5	814	51.4	1411	89.1	51	3.2	38	2.4
Total	**1,585**	**100**	**1,585**	**100**	**1,585**	**100**	**1,584**	**100**	**1,584**	**100**

5.4 Discussion

5.4.1 Predictive performance of the models and contribution of predictor variables

The TSS, AUC, and KAPPA values of the climate-only ensemble model were 0.85, 0.98, and 0.72, respectively, indicating that the model was robust with strong predictive power. A TSS value greater than 0.8 and AUC value higher than 0.9 indicate an excellent model (Hosmer & Lemeshow, 2000; Pittman & Brown, 2011), while a Kappa value of 0.61 to 0.8 exhibits substantial performance (Landis & Koch, 1977; Viera & Garrett, 2005), which is the case in the current scenario. Anyway, TSS is argued to be a more reliable measure in assessing the predictive performance of species distribution models. This is because TSS possesses all the advantages of Kappa while not being affected by the prevalence of a species, unlike Kappa (Allouche et al., 2006). Among the ten modelling algorithms utilised, Random Forest (RF) had the highest TSS value, which agrees with the outcome of previous studies where an ensemble approach is employed to model species distribution (Marmion, Parviainen, et al., 2009; Williams et al., 2009). SRE was excluded from further analysis due to its poor performance in predicting the honey bee distribution which was indicated by a TSS value of 0.27. SRE is not commonly used in recent literature due its lower performance when compared with other modelling algorithms used in SDM (Pecchi et al., 2019). CTA which was included in ensemble model of the current study due to a TSS value greater than 0.7, is gaining more popularity in SDM and is argued to provide a favourable trade-off, offering comparable accuracy to GLM or GAM (Thuiller et al., 2003).

On the other hand, the environment-only model, incorporating predictor variables, proximity to regional ecosystems, foliage projective cover and elevation, exhibited a high predictive performance with a TSS of 0.88, an AUC of 0.98, and a kappa value of 0.75. Unlike the ensemble model, the TSS values of individual algorithms in environment-only model were less than 0.7. Therefore, a threshold value of 0.6 was chosen, while for the other two models the threshold was set as 0.7. If the presence data and the algorithms remain the same and only the predictor variables are different, the smaller TSS values in the environment-only model can be attributed to the lower effectiveness of the environmental variables in explaining the underlying patterns and relationships within the data when compared to the climatic variables. This is further confirmed by the fact that, according to the climate-only model, a higher number of honey bee occurrences align with the highly and moderately suitable classes when compared to the environment-only model. Nonetheless, the combined environment and climate model also displayed a robust predictive power with a TSS 0.96 of ROC 0.99 of and a Kappa value of 0.92. Thus, it is evident that combining climate and environmental predictor variables in a model enhances the predictive performance. Moreover, to enhance the predictive performance of the models while mitigating problems associated with SDM, such as overfitting, several precautions were taken. These included rarefying the presence data, selection of a minimum number of predictor variables, and performing cross-validation using 80% of the data for model calibration and 20% for validation (Pant et al., 2021).

According to the climate-only model, the most influential variables in the model were Bio24 and Bio25 which represent the radiation of wettest quarter and radiation of driest quarter, correspondingly. Bio4 (temperature seasonality) also exhibits a significant influence on honey bee distribution. This is consistent with previous findings that solar radiation and temperature are the two most detrimental climatic factors that contribute to bee activity (Clarke & Robert, 2018). Moreover, it has been proven that bee abundance is highest in the areas with high solar insolation (Orr et al., 2021). Compared to the significance of the other two criteria, namely proximity to regional ecosystems and Foliage Projective Cover, in constructing the environment-only model, the contribution of elevation is minimal (8.54%). Nonetheless, elevation remains a crucial factor determining honey bee activity and has been extensively utilised in literature concerning land suitability analysis for apiary sites (Amiri & Shariff, 2012; Sarı et al., 2020; Zoccali et al., 2017). Furthermore, it was evident that elevation holds greater importance when compared to other topographic factors such as slope and aspect. The outcome further confirms the fact that access to floral resources is a prime criterion to be considered when locating a commercial apiary site (Tennakoon, Apan, & Maraseni, 2023).

In this study, climatic data, regional ecosystem maps (floral resource information), foliage projective cover and topographic factors were utilised as predictor variables for habitat suitability modelling. While studies that rely solely on satellite imagery may benefit from high spatial resolution, comprehensive coverage, ability to incorporate complicate input data (Radočaj et al., 2021) and increased computational efficiency, and accuracy of the prediction, they may also face limitations in capturing certain environmental variables or complex ecological processes. By incorporating a diverse set of predictor variables, the aim was to capture a broader range of ecological factors that influence habitat suitability. However, it is important to acknowledge that integrating multiple datasets may introduce challenges related to data compatibility, processing, and interpretation.

5.4.2 Response of the spatial distribution of honey bees to climate change in Australia

By the 2020-2039 period, approximately 88% of highly suitable habitats for honey bees are projected to transition from their current state to become moderate to marginally suitable areas. Due to climate change, this transformation is predicted to result in a complete change of highly suitable habitats to different categories by the years 2060 to 2079. However, there was a contrasting trend observed in the moderately suitable area, which showed a notable increase of 58% from 1990-2009 to 2020-2039. This increase can be attributed to favourable changes in climatic factors, such as a slight decline in temperature seasonality (Bio4) and an increase in radiation during the wettest (Bio24) and driest quarters (Bio25). As indicated in the literature, the foraging activity of bees is influenced by various weather factors, such as temperature and solar radiation. For example, previous studies have reported a positive correlation between temperature and bee activity (Clarke & Robert, 2018; Gebremedhn et al., 2014; Vicens & Bosch, 2000). In the case of solar radiation (SR), the data suggests a positive correlation up to a specific radiation threshold (460 W/m2) (Burrill & Dietz, 1981).

However, the projection from 2020-2039 to 2060-2079 revealed a significant decline in the moderately suitable area, primarily due to an increase in temperature seasonality and a drastic reduction in radiation during the driest quarter. This indicates the potential challenges that lie ahead for honey bee habitats due to changing climate. This aligns with the findings of a previous study, which proposed a detrimental effect on honey bees due to climate change, as demonstrated in field experiments (Karbassioon et al., 2023). Additionally, while there is a temporary decrease in the not suitable area by the 2020-2039 period, it subsequently increases by 2060-2079, highlighting the persistence of adverse climatic conditions for honey bees. Among the three scenarios, the environment-only model exhibited the largest extent of highly and moderately suitable areas for honey bees, accounting for 24% of the total extent. This emphasizes that the environmental factors in the study area are more favourable for honey bees than the climatic factors. The combined climate and environment model revealed a decrease of approximately 9% in this value, highlighting the limitations imposed by climate factors on habitat suitability.

By 2020-2039, new moderately suitable areas have emerged in all four regions, while most of the highly suitable areas have transitioned into moderately suitable or marginally suitable lands.

During the period from 2030 to 2070, a discernible westward shift can be observed in the distribution of marginally suitable areas, whereas only scattered patches of moderately suitable areas are found in Toowoomba, Western Downs and Southern Downs. Over time, the regions of Goondiwindi that were once highly and moderately suitable are predicted to transition into areas classified as marginally and not suitable.

In the suitability map produced by ensemble modelling for the 1990-2009 period, 97% of honey bee occurrence records were found within the highly suitable and moderately suitable areas. This high correspondence between the model predictions and actual occurrences further validates the accuracy of the model. However, a significant decline is observed in future projections, with the occurrence records dropping to zero by 2060-2079. This phenomenon is reinforced by pertinent literature indicating that honey bees are vulnerable to various environmental threats, with climate change being one of the factors contributing to these threats (Chakuya et al., 2022). Remarkably, by the same period, a substantial majority, comprising 89% of the current occurrences, will be classified as not suitable, indicating a concerning shift in habitat suitability for honey bees. Regional ecosystems with floral species suitable for honey bees are mainly confined to the eastern and southern parts of the study area, encompassing areas such as Goondiwindi, Western Downs, and Southern Downs. With the changing climate, it is predicted that the habitat suitability for honey bees will shift towards the western parts located in higher elevated areas, where there are fewer favourable regional ecosystems available. This anticipated change in suitability aligns with research findings suggesting that the warming climate is prompting alterations in the geographic ranges of honeybees. As temperatures rise, bees are experiencing a shift in habitable zones toward higher latitudes and elevations to match suitable climate conditions (Ali et al., 2023). This implies the vulnerability of the apiary industry, particularly in the study area, which covers a significant portion of the honey-producing region in Queensland.

5.4.3 Limitations of the present study and recommendations

Species Distribution Modelling (SDM) can be applied on both natural and managed ecosystems. This study aimed to assess the impact of climate change on both managed and naturally occurring honey bee colonies, yet a limitation encountered was the insufficient availability of natural honey bee occurrence records that can be derived from reliable sources.

The honey bee presence data mainly consists of managed apiary site locations. While these apiary sites are presumed to capture the natural landscape attributes suitable for honey bees, it will be interesting to model honey bee distribution using other "natural" locations for the presence data.

Pesticides have a detrimental effect on honey bees, and their habitat suitability (Krupke et al., 2012; Tome et al., 2020; Williams et al., 2015; Zhu, 2014). In this study, the assessment of suitable locations did not consider the exposure to pesticides, which is recognized as a limitation. Therefore, it is recommended to incorporate pesticide exposure as a factor when determining suitable locations for honey bees. Furthermore, this study overlooks the aspect of habitat connectivity between suitable habitats for honey bees. It is suggested to include an analysis of the land use to assess the proximity and potential barries among habitats. Integration of habitat connectivity measures into honey bee species distribution modelling, will provide insights into how the arrangement and accessibility of suitable habitats influence honey bee populations. This information will contribute to more accurate predictions of honey bee distribution and assist in identifying priority areas for conservation and management efforts. Furthermore, this study did not take into consideration the land use changes when predicting future habitat suitability for honey bees. Therefore, it is worthwhile to combine anticipated land use changes with the projected future maps to obtain more accurate results.

The uncertainties associated with using datasets of different spatial and temporal resolutions in this study include potential inconsistencies in data quality, accuracy, and representativeness across varying scales, which may impact the generalisability of the results. In addition to the topographic variable utilised in the current study, it is recommended considering the incorporation of supplementary topographic variables derived from DEM data. These variables may include but are not limited to the LS-factor, total catchment area, curvatures, topographic wetness index, analytical hill shading, convergence index, terrain ruggedness index, multi-scale analysis of valley bottom flatness, and landform types. While this study focused on fundamental topographic parameters, the inclusion of additional topographic indices could offer valuable insights into landscape characteristics and further enhance the robustness of habitat suitability models.

5.5 Conclusion

In this study, an ensemble modelling approach was employed for developing three models to examine the distribution of honey bees based on various predictor variables. These models include the climate-only model, the environment-only model, and the combined climate and environment model. The climate-only model utilised the most dominant climatic factors that impact honey bee suitability such as radiation in the wettest and driest quarters, as well as temperature seasonality. On the other hand, the environment-only model incorporated the environmental variables that primarily influence honey bee habitat suitability such as proximity to regional ecosystems, foliage projective cover (FPC), and elevation. To capture the collective influence of climate and environmental factors, the combined model was developed by integrating the variables used in both the climate-only and environment-only models. Using the climate-only model, three suitability maps were projected for the time periods 1990-2009, 2020-2039, and 2060-2079. All three models demonstrated strong predictive performances with TSS values greater than 0.8. Under the 2020-2039 scenario, it is projected that 88% of the highly suitable land will transition to moderately suitable (14.84%), marginally suitable (13.46%), and not suitable (71.10%) areas, leaving only a 0.6% of the land as highly suitable. By the period of 2060-2079, the highly suitable area will undergo a complete transformation, transitioning entirely into other classes: moderately suitable (0.54%), marginally suitable (17.56%), and unsuitable (81.9%). This predicted loss of suitable habitats, particularly in terms of climate suitability, highlights the vulnerability of honey bees for climate change. Thus, this decline is anticipated to have significant impacts on natural ecosystems and commercial apiary management, which is a crucial contributor to the national economy.

The results of this study reveal a significant decline in the suitable area for honey bees under changing climate conditions. Therefore, this study stresses the importance of mitigating the impacts of climate change on honey bee habitats. Accordingly, investigating potential adaptation strategies for honey bee management in the face of climate change is crucial. Such strategies may include exploration of supplementary food sources for honey bees , selective breeding, innovative hive management techniques, and landscape planning to enhance honey bee resilience and minimize the negative impacts of changing climatic conditions. Additionally, engaging stakeholders, including beekeepers, farmers, and relevant government authorities, in addressing the challenges posed by climate change on honey bee distribution is essential. Evaluating the effectiveness of current policies and offering recommendations for promoting sustainable honey bee management and conservation efforts are key avenues for further exploration. These potential extensions would provide valuable insights into the complex interactions among climate change, environmental factors, and honey bee distribution. They would enhance our comprehensive understanding of land suitability for honey bees and contribute to the development of targeted conservation and management strategies.

CHAPTER 6 - ASSESSING THE CONFLUENCE OF NATURAL HAZARDS AND HONEY BEE HABITAT SUITABILITY FOR PRIORITISED PROTECTION

6.1 Introduction

The Literature Review (Chapter 2) underscored a knowledge gap in the realm of threat overlay analysis concerning honey bee habitats, aiming to determine potential remedies for addressing these challenges. Research efforts are increasingly focused on mapping and predicting natural hazards, particularly bushfires and floods. However, the valuable insights generated from these studies have yet to be fully integrated into the honey bee industry, representing a missed opportunity to optimise results and minimise losses. The utilisation of threat overlay, considering both land cover and land use, for the purpose of proposing mitigation strategies has not been documented in the existing literature.

While Chapters 4 and 5 delved into the creation of current and future honey bee habitat suitability maps, the current chapter shifts its focus to the intersection of bushfires, floods, and honey bee habitats. The aim of this Chapter was to identify areas requiring prioritised protection from bushfires and floods while also introducing management strategies aimed at mitigating the negative effects on honey bees and their habitats. The specific objectives addressed by this present Chapter are the following: (1) to map and analyse the threats of bushfire and flood on honey bee suitability areas; (2) to identify and map honey bee habitats that need to be prioritised for protection against bushfire and flood; and (3) to suggest management strategies to protect honey bee habitats from bushfire and flood hazards. The results of this study could inform the development of policies and management strategies aimed at safeguarding this valuable species and the industry. This chapter offers several innovations: (1) this is the first study that attempts to assess the impact of natural hazards on honey bee habitats from a spatial distribution perspective; (2) this study applies a novel methodology for identifying priority areas requiring protection against the threats of bushfires and floods; and (3) this study suggests management strategies to safeguard the valuable honeybees from bushfires and floods, taking into consideration the associated land cover and land use in the vulnerable areas.

This chapter is organised into six sections as follows: 1) Introduction, 2) Background literature on threat overlay analysis, 3) Methods, 4) Results, 5) Discussion, and 6) Conclusion.

6.2 Integrating honey bee habitat suitability and natural hazards for determining mitigation and management strategies

Pollination plays a pivotal role in sustaining the populations of numerous plants, encompassing both wild and cultivated species (Ollerton et al., 2011). Its significance is particularly pronounced in modern agriculture, where approximately 75% of the worldwide crop varieties rely on animal pollinators for the formation of fruits and seeds (Klein et al., 2007). Among all biotic pollinators, the European honey bee (*Apis mellifera*), henceforth referred to as the "honey bee", is the primary species responsible for global crop production (Easton-Calabria et al., 2019). More specifically, the Australian honey bee industry, valued at over 14 billion dollars annually, exerts a vital influence on Australian agriculture. Approximately 35% of crops rely solely on honey bees for pollination, while an impressive 75% of crops derive significant benefits from this essential pollination process (Department of Agriculture Fisheries and Forestry, 2023).

In spite of the significance of this invaluable industry, honeybees remain persistently imperilled by an array of factors, encompassing pests and diseases (Core et al., 2012), use of pesticides (Henry et al., 2012; Sanchez-Bayo & Goka, 2016; Tome et al., 2020), climate change (Le Conte & Navajas, 2008) and habitat loss (Vanbergen & Initiative, 2013). Several studies have endeavoured to address these challenges faced by the honey bee industry (Flores et al., 2019; Krupke et al., 2012; Prendergast et al., 2021). However, only a limited number of studies so far has attempted to quantify the threat imposed by loss of habitats for honey bees due to natural disasters. The nature of natural disasters and the extent of their effect can vary across different geographic locations. Nevertheless, the significance of bushfire and flood incidents cannot be underestimated, given their occurrences across the globe (Xie & Peng, 2019) and potential effects they might impose on both honeybee populations and their habitats (Agriculture Victoria, 2023).

Figure 6. 1 Bushfire event occurring in a woodland in Australia (Campion, 2023)

Figure 6. 2 Flooding washes away beehives in Australia (Johnson, 2023)

Species Distribution Modelling (SDM) is an extensively utilised approach for predicting both the spatial and temporal distribution of a species in relation to pertinent environmental variables (Anderson et al., 2011; Guisan & Zimmermann, 2000; Naimi & Araújo, 2016). An ensemble modelling approach that combines predictions from various modelling techniques, including regression, classification, and machine learning algorithms, has been proven to enhance accuracy in predicting species distribution in numerous cases (Araújo & New, 2007; Grenouillet et al., 2011; Marmion, Parviainen, et al., 2009). Furthermore, SDM can be employed to create suitability maps for various species using different software, such as biomod (Kindt, 2018). Identifying regions prone to natural hazards such as bushfires and floods and superimposing these areas with suitability maps for honey bees, can facilitate the identification of locations requiring protection. A GIS platform presents valuable opportunities to evaluate the spatial concurrence of honeybee threats and habitat suitability. This study uses the suitability map for honey bees developed based on most influential bioclimatic and environmental variables in the previous chapter which will then be superimposed with two significant threat layers: bushfire and flood. In this study, validated bushfire and flood layers specific to Queensland, extracted from the Queensland Spatial Catalogue portal, were utilised.

In Chapter 2, an in-depth literature review is presented, focusing on the profound effects of natural hazards on honey bees and the two prevalent natural hazards: bushfires and floods. Accordingly, the impacts can manifest in various forms, including biological and physiological reactions, population reductions, colony losses, and the conversion of habitats to unsuitability for an extended period. Moreover, it explores threat overlay analysis in GIS. Through hazard mapping, valuable insights can be acquired into the distribution of vulnerable locations, facilitating well-informed and strategic mitigation endeavours.

6.3 Methods

6.3.1 Study area

A representative segment of Queensland's primary honey producing region was selected as the study area. This region encompasses four local government areas: Toowoomba, Southern Downs, Western Downs, and Goondiwindi with an extent of 37,612km^2. This area is predominantly rural, featuring vast agricultural expanses, extensive rangelands, and diverse regional ecosystems. These ecosystems consist mainly of both remnant and non-remnant forests, woodlands, and shrublands. Specifically, the agricultural area covers 11,712 km2, the rangelands span over 11,899 km2, and the regional ecosystems extend over the largest area, totalling 13,488 km2. The study area is located in the main honey-producing region of Queensland, covering 35% of the apiary sites. More information on the study area is presented in Chapter 3.

6.3.2 Input maps

Honey bee habitat suitability map

This study utilised a honey bee habitat suitability map generated through the biomod2 package within the R platform, incorporating a combined climate and environment model. The methods employed and output generated (Figure 6.3) in that part of the study were explained in Chapter 5. The model development was based on an ensemble modelling approach (Araújo & New, 2007). The spatial resolution of the suitability map is 250m. The relevant environmental factors considered in building the spatial distribution model include proximity to regional ecosystems (floral resources), foliage projective cover (FPC), and elevation. Additionally, the model incorporated bioclimatic variables in its construction, encompassing Bio4 (temperature seasonality), Bio24 (radiation during the wettest quarter), and Bio25 (radiation during the driest quarter). Honey bee habitats were categorized into three suitability levels: a) highly suitable, b) moderately suitable, and c) marginally suitable. The highly suitable areas for honey bees cover approximately 5.5% of the total area, spanning 2,055.75 km^2. Moderately suitable regions encompass 9.2% of the area, totalling 3,475.75 km^2, while marginally suitable areas account for 7.9%. The remaining 77.4% of the area, equivalent to 29,100.5 km^2, is deemed unsuitable for honey bees. More details about this study and the output suitability maps are presented in Chapter 5.

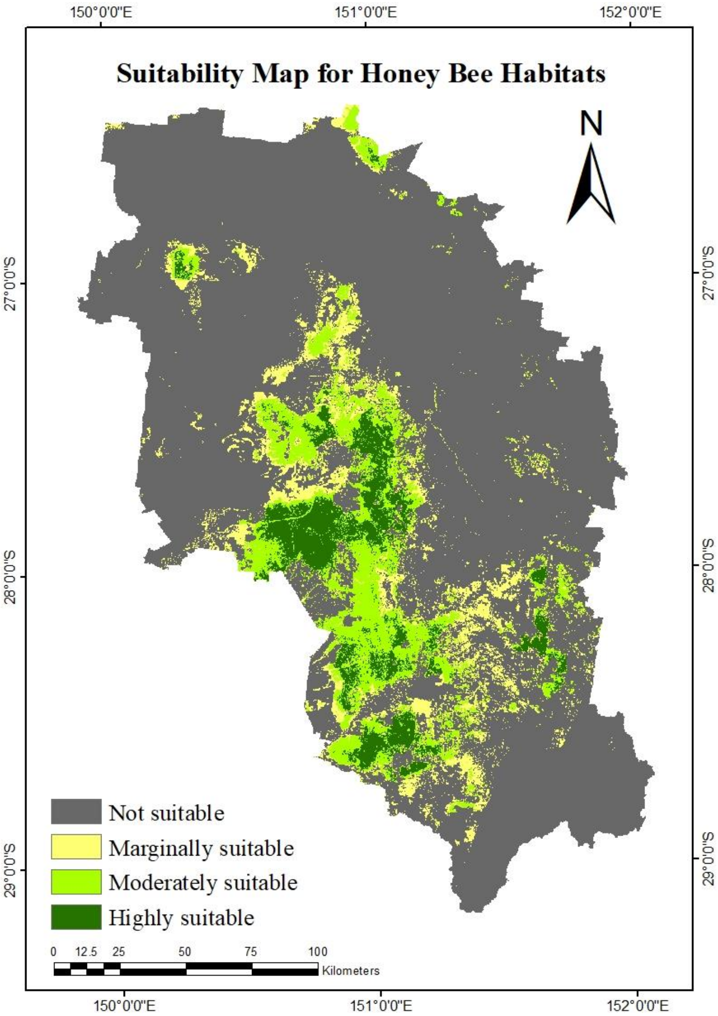


Figure 6. 3 Honey bee habitat suitability map (modelled in Chapter 5)

Bushfire intensity map

The bushfire intensity map pertaining to the study area was extracted from the Queensland Spatial Catalogue data portal at a 25m resolution (Figure 6.4). According to the methodology adopted by Leonard et al. (2014), the bushfire-prone area is characterised as an area capable of sustaining a significant bushfire or being susceptible to a significant bushfire attack. The bushfire-prone area is classified into four classes, i.e., a) very high potential bushfire intensity, b) high potential bushfire intensity, c) medium potential bushfire intensity, and d) potential impact buffer (Figure 6.5), while the bushfire-safe area is classified as a e) low-hazard area. Very high potential intensity is characterised by a fire line intensity of 40,000+kW/m, while the value for high potential intensity ranges from 20,000 to 40,000kW/m. Fire line intensity is referred as a standardised metric indicating the pace at which a leading fire front would consume fuel energy over a specified period and length of fire front (Byram, 1959). Medium potential intensity is characterised by a fire line intensity ranging from 4,000 to 20,000kW/m. Land that may face substantial bushfire threats from embers, flames, or radiant heat is encompassed within a potential impact buffer, typically extending 100m from all areas categorised as having a very high, high or medium potential bushfire intensity. In bushfire prone areas, bushfires can pose a significant threat, with the potential for high to extreme levels of flame attack, radiant heat, and ember attack. These risks are influenced by factors such as high fuel loads (representing accumulations of combustible material in unburnt or unreduced vegetation), steep terrain, and severe fire weather conditions, including recent precipitation, current wind speed, relative humidity, and temperature. The impact of bushfires in these bushfire prone areas can be detrimental to both people and property.

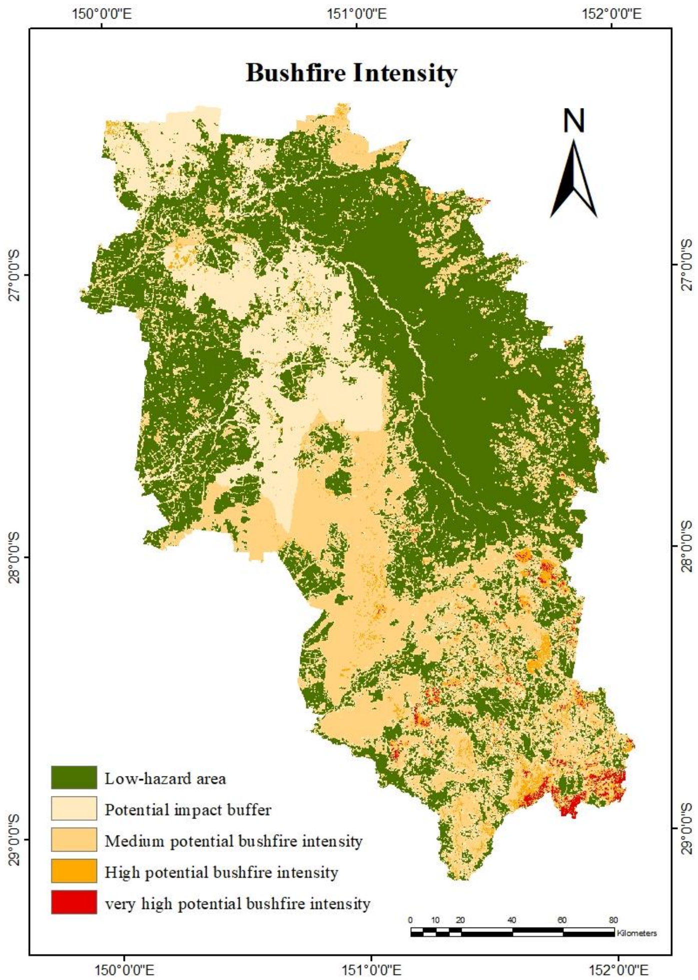


Figure 6. 4 Bushfire intensity map extracted from Commonwealth Scientific and Industrial Research Organisation (CSIRO) et al. (2015)

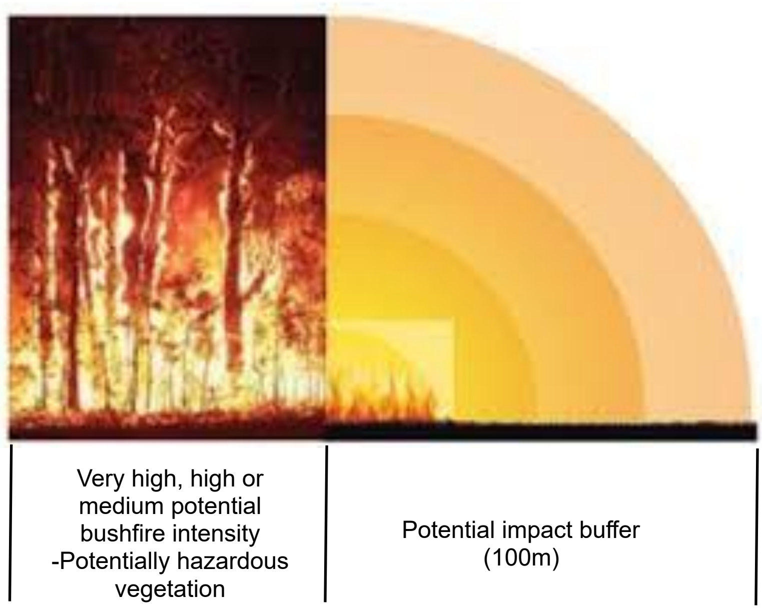


Figure 6. 5 Bushfire prone area
(Leonard et al., 2014)

Floodplain assessment overlay

The Queensland Floodplain Assessment Overlay delineates floodplain regions within Queensland's drainage sub-basins. This data has been generated using a drainage sub-basin analysis approach, incorporating various data sources such as 10m contour data, historical flood records, vegetation and soil mapping, and satellite imagery (Department of Resources, 2013). The map was extracted from the Queensland Spatial Catalogue data portal (Figure 6.6).

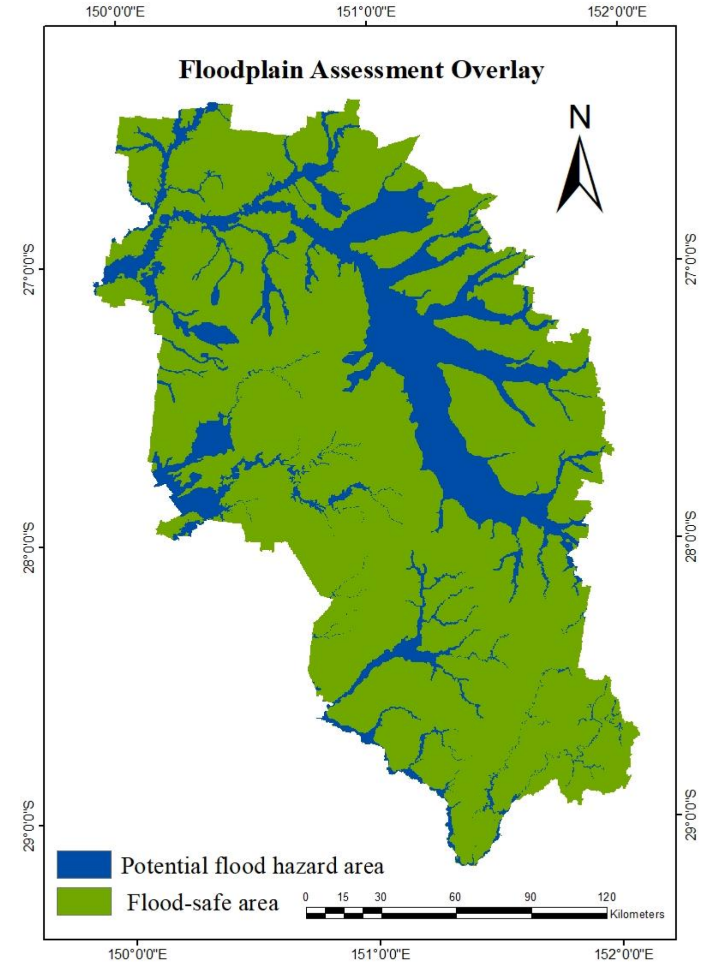


Figure 6. 6 Floodplain assessment overlay extracted from Department of Resources (2013)

Land cover

The land cover map, based on Sentinel-2 data with a 10m resolution, was extracted from the ESRI Land Cover-Living Atlas (ESRI Land Cover, 2022). The map delineates nine distinctive classes, representing water, trees, flooded vegetation, crops, built areas, bare ground, clouds, rangeland, and snow. The study area considered encompasses eight classes, excluding snow (Figure 6.7).

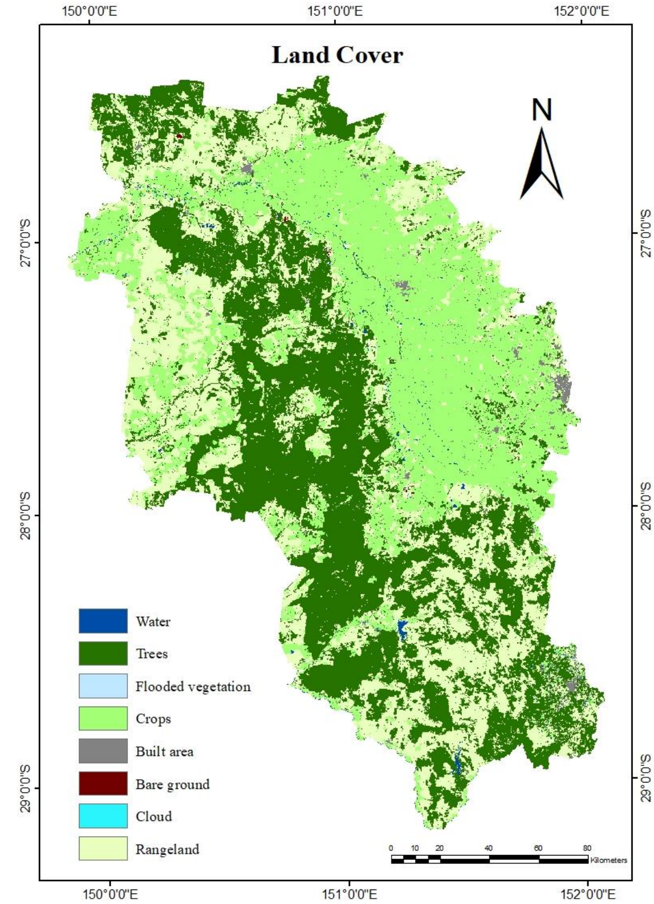


Figure 6. 7 Land cover extracted from ESRI Land Cover (2022)

Land use

The land use map is a digital representation of land use within Queensland's South East Queensland Natural Resource Management (NRM) region and was created by the Queensland government. The vector layer consists of polygon data, with each category featuring attributes that provide descriptions of land use. Land use classification adheres to the Australian Land Use and Management Classification (ALUMC) Version 7. There are five primary-level classes, categorized based on their degree of intervention or potential impact on the natural landscape, with water represented as a distinct sixth primary class (Department of Environment and Science, 2023). In this study, the tertiary-level land use classification was used in addition to the primary classification for further analysis of land use classes. The maps were sourced from the Queensland Spatial Catalogue portal (Figure 6.8).

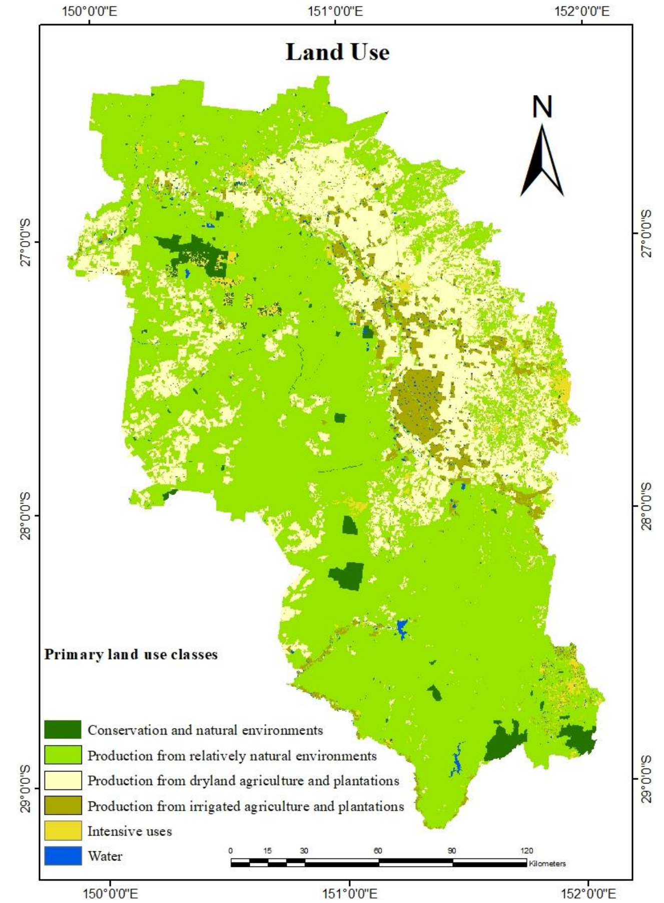


Figure 6. 8 The primary-level land use classes extracted from Department of Environment and Science (2023)

6.3.3 Overview of the research methodology

The overall research methodology followed in the present study is depicted in Figure 6.9. The honey bee suitability map was combined with a bushfire intensity map and a floodplain assessment overlay to create the a) bushfire threat zone map, b) flood hazard zone map, and c) combined map of both bushfire and flood. The priority areas for protection were delineated from the bushfire threat zone and flood hazard zone maps, taking into consideration the suitability of habitats, the intensity of bushfires, and the presence of flood hazards. These priority areas were then integrated with land cover and land use maps to develop management strategies aimed at minimizing the impacts of natural hazards. ArcMap 10.7.1 was utilised for the combination of raster layers with 250m resolution and GDA2020 projection.

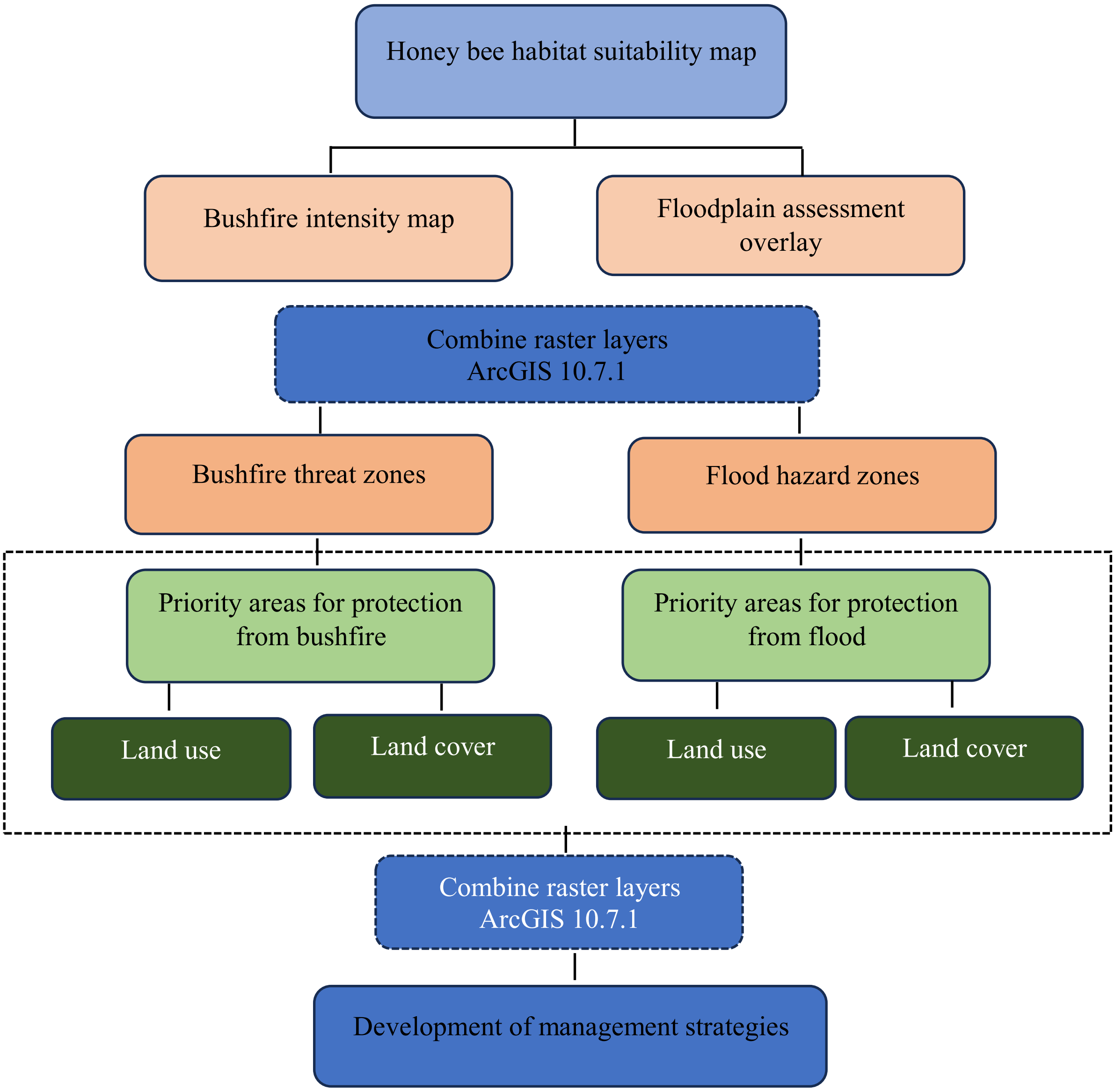


Figure 6. 9 The overall research methodology

Development of threat zones for bushfire

Utilising the "Combine" tool (i.e., multiple rasters are combined so that a unique output value is allocated to each unique combination of input values) in ArcMap 10.7.1, the honey bee habitat suitability map was merged with the bushfire intensity map. All raster layers were adjusted to the GDA2020 projection and resampled to achieve a 250m resolution, ensuring consistency with the suitability map. The application of the combine tool yielded a total of 20 distinct combinations, which were subsequently classified into six different categories for the purpose of defining threat zones (Table 6.1). When delineating the threat zones, both the level of suitability and the magnitude of bushfire intensity were considered. Specifically, areas exhibiting a high degree of suitability (either highly suitable or moderately suitable) yet susceptible to a high level of bushfire intensity, such as those with very high potential or high potential, were grouped together. This classification was rooted in the potential extent of damage that a bushfire could inflict upon honey bees in these specific regions. Furthermore, separate zones were defined as the level of suitability or bushfire intensity decreased.

Table 6. 1 Bushfire threat zones generated from combining honey bee habitat suitability class and bushfire intensity class

Honey bee habitat suitability class	Bushfire intensity class	Threat zone for bushfire
Highly suitable	Very high potential bushfire intensity	Zone 1
Highly suitable	High potential bushfire intensity	Zone 1
Moderately suitable	Very high potential bushfire intensity	Zone 1
Moderately suitable	High potential bushfire intensity	Zone 1
Highly suitable	Medium potential bushfire intensity	Zone 2
Highly suitable	Potential impact buffer	Zone 2
Moderately suitable	Medium potential bushfire intensity	Zone 2
Moderately suitable	Potential impact buffer	Zone 2
Marginally suitable	Very high potential bushfire intensity	Zone 3
Marginally suitable	High potential bushfire intensity	Zone 3
Marginally suitable	Medium potential bushfire intensity	Zone 3
Marginally suitable	Potential impact buffer	Zone 3
Not suitable	Low-hazard area	Zone 4
Highly suitable	Low-hazard area	Zone 5
Moderately suitable	Low-hazard area	Zone 5
Marginally suitable	Low-hazard area	Zone 5
Not suitable	Very high potential bushfire intensity	Zone 6
Not suitable	High potential bushfire intensity	Zone 6
Not suitable	Medium potential bushfire intensity	Zone 6
Not suitable	Potential impact buffer	Zone 6

Prioritisation of protection areas for bushfire

The areas that should be prioritised for protection from bushfires were determined based on the potential harm that could befall the honey bee population in specific regions during bushfire events. Specifically, honey bee habitats ranging from highly to moderately suitable, and exposed to very high to medium potential bushfire intensity as well as the potential impact of bushfires (corresponding to a combination of zones 1 and 2 as presented in Table 6.1 and Figure 6.10), are suggested to be prioritised for protection from bushfires. The threat zones and the prioritised areas for protection were further overlaid with the land cover and land use maps for the development of management strategies for protection.

Development of threat zones for flood

The honey bee habitat suitability map was combined with the Queensland floodplain assessment overlay map to generate a unified output. The original vector layer of the floodplain assessment overlay was transformed into a raster format with a resolution of 250m and GDA2020 projection. The areas with a high to moderate suitability for honey bees that are also susceptible to potential flood hazards were categorized as a single zone, taking into account the potential impact of floods on honey bee populations in those habitats. Additionally, honey bee habitats with varying suitability levels that are free from potential flood hazards were categorized separately, considering their suitability as honey bee habitats unaffected by floods (Table 6.2).

Table 6. 2 Flood hazard zones generated from combining honey bee habitat suitability class and flood status.

Honey bee habitat suitability class	Flood status	Threat zone for flood
Highly suitable	Potential flood hazard	Zone 1
Moderately suitable	Potential flood hazard	Zone 1
Marginally suitable	Potential flood hazard	Zone 2
Not suitable	Flood-safe	Zone 3
Highly suitable	Flood-safe	Zone 4
Moderately suitable	Flood-safe	Zone 4
Marginally suitable	Flood-safe	Zone 4
Not suitable	Potential flood hazard	Zone 5

Prioritisation of protection areas for flood

Priority areas for safeguarding against potential flood hazards were identified by assessing the potential risk to honey bee populations in specific regions during flood events. In particular, it is recommended giving priority to protecting honey bee habitats categorized as highly to moderately suitable and at risk of potential flood hazards, corresponding to zone 1 in Table 6.2 and Figure 6.11. Furthermore, these designated protection areas were combined with the land cover and land use maps to gain insights into the composition of the underlying region and to plan the management strategies accordingly.

Development of threat zones for both bushfire and flood

The honey bee habitat suitability map was integrated with both the bushfire intensity map and the Queensland floodplain assessment overlay map to generate an output specifically illustrating areas that are vulnerable to both disasters and areas that are resilient to both bushfire and flood events. Thirteen distinct zones were delineated based on the honey bee habitat suitability class, bushfire intensity level, and flood status, which indicates whether they are prone to bushfire and flood hazards or safeguarded against them (Table 6.5, Figure 6.12).

6.4 Results

6.4.1 Bushfire threat zones: overlaying honey bee habitats and non-habitats with varied intensity levels of bushfires

Bushfire threat zones, defined by assessing the interaction between honey bee habitats at varying suitability levels and the distinct levels of bushfire intensity (as presented in Table 6.1), were mapped (Figure 6.10) and the corresponding areas were calculated (Table 6.3). It offers valuable insights into the impact of varying bushfire intensity levels on honey bee habitats in terms of the extent affected. The concerning fact is that most of the area (97.62%) suitable for honey bees, whether highly, moderately, or marginally, is under the threat of bushfires.

Table 6. 3 Bushfire threat zones

Zone	Definition	Area	
		km^2	Percentage (%)
Zone 1	Honey bee habitats, ranging from highly to moderately suitable, exposed to very high and high potential bushfire intensity	342.4	0.9
Zone 2	Honey bee habitats, ranging from highly to moderately suitable, exposed to medium potential bushfire intensity and the potential impact of bushfires	5,139.3	13.7
Zone 3	Honey bee habitats with marginal suitability exposed to very high, high and medium potential bushfire and potential impact of bushfires	2,827.3	7.5
Zone 4	Bushfire-safe honey bee habitats (Highly suitable to marginally suitable honey bee habitats exposed to low bushfire hazard)	202.9	0.5
Zone 5	Bushfire-safe non-honey bee habitats (Areas unsuitable for honey bees and subjected to low bushfire hazard)	18,208.2	48.4
Zone 6	Areas unsuitable for honey bees and exposed to bushfires ranging from very high to medium potential intensity, along with the potential impact of bushfires	10,892.2	29.0

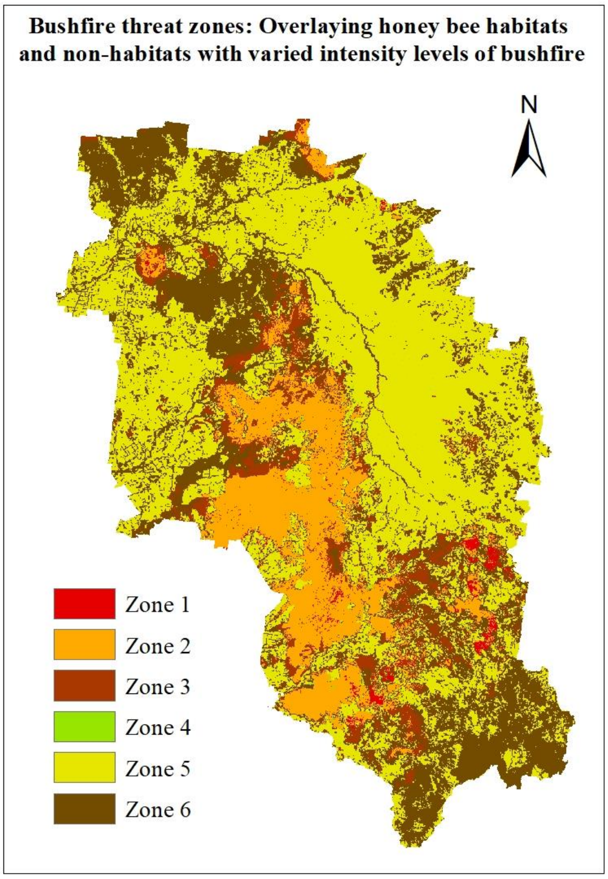


Figure 6. 10 Bushfire threat zones: overlaying honey bee habitats and non-habitats with varied intensity levels of bushfire (defined in table 6.3)

The flood assessment overlay and honey bee habitat suitability maps were integrated to generate an output categorized into five distinct zones. These zones indicate the level of suitability and whether the area is susceptible to potential flood hazards or devoid of such risks. Notably, flood-safe honey bee habitats constitute a significant portion, covering 21.5% of the total study area and accounting for 95% of the highly to marginally suitable areas for honey bees (Table 6.4).

Table 6. 4 Flood threat zones: Overlaying honey bee habitats and non-habitats with potential flood hazard and flood-safe areas

Zone	Definition	Area	
		km^2	Percentage (%)
Zone 1	Honey bee habitats, ranging from highly to moderately suitable, subjected to potential flood hazard	183.3	0.5
Zone 2	Marginally suitable honey bee habitats subjected to potential flood hazard	241.4	0.6
Zone 3	Flood safe non-honey bee habitats (Areas unsuitable for honey bees and safe from flood hazard)	21,815.6	58.0
Zone 4	Flood-safe honey bee habitats (Honey bee habitats ranging from highly suitable to marginally suitable and safe from flood hazard)	8,087.2	21.5
Zone 5	Non-honey bee habitats subjected to potential flood hazard (Areas unsuitable for honey bees and subjected to potential flood hazard)	7,284.9	19.4

6.4.2 Bushfire and flood impact: overlaying honey bee habitats and non-habitats with varied intensity levels of bushfire and flood hazard

Honey bee habitats, classified as highly to marginally suitable, were integrated with overlay rasters depicting bushfire intensity and flood assessments to identify regions susceptible to both hazards while ensuring safety from both. Among the areas falling into the highly suitable, moderately suitable, or marginally suitable categories for honey bee habitats, only 1.03% face simultaneous threats from both hazards. In contrast, 21.06% of the habitat areas suitable for honey bees are exposed to varying intensities of bushfires but remain unaffected by potential flood hazards. A mere 0.001% of the regions susceptible to potential flood hazards are devoid of bushfire risks. Zone 9 represents honey bee habitats completely free from both hazards, although this encompasses a relatively small area of 166.06 km2 (0.44%) (Table 6.5 and Figure 6.12).

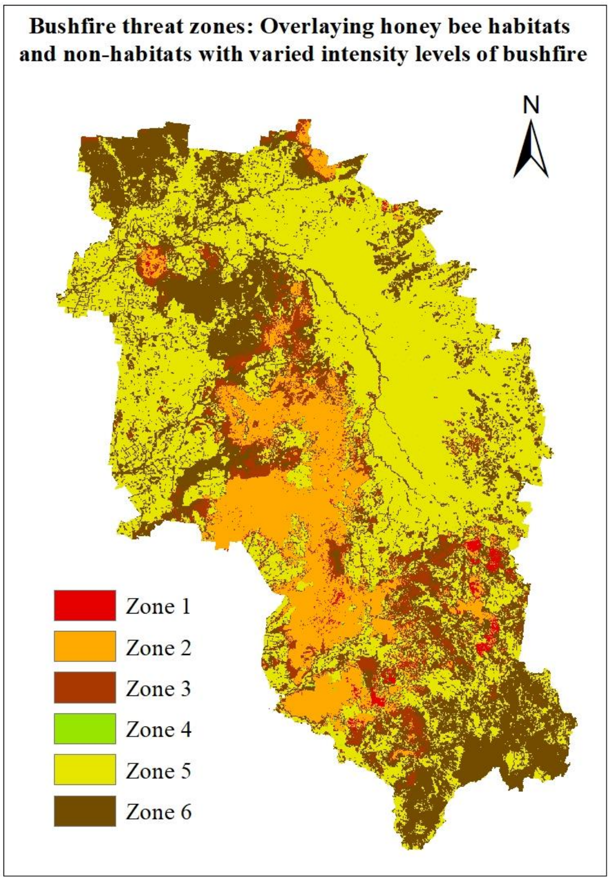


Figure 6. 11 Flood threat zones: overlaying honey bee habitats and non-habitats with potential flood hazard and flood-safe areas (defined in table 6.4)

Table 6. 5 Bushfire and flood threat zones: overlaying honey bee habitats and non-habitats with varied intensity levels of bushfire and flood hazard

Zone	Definition	Area	
		km^2	Percentage (%)
Zone 1	Honey bee habitats, ranging from highly to moderately suitable, exposed to very high to high potential bushfire intensity and potential flood hazard	0.7	0.0
Zone 2	Honey bee habitats, ranging from highly to moderately suitable, exposed to medium potential bushfire intensity and the potential impact of bushfires and potential flood hazard	177.7	0.5
Zone 3	Honey bee habitats, ranging from highly to moderately suitable, exposed to very high to high potential bushfire intensity but free from potential flood hazard	341.8	0.9
Zone 4	Honey bee habitats, ranging from highly to moderately suitable, exposed to medium potential bushfire intensity and the potential impact of bushfires but free from potential flood hazard	4,961.6	13.2
Zone 5	Marginally suitable honey bee habitats exposed to potential impact of bushfire and potential flood hazard	209.5	0.6
Zone 6	Marginally suitable honey bee habitats exposed to potential impact of bushfire but free from potential flood hazard	2,617.8	7.0
Zone 7	Bushfire-safe honey bee habitats ranging from high suitability to marginal suitability but exposed to potential flood hazard	4.9	0.0
Zone 8	Bushfire-safe, marginally suitable honey bee habitats exposed to potential flood hazard	31.9	0.1
Zone 9	Bushfire-safe and flood-safe honeybee habitats	166.1	0.4
Zone 10	Bushfire-safe and flood-safe non honey bee habitats	12,639.7	33.6
Zone 11	Bushfire-safe non honey bee habitats exposed to potential flood hazard	5,568.6	14.8

Zone	Definition	Area	
		km^2	Percentage (%)
Zone 12	Flood-safe, non-honey bee habitats exposed to very high to medium potential bushfire intensity and potential impact of bushfire	9,175.9	24.4
Zone 13	Non-honey bee habitats exposed to very high to medium potential bushfire intensity and potential impact of bushfire and potential flood hazard	1,716.4	4.5

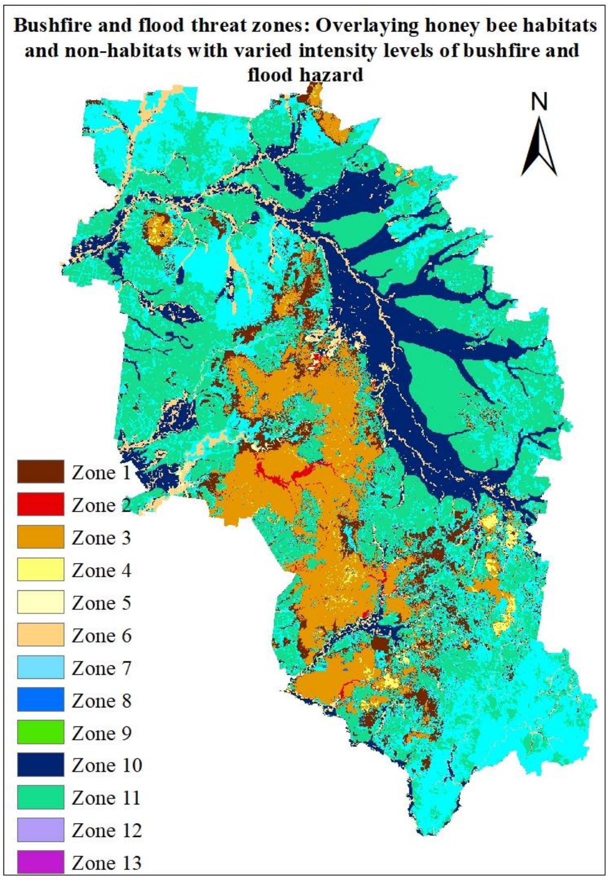


Figure 6. 12 Bushfire and flood threat zones: overlaying honey bee habitats and non-habitats with varied intensity levels of bushfire and flood hazard (defined in Table 6.5)

6.4.3 Honey bee habitats that need to be prioritised for protection against bushfire

Honey bee habitats ranging from highly to moderately suitable and exposed to very high to medium potential bushfire intensity as well as the potential impact of bushfires (a combination of zones 1 and 2 from Table 6.1/Figure 6.9), are suggested to be prioritised for protection from bushfires. This area accounts for 14.57% of the study area with an extent of 5,481.75km^2 (Figure 6.13).

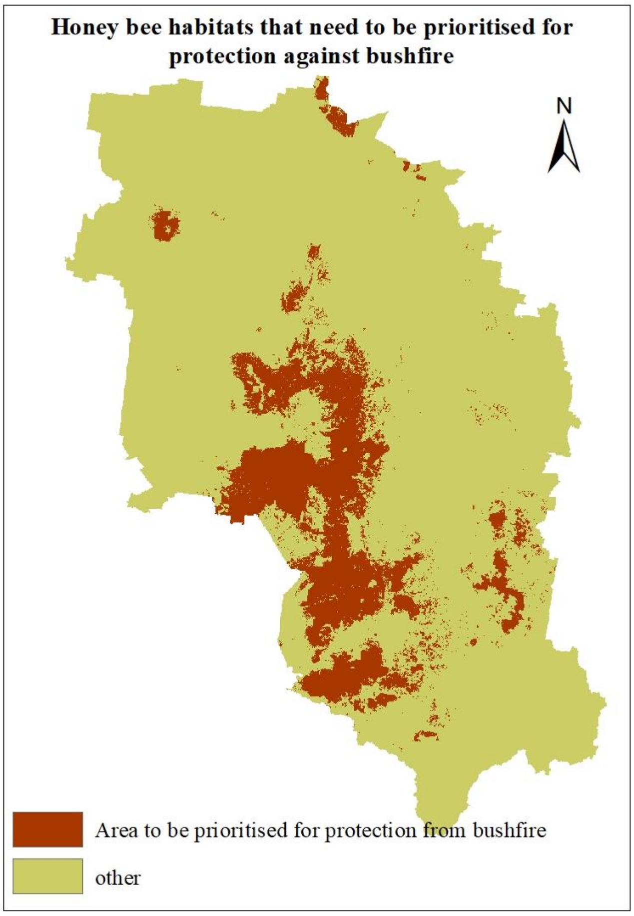


Figure 6. 13 Honey bee habitats that need to be prioritised for protection from bushfire hazard

6.4.4 Overlaying prioritised areas for protection from bushfire with land cover and land use

Table 6.6 illustrates the land cover types within the two bushfire threat zones prioritised for protection. Trees dominate the area exposed to bushfire hazard, accounting for 94.11% of the land, while rangelands encompass 5.22% of the region. Remarkably, cropping areas are included in the bushfire impact zone, constituting an area of 33.06 km^2, which represents 0.6% of the total bushfire impact area.

Table 6. 6 Overlaying prioritised area (bushfire threat zones1 and 2) with land cover.

Bushfire impact zone	Land cover type	Area (km^2)	Percentage (%)
Zone 1	Trees	321.8	5.9
Zone 1	Rangeland	19.2	0.3
Zone 1	Built area	0.1	0.0
Zone 1	Crops	1.1	0.0
Zone 1	Built area	0.1	0.0
Zone 2	Trees	4,833.6	88.2
Zone 2	Rangeland	266.9	5.0
Zone 2	Crops	32	0.6
Zone 2	Built area	2.0	0.0
Zone 2	Flooded vegetation	0.1	0.0
Zone 2	Bare ground	0.7	0.0

Table 6.7 depicts the intersection between bushfire threat zones and tertiary-level land use classes. Production native forests encompass a substantial area of 3,655.57km^2, representing 66.72% of the total. Furthermore, 99.15% of the bushfire-affected region falls within the primary-level land use categories of conservation and natural environments, as well as production from relatively natural environments.

Table 6. 7 Overlaying prioritised area (bushfire threat zones1 and 2) with tertiary land use

Bushfire threat zone	Land use type (tertiary level)	Area (km^2)	Percentage (%)
Zone 1	Production native forests	175.9	3.2
Zone 1	Grazing native vegetation	147.5	2.7
Zone 1	Residual native cover	1.9	0.0
Zone 1	National park	1.7	0.0
Zone 1	Other conserved area	14.7	0.3
Zone 2	Production native forests	3,479.7	63.5
Zone 2	Grazing native vegetation	1,481.5	27.0
Zone 2	National park	11.2	0.2
Zone 2	Residual native cover	28.2	0.5
Zone 2	Other conserved area	98.7	1.8
Zone 2	Rural residential without agriculture	16.0	0.4
Zone 2	Cropping	12.3	0.2
Zone 2	Other	9.8	0.2

6.4.5 Honey bee habitats that need to be prioritised for protection against flood

Honey bee habitats, ranging from highly to moderately suitable and subjected to potential flood hazard are suggested to be prioritised for protection from potential flood hazard. This area covers 183.31km^2, accounting for 0.49% of the total study area (Figure 6.14).

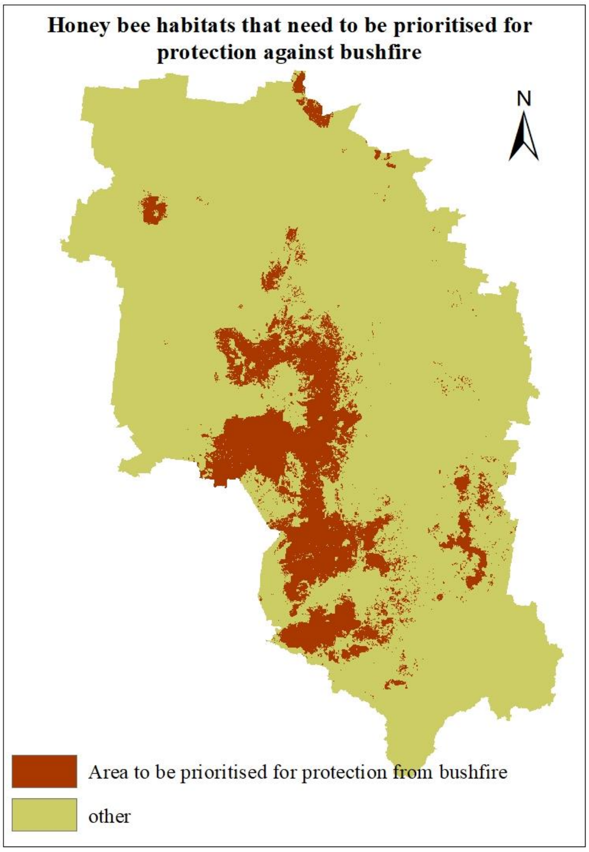


Figure 6. 14 Honey bee habitats that need to be prioritised for protection from potential flood hazard

Among honey bee habitats spanning from highly to moderately suitable and exposed to potential flood hazards, 'trees' are the dominant land cover type, accounting for 84.41% of the coverage, followed by 'rangelands' at 12.95% (Table 6.8).

Table 6. 8 Overlaying flood threat zones with land cover

Flood impact zone	Land cover type (primary-level)	Area (km^2)	Percentage (%)
Zone 1	Trees	154.4	84.4
Zone 1	Rangeland	23.7	13.0
Zone 1	Crops	3.9	2.1
Zone 1	Other	0.9	0.5

The majority, specifically 97.92%, of honey bee habitats prone to flood hazards can be found within various land use categories, including production native forests, grazing native vegetation, other conserved areas, and natural feature protection (Table 6.9). Additionally, a substantial 97.64% of the flood-prone region is situated within the primary-level land use categories of conservation and natural environments, as well as production from relatively natural environments.

Table 6. 9 Overlaying flood impact zones with land use

Flood impact zone	Land use type	Area (km^2)	Percentage (%)
Zone 1	Production native forests	126.0	68.8
Zone 1	Grazing native vegetation	52.1	28.5
Zone 1	Cropping	2.8	1.5
Zone 1	Other conserved area	0.9	0.5
Zone 1	Natural feature protection	0.2	0.1
Zone 1	Other	1.1	0.6

6.5 Discussion

6.5.1 Threats of bushfire and flood on honey bee suitability areas

This study highlights the significant vulnerability of the study area to two major threats: bushfire and flood, which is deeply concerning. Specifically, approximately 8,309 km^2 (22%) of the study area, encompassing habitats ranging from those highly suitable for honey bees to those marginally suitable, face varying levels of exposure to bushfire hazards. These fires have the capacity to pose significant risks to both honey bee populations and their respective habitats. This aligns with the findings of previous studies conducted in various regions, consistently demonstrating the adverse impact of bushfires on honey bees (Chemurot et al., 2013; Nyunza, 2018). Moreover, when focusing solely on areas suitable for honey bees, including highly suitable to marginally suitable habitats, an overwhelming 97.6% of this area is at risk from bushfire incidents. This leaves only a limited, comparatively small area untouched by the threat of bushfires. The repercussions of bushfire vulnerability extend to ecological balance, agricultural productivity, and food security. Given the crucial role honey bees play in pollination, the potential decline in their populations could have far-reaching consequences for both natural ecosystems and human societies.

Land cover type ‘trees’ dominate approximately 94% of the bushfire impact zones, specifically zones 1 and 2. These zones encompass highly to moderately suitable honey bee habitats and are exposed to very high, high, and moderate bushfire intensities, as well as the potential impact of bushfires. As for the tertiary-level land use classes within the bushfire impact area, 99.15% comprises native vegetation including forests and grazing vegetation, conserved areas, and national parks. For instance, bushfires across Australia in 2020 ravaged approximately 18.5 million hectares of land, equivalent to the size of Syria. The impact was particularly severe in the eastern and southern regions, affecting approximately 10.4 million hectares of forests, woodlands, and heathlands with unprecedented severity (Dorey et al., 2021; Legge et al., 2021). The land cover type 'trees' dominates the bushfire-affected areas as vegetation (fuel) becomes increasingly abundant along the path of the fire. Coupled with high temperatures, strong winds, and low precipitation, the fire gains momentum, resulting in significant bushfire incidents in previous occurrences (Bessie & Johnson, 1995; Deb et al., 2020; Littell et al., 2009). Accordingly, the dominance of 'trees' in bushfire impact zones signifies not only a localised threat to honey bee habitats but also a broader ecological challenge.

In contrast, the potential for flood hazards appears far less pervasive, with only 5% of habitats suitable for honey bees, spanning from highly to marginally suitable, falling under the threat of potential flood risk. Similarly, the land cover category 'trees' exerts a significant presence within the flood-affected region, accounting for an impressive 84.41% of the total coverage. Based on the tertiary-level land use classification, a substantial 93.2% of the area is enveloped by native vegetation, encompassing forests, grazing lands, and conserved areas. Interestingly, the analysis also uncovers a noteworthy intersection of threats, where approximately 4.5% of honey bee habitats, ranging from highly to marginally suitable, confront the dual perils of bushfire hazards at varying intensities and potential flood risks.

The dual threats of bushfire and flood signify a profound vulnerability in the study area, with far-reaching implications for both honey bee populations and the broader ecosystem. The extensive coverage of 'trees' in bushfire impact zones, constituting 94%, emphasises the localised and ecosystem-wide risks associated with this dominant land cover type. The potential consequences extend beyond immediate threats to honey bee habitats to encompass ecological balance, agricultural productivity, and food security. Notably, the 97.6% risk exposure in areas suitable for honey bees underscores the urgency of addressing and mitigating bushfire impacts. Meanwhile, flood hazards, though less pervasive at 5%, still present a significant concern, especially given the notable intersection of threats where 4.5% of honey bee habitats face both bushfire hazards and potential flood risks. The concentration of 'trees' in flood-affected regions, at 84.41%, further complicates the ecological landscape. These findings emphasise the complexity of managing multiple environmental threats and underscore the need for integrated strategies to safeguard honey bees, preserve ecosystems, and enhance overall resilience in the face of climate-related challenges.

6.5.2 Honey bee habitats that need to be prioritised for protection against bushfire and flood

The critical intersection between honey bee habitats and bushfire risk provides valuable insights into the potential impact of bushfires on these vital ecosystems. In line with previous researches that utilise spatial data on the GIS platform to identify areas for protection (Salem, 2003; Turkyilmaz et al., 2007), this study conducted a combined assessment of suitability and bushfire risk at varying intensity levels to identify specific zones requiring prioritised protection efforts. The analysis highlights the necessity of focusing management strategies on areas that are both highly suitable and moderately suitable for honey bee habitats, while also being exposed to very high to medium potential bushfire intensity and the potential impact of bushfires. These priority areas constitute the most vulnerable regions where the intersection of habitat quality and bushfire risk poses the greatest threat to honey bee populations. By concentrating our efforts on habitats falling into the categories of high to moderate suitability, which are also exposed to potential flood hazards, we can pinpoint regions where the intersection of habitat quality and flood vulnerability necessitates immediate attention.

Moreover, the prioritised areas, encompassing vital ecosystems such as native vegetation and conserved areas, hold dual importance for honey bee populations, both ecologically and economically. These regions play a pivotal role in supporting honey bee health and biodiversity, contributing significantly to agricultural productivity through pollination services. Failing to adequately protect these areas could lead to adverse consequences, including dwindling bee populations and reduced crop yields, underscoring the need for vigilant conservation efforts to safeguard these critical habitats.

6.5.3 Management strategies to protect honey bee habitats from bushfire

Preserving the apiary industry from bushfires necessitates tailored management strategies that adapt to the distinct environmental and anthropogenic variables inherent in each region or country. For instance, different studies have suggested various strategies depending on the specific circumstances (Chemurot et al., 2013). As suggested by previous studies, remote sensing, and GIS technology stand out among the technologies explored for planning bushfire risk management (Perera et al., 2021; Smith et al., 1999). Moreover, it is suggested that analysing various regions for fire risk mapping, similar to the approach in this study, proves to be a successful method, offering valuable insights into areas prone to fires. In this study, considering the land cover and land use composition of the area that is proposed for prioritised protection, the following management strategies are advised.

Strategies to safeguard feral honey bees

- Firebreaks and refuges: Establishment of firebreaks and refuge areas within honeybee habitats to provide safe zones where bees can seek shelter during bushfires.
- Monitoring and Research: Conducting regular monitoring of feral honeybee populations and their habitats to assess their health and responses to fire events.

Strategies to safeguard managed apiary sites:

- Fire-Resistant Apiary Sites: Selection of apiary sites with fire-resistant features such as cleared buffer zones, reduced vegetation, and appropriate distance from potential ignition sources.

- Beehive Protection: Use of fire-resistant materials for hive construction, cover hives with non-combustible materials, and provide adequate ventilation to prevent heat buildup. For instance, Lakov et al. (2022) have developed a collapsible movable frame hive made of ceramic structural elements (panels and profiles) with thermal insulation air chambers. Among its many other benefits, the hive provides protection from fire.
- Beekeeper Training: Provision of beekeepers with training in bushfire preparedness, safety measures, evacuation procedures, and proper equipment usage.
- Government Support: Government funding, grants, and support to aid beekeepers in implementing fire mitigation measures.

6.5.4 Management strategies to protect honey bees from flood

Strategies to safeguard feral honey bees:

- Habitat Preservation: Focus on conserving natural habitats and nesting sites for honey bees in areas less susceptible to flooding.
- Government Support: Government support and funding to aid in habitat restoration efforts after flood events.

Strategies to safeguard managed apiary sites:

- Apiary site selection: Avoiding the areas exposed to potential flood hazard.
- Elevated Hive Stands: Placing beehives on elevated stands to keep them above potential floodwaters.

6.5.5 Limitations

The major limitation of this study stems from the unavailability of more recent maps, particularly those reflecting updated bushfire intensity and flood data. Another limitation of this study is that flood hazards have not been categorised based on their intensity or potential damage, facilitating prioritisation of protection based on the degree of intensity. This emphasizes the importance of developing more detailed flood hazard zones, enabling more informed decision-making. While this study focuses solely on the current threats of bushfire and flood hazards, it is valuable to develop threat zones for future time periods to facilitate decision-making. Considering the significant impact of climate change on natural hazards, it underscores the importance of future research on bushfire and flood prediction in the face of climate change.

6.6 Conclusion

This study contributes valuable insights into the vulnerability of honey bee habitats to natural hazards, specifically bushfires and floods, through the integration of a honey bee suitability map with hazard data. The prioritisation of protection zones, considering both environmental suitability and susceptibility to natural hazards, highlights the precarious situation faced by both honey bee populations and their habitats. The findings underscore the overwhelming impact of bushfires on honey bee habitats, with 97% of these areas at varying levels of risk. This information is crucial for prioritizing conservation efforts and developing effective management strategies, especially given the dominance of 'trees' as the prevalent land cover in bushfire-affected regions. Moreover, the relatively lower risk posed by floods provides a contrasting perspective, enabling a more subtle approach to protection planning. Ultimately, these findings offer actionable intelligence for conservation planning and management, emphasizing the need for targeted efforts in safeguarding honey bee populations and their habitats, particularly in the face of escalating natural hazards. This research not only enhances our understanding of the threats to honey bee habitats but also provides a foundation for informed decision-making in prioritising protection measures to ensure the resilience and sustainability of these vital pollinators.

This study emphasises the critical need for future research in several key areas. There is a pressing need to investigate the behavioural adaptations of honey bees in response to shifting environmental conditions triggered by bushfires and floods. Additionally, it is of paramount need to explore innovative landscape design and management approaches that enhance resilience to these natural disasters. Furthermore, research should delve into the long-term effects of climate change on honey bee habitats and food sources, with a particular focus on predicting how alterations in climate patterns may exacerbate the risks associated with bushfires and floods. An examination of the genetic diversity within honey bee populations is essential to identify traits that confer resilience to environmental stressors. Lastly, understanding the interplay between anthropological activities, farming practices, and honeybee suitability areas is crucial for developing effective conservation strategies and policies. These research endeavours collectively aim to deepen our understanding of honey bee resilience and pave the way for effective strategies to conserve and safeguard these vital pollinators against the threats posed by natural disasters. The findings of this study underscore the significant level of risk faced by honey bee habitats and emphasize the urgent necessity for the implementation of effective management strategies.

CHAPTER 7 - CONCLUSION

7.1 Introduction

This study endeavoured to develop a suitability map to establish apiary sites by analysing pertinent climatic, environmental, and anthropogenic factors. It also predicted changes in honey bee habitat suitability under shifting climate conditions and explored the convergence of natural hazards with honey bee habitats. To accomplish this, the study was structured around three objectives outlined in Chapter 1, with each one being addressed in Chapters 4 to 6.

The thesis presents a comprehensive assessment of land suitability for apiary sites through the application of two fuzzy-based multi-criteria decision analysis (MCDA) methods. It delves into the key bioclimatic and environmental factors influencing suitability, forecasts future trends using an ensemble modelling approach, and formulates strategic management approaches to safeguard the industry. This protection involves a perceptive understanding of the convergence between honey bee habitats, two significant natural hazards, bushfires and floods, and considerations of land cover and land use.

This study is the first to employ a systematic method for rating floral resources concerning honey bees, the most crucial criterion determining land suitability for honey bee habitation, utilising fuzzy logic-based multi-criteria decision analysis (MCDA) methods and relatively high-resolution (250m) climate data. Another innovation offered by this study is the use of an ensemble modelling approach to predict the future distribution of honey bees under changing climate. Moreover, this study assesses the impact of natural hazards on honey bee habitats from a spatial distribution perspective, introducing a novel methodology for identifying priority areas in need of protection against threats such as bushfires and floods. Furthermore, this study proposes management strategies to safeguard valuable honeybee populations from these hazards, considering associated land cover and land use in vulnerable areas.

The innovative aspects of this study, including the utilisation of fuzzy logic-based Multi-Criteria Decision Analysis (MCDA) methods and ensemble modelling, represent significant contributions to assessing honey bee habitat suitability. Fuzzy logic-based MCDA methods offer a sophisticated approach to decision-making by considering the imprecision and uncertainty inherent in ecological data, thereby providing a more comprehensive understanding of habitat suitability for honey bees. Furthermore, ensemble modelling techniques enable the integration of multiple modelling approaches, resulting in more robust predictions of honey bee habitat suitability across diverse landscapes. By explicitly stating the significance of these methods in improving upon existing methodologies, this study enhances the ability to accurately assess and prioritise honey bee habitats, contributing to informed conservation and management efforts.

This chapter presents the summary of findings and overall conclusion of the entire dissertation, along with several recommendations for future research. Organised into four sections, Section 7.2 outlines the summary of findings, while Section 7.3 provides the overall conclusion and major contributions of the study. The chapter concludes with Section 7.4, which offers recommendations for future studies.

This study has contributed new knowledge and fresh insights to the assessment of land suitability for honey bees and the establishment of apiary sites. It also delves into predicting the future distribution of suitable habitats and examines the intersection of threats and habitat suitability. The investigation was conducted using GIS-based techniques and the application of species distribution models.

7.2.1 Spatial and temporal assessment of land suitability for apiary sites using GIS-based fuzzy AHP and fuzzy overlay

The study explained in Chapter 4 developed innovative mapping techniques to detect variations in land suitability for apiary sites, demonstrated through a case study in southern Queensland, Australia. The study employed two Multi-Criteria Decision Analysis (MCDA) techniques infused with fuzzy logic—specifically GIS-based fuzzy AHP and fuzzy overlay. Maps were generated using eleven criteria relevant to assessments, encompassing regional ecosystems, land cover, land use, slope, aspect, elevation, distance to water, distance to roads, rainfall, temperature, and solar radiation. The resulting suitability maps were categorised into four classes: "highly suitable," "moderately suitable," "marginally suitable," and "not suitable." The fuzzy AHP analysis indicated that the study area was predominantly moderately suitable for apiary during spring (67.78%), while the fuzzy overlay analysis suggested marginal to moderate suitability at 69.44% in the same season. Similar trends were observed in the remaining seasons for fuzzy AHP. In contrast, fuzzy overlay consistently displayed a pattern ranging from not suitable to moderately suitable, with nearly equal percentages of around 30% during summer, autumn, and winter. The results underwent validation against existing apiary sites, with fuzzy AHP demonstrating the highest validity across all seasons, ranging from 60% to 70%, and fuzzy overlay accounting for approximately 80% validity in spring but less than 60% in the other seasons.

Furthermore, it was inferred that fuzzy AHP is more effective than fuzzy overlay but should be used with caution. The study's findings can contribute to sustainable apiary management by delineating suitable areas for apiary sites in each of the four seasons. This information can guide apiarists in choosing optimal locations for placing hives based on specific times of the year.

7.2.2 An ensemble modelling approach to predict honey bee habitat suitability for time spans: 2020-2039 and 2060-2079 under changing climate

Chapter 5 illustrated the utilisation of an ensemble modelling approach employing the biomod2 package in R to construct three models: a climate-only model, an environment-only model, and a combined climate and environment model. The climate-only model focused on bioclimatic factors such as radiation of the wettest and driest quarters and temperature seasonality. Using bioclimatic data spanning from 1990 to 2009 and incorporating observed honey bee presence along with pseudo absence data, this model predicted honey bee distribution for two future periods: 2020-2039 and 2060-2079. With a True Skill Statistic (TSS) value of 0.85, the climate-only model highlighted the crucial influence of radiation and temperature seasonality in shaping honey bee distribution. The environment-only model integrated environmental variables, including proximity to regional ecosystems (floral resources), foliage projective cover, and elevation. This model demonstrated robust predictive performance, yielding a TSS of 0.88, underscoring the significance of environmental variables in determining habitat suitability for honey bees. Notably, the combined model exhibited an even higher TSS of 0.96, indicating that the amalgamation of climate and environmental variables enhances the model's accuracy.

Projections for the 2060-2079 period unveiled a concerning trend, with 100% of highly suitable land transitioning into moderately (0.54%), marginally (17.56%), or unsuitable areas (81.9%) for honey bees. These findings underscore the urgent need for targeted conservation efforts and the implementation of policies aimed at preserving honey bees and sustaining the vital apiary industry.

7.2.3 Assessing the confluence of natural hazards, and honey bee habitat suitability to prioritise protection and management strategies.

Chapter 6 endeavoured to pinpoint areas necessitating prioritised protection against bushfires and floods, proposing comprehensive management strategies. Focused on Queensland's primary honey-producing region, the study integrated honeybee habitat suitability, bushfire intensity, and flood vulnerability to map and analyse these threats utilising GIS. The findings indicate that 8,309 km² (97.62%) of honeybee suitable areas, spanning from high to marginal suitability, are at risk of bushfires. Flood-resistant honeybee habitats, constituting 21.5% of the study area, encompass 8,087.25 km² (95%) of areas rated as highly to marginally suitable. Merely 1.03% of honeybee habitats face simultaneous threats from both bushfires and floods.

Areas under threat from bushfires are predominantly characterized by trees (94.11%), with rangelands covering 5.22%. Production native forests represent 66.72% of land within bushfire threat zones, with 99.15% falling under conservation and natural environments. Flood-prone honeybee habitats, ranging from highly to moderately suitable, are mainly characterized by 'trees' (84.41%). Most flood-prone habitats (97.92%) fall under land use categories, conservation, and natural environments.

Management strategies identified for bushfire protection encompass a range of measures, including creating firebreaks, establishing refuge areas, implementing monitoring systems, setting up fire-resistant apiary sites, providing hive protection, offering beekeeper training programs, and government support for fire mitigation. For flood protection, strategies include habitat preservation, government-backed habitat restoration initiatives, site selection criteria, and the use of elevated hive stands. This study emphasizes the critical importance of safeguarding honeybee habitats amid natural disasters, providing valuable insights and strategies to protect these crucial pollinators and the ecosystems they support.

7.2.4 Overall summary

In summary, this thesis has shown the following:

a. The ratings for floral resources allocated to honey bees demonstrate a positive correlation with the highly suitable area for each season, underscoring the substantial reliance of honey bee suitability on the availability of melliferous floral species for a considerable period of time. Thus, when developing a methodology to map suitable locations for apiary sites, the inclusion of floral resource information is the most important aspect.
b. Overall, fuzzy AHP is proven to be a more accurate method for assessing honey bee habitat suitability than fuzzy overlay.
c. Radiation of the wettest and driest quarters and the temperature seasonality are the primary bioclimatic variables that determine the habitat suitability for honey bees. Proximity to regional ecosystems (floral resources), foliage projective cover, and elevation are the most influential environmental variables for honey bee habitat suitability.
d. Due to climate change, by the 2020-2039 period, approximately 88% of highly suitable habitats for honey bees are predicted to transition from their current state to become moderate to marginally suitable areas. This transformation is predicted to result in a complete change of highly suitable habitats to different categories by the years 2060 to 2079.
e. Most honeybee-suitable areas (97.62%) face bushfire risks, while flood-safe habitats (21.5% of the area) cover 95% of those with high to marginal suitability. Only 1.03% of habitats face both bushfire and flood threats. Bushfire-threatened zones are tree-dominated (94.11%), with most land (66.72%) in these zones being production native forests under conservation. Flood-prone honeybee habitats (84.41% trees) are mostly under conservation (97.92%).

The above findings suggest the following:

a. When developing a methodology to map suitable locations for apiary sites, the inclusion of floral resource information is the most important aspect apart from other biophysical parameters.

b. Even though the fuzzy AHP method is deemed more appropriate for suitability analyses in apiary management, in instances where it can be assumed that the contribution of each criterion towards suitability is equal, fuzzy overlay can be used since the implementation of fuzzy overlay is relatively easier when compared with Fuzzy AHP.

c. Due to climate change, there is a projected significant impact on the habitats suitable for honey bees.

d. Honeybee habitats face a higher vulnerability to bushfires compared to floods.

e. When devising effective management strategies for mitigation, the focus should be on understanding the environments where honey bees thrive, the challenges they encounter, and potential conservation measures.

7.3 Conclusion

This research significantly advances existing knowledge on assessing land suitability for apiary sites, employing innovative approaches such as fuzzy logic-based multi-criteria decision analysis methods (MCDA). Through fuzzy AHP and fuzzy overlay methods, land suitability maps were developed for southern Queensland, Australia, offering valuable insights for apiarists and authorities. While fuzzy AHP proves more suitable for land suitability analyses, fuzzy overlay offers simplicity, suggesting the potential benefits of employing multiple MCDA methods. Moreover, ensemble species distribution modelling explores projected shifts in honey bee habitats amidst changing climates across two future time periods. Predictive maps indicate significant declines in suitable honey bee habitats, highlighting vulnerability to climate change and its potential impacts on ecosystems and the economy. Furthermore, this study contributes novel knowledge to identifying priority areas for safeguarding against bushfires and floods. Integrating honey bee suitability maps with hazard data underscores the vulnerability of honey bee habitats to natural hazards, particularly bushfires, emphasising the need for targeted conservation efforts. Conversely, floods present a relatively lower risk, allowing for a nuanced approach to protection planning.

As the findings of this study reveal a concerning trend: honey bee land suitability is significantly decreasing due to the impacts of climate change and the extent of suitable land is further reduced due to confluence of natural hazards. As climate change exacerbates the frequency and intensity of events such as bushfires and floods, the current extent of land suitable for honey bees is further diminished. This reduction in suitable habitat poses serious implications for honey bee conservation and apiary management. With fewer areas available for foraging and nesting, honey bee populations may face increased stress and decline. Additionally, beekeepers may experience challenges in maintaining healthy hives and securing adequate resources for their bees. To address these issues, urgent action is needed to mitigate the impacts of climate change and natural hazards, protect and restore critical honey bee habitats, and implement adaptive management strategies within apiaries. Without proactive measures, the future viability of honey bee populations and the sustainability of apiary operations are at risk.

7.4 Contributions

The present work makes significant contributions to science, including the following:

- Enhanced understanding of the application of fuzzy AHP and fuzzy overlay in assessing the land suitability for apiary sites. More specifically, the standardisation of criteria in fuzzy overlay reveals how variations in each criterion impact the suitability of land for apiary sites.
- This study pioneered the examination of spatial and temporal variations in land suitability for apiary sites, being the first study to investigate deviations influenced by seasonal changes.
- This study presents a novel method for assessing the rating of floral resources for honey bees. The approach takes into account both the specific value of a floral species to honey bees and the duration of flowering for the same species.
- The land suitability assessment, considering both spatial and temporal variations of relevant criteria, could be applied to honey bee industries and agricultural systems worldwide.

- The first study to use an ensemble modelling approach to create current and future honey bee habitats.
- New knowledge on shifts in honey bee habitats in the face of climate change.
- Identification of the most influential bioclimatic and environmental variables and quantification of their contribution towards honey bee habitat suitability.
- A methodology to determine honey bee habitats that need prioritisation for protection from natural hazards.
- New knowledge on introducing management strategies to protect honey bee habitats and colonies from bushfires and floods, considering the underlying land cover and land use.
- The findings have global relevance for informing honey bee conservation and apiary management. Understanding how climate change and natural hazards affect honey bee land suitability helps stakeholders anticipate challenges worldwide and guides the development of adaptive strategies to support global honey bee populations and the apiary industry's sustainability.
- Recognition of the economic importance of honey bee habitats and pollination services underscores the need for global conservation measures.

7.5 Recommendations

Based on the preceding discussions, the study results could be applied in the following practical scenarios:

- The methodology generated by the study to rate floral resources for honey bees could be adopted in other studies concerning land suitability analysis for honey bees or apiary sites.
- The land suitability assessment methodology followed in the study could be implemented for other agricultural crops.
- Assess the efficacy of existing policies and investigate the potential policy implications of the research findings.
- The methodology outlined in Chapter 6, designed to identify areas requiring prioritised protection from natural hazards following the determination of risk mitigation

strategies, can be effectively applied to other agricultural regions vulnerable to such hazards.

Also, the following are recommended for future research:

- It is recommended to conduct a comparative analysis between fuzzy AHP and AHP in assessing the suitability of sites for apiaries. This comparison can serve as a means to evaluate the effectiveness of employing a crisp number, as in the traditional AHP, versus the defuzzification approach. Such an examination may potentially support the argument that the AHP scale inherently encompasses fuzzy elements.
- Another potential expansion of this research involves evaluating alternative MCDA methods in conjunction with fuzzy logic.
- Moreover, the study could be broadened by examining the monthly fluctuations of pertinent criteria instead of focusing solely on seasonal variations, aiming to improve precision.
- It is recommended to explore potential strategies for adapting honey bee management to address the challenges posed by climate change. These approaches may involve examining additional food sources for honey bees, implementing selective breeding, adopting inventive hive management techniques, and strategically planning landscapes to boost honey bee resilience while mitigating the adverse effects of evolving climatic conditions.
- It is recommended to examine the long-term effects of climate change on floral resources for honey bees.
- It is essential to contribute the current knowledge base on honey bee genetic diversity by conducting research on the genetic diversity within honey bee populations.
- It is suggested to identify specific genetic traits that confer resilience to environmental stressors, particularly those associated with bushfires and floods.

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APPENDIX A – SUPPLEMENTARY DATA

Appendix Table 1: Thirty-five bioclimatic variables used for multicollinearity testing (Sourced from the New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling (NARCliM) database) (Hutchinson & Xu, 2015)

Variable Number	Variable	Minimum temp (°C)	Maximum temp (°C)	Rainfall (mm month^{-1})	Radiation (W m^{-2}d^{-1})	Pan evaporation (mmd^{-1})
Bio01	Annual mean temperature (°C)	×	×			
Bio02	Mean diurnal temperature range (mean(period max-min)) (°C)	×	×			
Bio03	Isothermality (Bio02 ÷ Bio07)	×	×			
Bio04	Temperature seasonality (C of V)	×	×			
Bio05	Max temperature of warmest week (°C)		×			
Bio06	Min temperature of coldest week (°C)	×				
Bio07	Temperature annual range (Bio05-Bio06) (°C)	×	×			
Bio08	Mean temperature of wettest quarter (°C)	×	×	×		
Bio09	Mean temperature of driest quarter (°C)	×	×	×		
Bio10	Mean temperature of warmest quarter (°C)	×	×			
Bio11	Mean temperature of coldest quarter (°C)	×	×			
Bio12	Annual precipitation (mm)			×		
Bio13	Precipitation of wettest week (mm)			×		
Bio14	Precipitation of driest week (mm)			×		
Bio15	Precipitation seasonality (C of V)			×		
Bio16	Precipitation of wettest quarter (mm)			×		
Bio17	Precipitation of driest quarter (mm)			×		

Variable Number	Variable	Minimum temp (°C)	Maximum temp (°C)	Rainfall (mm month^{-1})	Radiation (W m^{-2}d^{-1})	Pan evaporation (mm d^{-1})
Bio18	Precipitation of warmest quarter (mm)	×	×	×		
Bio19	Precipitation of coldest quarter (mm)	×	×	×		
Bio20	Annual mean radiation (W m-2)				×	
Bio21	Highest weekly radiation (W m-2)				×	
Bio22	Lowest weekly radiation (W m-2				×	
Bio23	Radiation seasonality (C of V)				×	
Bio24	Radiation of wettest quarter (W m-2)			×	×	
Bio25	Radiation of driest quarter (W m-2)			×	×	
Bio26	Radiation of warmest quarter (W m-2)	×	×		×	
Bio27	Radiation of coldest quarter (W m-2)	×	×		×	
Bio28	Annual mean moisture index			×		×
Bio29	Highest weekly moisture index			×		×
Bio30	Lowest weekly moisture index			×		×
Bio31	Moisture index seasonality (C of V)			×		×
Bio32	Mean moisture index of wettest quarter			×		×
Bio33	Mean moisture index of driest quarter			×		×
Bio34	Mean moisture index of warmest quarter	×	×	×		×
Bio35	Mean moisture index of coldest quarter	×	×	×		×

Appendix Table 2: The ODMAP protocol followed for the development of honey bee species distribution models and prediction of habitat suitability in future

ODMAP Section/ Subsection	ODMAP Elements
OVERVIEW	
Authorship	▪ **Authors:** Sarasie Tennakoon, Armando Apan, and Tek Maraseni ▪ **Contact e-mail:** sarasie.tennakoon@gmail.com, sarasie.tennakoon@usq.edu.au ▪ **Title:** Unravelling the Impact of Climate Change on Honey Bees: An Ensemble Modelling Approach to Predict Shifts in Habitat Suitability in Queensland, Australia
Model objective	▪ **Objective:** Identify the most influential bioclimatic and environmental variables and quantify their relative importance on honey bee distribution. Predict habitat suitability for honey bees in two future time-spans: 2020-2039 and 2060-2079. ▪ **Target outputs:** Habitat suitability maps based three climate scenarios: 1990-2009, 2020-2039 and 2060-2079, environmental variables and a combined climate and environment variables.
Taxon	European honey bee, *Apis mellifera*, Apis, Apidae, Hymenoptera, Insecta
Location	Queensland, Australia
Scale of analysis	▪ **Spatial extent (Lon/Lat):** 150^{0}12' - 151^{0}97' E, 27^{0}77' - 27^{0}68' S, covering an extent of 37,650 km^2 in Southern Queensland, Australia ▪ **Spatial Resolution:** 250m ▪ **Temporal extent/time period:** Honey bee occurrence data- 1990 to present; environmental data - present, and bioclimatic variables – 1990-2009, 2020-2039 and 2060-2079 ▪ **Type of extent boundary:** Political (Local Area Boundaries)
Biodiversity data overview	▪ **Observation type:** Managed apiary site locations (records), human observations, machine observations ▪ **Response/Data type:** Presence-only

ODMAP Section/ Subsection	ODMAP Elements
Type of predictors	Bioclimatic and environmental variables
Conceptual model / hypothesis	▪ **Hypothesis about species-environment relationships:** Distribution of a species is in equilibrium with the environmental and climatic factors that have an influence on that species. Honey bee distribution is mainly influenced by the bioclimatic variables, radiation in wettest and driest quarters, and temperature seasonality and the environmental variables proximity to regional ecosystems (floral resources), foliage projective cover and elevation.
Assumptions	▪ Species' distribution is at equilibrium with their environment ▪ Species presence data are a representative sample of the species distribution across the study area ▪ Pseudo absence data/background data can be treated as absence data ▪ All the key predictor variables of the species under consideration are accounted for in the model
SDM algorithms	**Algorithms:** Artificial Neural Network (ANN) Classification Tree Analysis (CTA) Flexible Discriminant Analysis (FDA) Generalised Additive Model (GAM) Generalised Boosting Model (GBM) Generalised Linear Model (GLM) Multiple Adaptive Regression Splines (MARS) Maximum Entropy (MAXENT) Random Forest (RF) Surface Range Envelope (SRE) ▪ **Model complexity:** Ten modelling algorithms were used

ODMAP Section/ Subsection	ODMAP Elements
	▪ **Model averaging:** The models with TSS>0.7 were used to develop ensemble models pertaining to climate-only and the combined climate and environment scenarios whereas the models with a TSS>0.6 were incorporated in building the environment only model
Model workflow	▪ Included honey bee presence data pertaining to both human managed systems and natural occurrences ▪ The presence data were rarefied using the SpThin package in R to reduce sample bias. ▪ Initially, 8 environmental variables and 35 bioclimatic variables were selected and tested for multicollinearity using USDM (Uncertainty Analysis for Species Distribution Models) package in R to avoid model overfitting and reduce uncertainty in model parameters. ▪ Variables with a correlation coefficient >0.8 and variance inflation factor (VIF) >5 were excluded from further analysis. ▪ The most influential 3 bioclimatic variables and the 3 environmental variables were retained following a stepwise removal of the least contributing variables. ▪ Five-thousand pseudo absence data were generated, and this process was repeated for three times to avoid random bias. ▪ Presence and absence data were divided into training (80%) and testing data (20%). ▪ The raster layers were processed to have a cell size of 250m×250m and projected to WGS84 coordinate system using ArcMap 10.8.1 ▪ The modelling process consisted of 90 model runs that included ten modelling algorithms, three pseudo absence generation runs, and three evaluation runs. ▪ Using the ensemble modelling option available in BIOMOD2, an ensemble species distribution model was constructed by applying multiple algorithms above a selected threshold.

ODMAP Section/ Subsection	ODMAP Elements
	▪ Three models namely the climate-only model, the environment-only model, and the combined climate (1990-2009) and environment model were developed. ▪ The climate-only model was developed using the three most influential bioclimatic variables for honey bees, namely Bio4 (temperature seasonality), Bio24 (radiation of the wettest quarter), and Bio25 (radiation of the driest quarter). ▪ The three environmental variables with the highest contribution to the model i.e., proximity to regional ecosystems (floral resources), foliage projective cover, and elevation were used in building the environment-only model. ▪ The combined climate and environment model was developed by incorporating the environmental and bioclimatic variables from both environment-only and climate-only models. These variables included foliage projective cover, proximity to regional ecosystems, elevation, bio4, bio24, and bio25. ▪ Suitability maps were generated using BIOMOD2 for each scenario under consideration, namely: climate-only (1990-2009), environment-only, and the combined climate and environment model. Using ensemble forecasting, suitability maps for the two future scenarios i.e., 2020-2039 and 2060-2079 were generated.
Software, codes, and data	▪ **Modelling platform:** BIOMOD2 package on R (Version 4.2.2) ▪ **Code:** Code is shared in DRYAD data repository ▪ **Data:** Data is shared in DRYAD data repository
DATA	
Biodiversity data	▪ **Taxon names:** *Apis mellifera* ▪ **Taxonomic reference system:** N/A ▪ **Ecological level:** Species level ▪ **Data source:**

ODMAP Section/ Subsection	ODMAP Elements
	Honey bee presence data were derived from the Queensland Spatial Catalogue and Atlas of Living Australia (time period from: 1990 to present) ▪ **Sampling design:** N/A ▪ **Sample size:** 1,595 presence records collected from the study area in Southern Queensland, Australia ▪ **Absence data:** Five-thousand pseudo-absence data were generated ▪ **Data cleaning and filtering:** SpThin package in R was used to rarefy the presence data
Data partitioning	▪ The honey bee presence and pseudo-absence data were divided into training (80%) and testing (20%) sets
Predictor variables	▪ **Predictor variables:** a. Bioclimatic variables — Temperature seasonality (BIO4), Radiation in wettest quarter (BIO24), and Radiation in driest quarter (BIO25) b. Environmental variables — Proximity to regional ecosystems (floral resources), Foliage Projective Cover, and Elevation ▪ **Data sources:** 1. Bioclimatic variables: New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling (NARCliM) 2. Regional ecosystems and foliage projective cover: Queensland Spatial Catalogue: Queensland Government (https://qldspatial.information.qld.gov.au) 3. Elevation: GEODATA 9 Second Digital Elevation Model (DEM-9S) Version 3 from Geoscience Australia (https://ecat.ga.gov.au) ▪ **Data processing:** The raster layers were extracted, projected, and resampled using Arcmap10.8.1 ▪ **Spatial resolution of raw data:** 250m, 25m ▪ **Projection:** WGS84

ODMAP Section/ Subsection	ODMAP Elements
MODEL	
Variable pre-selection	▪ Thirty-five bioclimatic variables and eight environmental variables were selected. ▪ The variables with correlation coefficients >0.8 and VIF>5 were removed from further analysis. Only 4 bioclimatic variables and all 8 environmental variables were retained based on the results of multicollinearity testing. ▪ The most influential variables were retained following a process of removing the least contributing variables.
Multicollinearity	▪ Multicollinearity among the predictor variables were tested using the USDM (Uncertainty Analysis for Species Distribution Models) package in R.
Model settings	▪ Default settings for BIOMOD2
Model estimates	▪ **Model coefficient:** TSS, ROC and KAPPA ▪ **Variable importance:** Importance of predictor variables in the three different models were calculated
Model averaging / ensembles	▪ To develop climate-only and the combined model, the models with a TSS>0.7 were selected whereas to develop the environment-only model, the algorithms with TSS>0.6 were selected.
Non-independence	▪ No test was performed to test for non-independence of the models.
ASSESSMENT	
Performance statistics	▪ **Performance statistics estimated on training data:** Model performances were assessed using the TSS scores
Plausibility checks	▪ **Response plots:** Ecological plausibility was tested using the response curves for the predictor variables.
PREDICTION	

ODMAP Section/ Subsection	**ODMAP Elements**
Prediction output	▪ The continuous probability maps were classified into four categories as highly suitable, moderately suitable, marginally suitable and not suitable.
Uncertainty quantification	▪ **Algorithmic uncertainty:** Ensemble forecasting was employed to reduce model-based uncertainty and consensus method was utilised to combine outputs of individual algorithms ▪ **Reality check:** On-ground reality was validated against the existing locations of managed apiary sites and honey bee occurrences.

Appendix Table 3: Performance of models resulting from different combinations of predictor variables

	TSS	ROC	KAPPA	Variable Importance
Climate Only				
Bio4 + Bio24 + Bio25	0.85	0.98	0.72	Bio4 36.42% Bio24 36.73% Bio25 26.86%
Environment Only				
RE + Elevation + Distance to roads	0.80	0.95	0.60	RE 40.84% Elevation 1.9% Distance to roads 57.29%
RE + Elevation + Aspect	TSS value of each algorithm < 0.6			
RE + Elevation + Slope	TSS value of each algorithm < 0.6			
RE + Elevation + Distance from trees	TSS value of each algorithm < 0.6			
RE + Elevation + Distance to water	TSS value of each algorithm < 0.6			
RE + Elevation + FPC (TSS cut off 0.6)	0.88	0.98	0.75	RE 34.10% Elevation 8.54% FPC 57.36%
RE + FPC (TSS cut off 0.6)	0.80	0.96	0.64	RE 25.82% FPC 74.18%
Climate + Environment				
RE + FPC + Bio4 + Bio24 + Bio25	0.93	0.99	0.89	RE 19.90% FPC 21.42% Bio4 7.19% Bio24 32.34% Bio25 19.15%
RE + FPC + Elevation+ Bio4 + Bio24 + Bio25	0.92	0.99	0.87	RE 16.76% FPC 24.10% Elevation 5.57% Bio4 5.01% Bio24 29.63% Bio25 18.93%

APPENDIX B - PUBLICATIONS DURING THE PHD STUDY PERIOD

Journal Paper

Sarasie Tennakoon, Armando Apan, Tek Maraseni, Richard Dein D. Altarez, Decoding the impacts of space and time on honey bees: GIS based fuzzy AHP and fuzzy overlay to assess land suitability for apiary sites in Queensland, Australia, *Applied Geography*, Volume 155, 2023, 102951, ISSN 0143-6228, https://doi.org/10.1016/j.apgeog.2023.102951. (https://www.sciencedirect.com/science/article/pii/S0143622823000826)

Tennakoon, S., Apan, A., & Maraseni, T. (2024). Unravelling the impact of climate change on honey bees: An ensemble modelling approach to predict shifts in habitat suitability in Queensland, Australia. Ecology and Evolution, 14(4), e11300. https://doi.org/10.1002/ece3.11300

Paper in Preparation

Sarasie Tennakoon, Armando Apan, Tek Maraseni, Assessing the confluence of natural hazards, and honey bee habitat suitability: A geospatial approach to prioritise protection and management strategies, *Science of the Total Environment*.

Conference Presentations

Sarasie Tennakoon, Armando Apan, Tek Maraseni, Richard Dein D. Altarez, Spatial and Temporal Assessment of Land Suitability for Beekeeping in Queensland, Australia using GIS Based Fuzzy AHP and Fuzzy Overlay. *Locate23, The Geospatial Event*, 10 – 13 May 2023, Adelaide, Australia