IMPACT OF PROJECTED CLIMATE CHANGE ON THE SPREAD AND DISTRIBUTION OF THE INVASIVE ALIEN SPECIES *Maesopsis eminii* Engl. IN WAYANAD DISTRICT OF KERALA

by

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(2016-20-021)

THESIS

Submitted in partial fulfilment of the requirements for the degree of

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DECLARATION

I, Aswathykrishna. P. N, (2016-20-021) hereby declare that this thesis entitled "**Impact of projected climate change on the spread and distribution of the Invasive Alien Species *Maesopsis eminii* Engl. in Wayanad district of Kerala**" is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar titles, of any other University or Society.

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<u>CERTIFICATE</u>

Certified that this thesis entitled **"Impact of projected climate change on the spread and distribution of the Invasive Alien Species *Maesopsis eminii*** Engl. **in Wayanad district of Kerala"** is a record of research work done independently by Ms. Aswathykrishna. P. N., under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

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ABBREVIATIONS

AUC	Area under the curve
Bio 1	Annual mean temperature
Bio 2	Mean diurnal range
Bio 3	Isothermality
Bio 4	Temperature seasonality
Bio 5	Maximum temperature of the warmest month
Bio 6	Minimum temperature of the coldest month
Bio 7	Temperature annual range
Bio 8	Mean temperature of wettest quarter
Bio 9	Mean temperature of driest quarter
Bio 10	Mean temperature of warmest quarter
Bio 11	Mean temperature of coldest quarter
Bio 12	Annual precipitation
Bio 13	Precipitation of wettest month

Bio 14	Precipitation of driest month
Bio 15	Precipitation seasonality
Bio 16	Precipitation of wettest quarter
Bio 17	Precipitation of driest quarter
Bio 18	Precipitation of warmest quarter
Bio 19	Precipitation of coldest quarter
ES	Ecosystem services
GCMs	General Circulation Model
IAS	Invasive alien species
LULC	Land cover and landuse changes
MaxEnt	Maximum Entropy Modelling
RCPs	Representative Concentration Pathways

CHAPTER 1

INTRODUCTION

The 21st century has seen an advert increase in the impacts due to climate change. Climate change has its adverse impacts on floral and faunal communities finally questioning human existence in total. The uncontrollable greenhouse gas emissions and harmful gases which are released from anthropogenic activities contribute to tremendously increasing the levels of climate change impacts. Anthropogenic activities, according to the IPCC, have caused global temperatures to rise by 0.8 to 1 ºC. In the future mid-latitudes will experience extreme hot days with tropics seeing the rise. At the same time, excess rain at several locations around the world has been predicted. These will influence biodiversity and ecosystems, resulting in the extinction of species. If the temperature rises by 1.5 degree Celsius, six percent of insects, eight percent of plants and four percent of insects might be wiped out of their climatologically accepted habitats (IPCC, 2018).

The threat by invasive alien species (IAS) is regarded as the second most reason for the destruction to biodiversity and species habitats. This includes the introduced flora, fauna as well as other organisms which threaten the ecosystem and habitats of other species with their way of spread and establishment. Areas where high human interventions have been noticed, be it agricultural farmlands or landscapes modified for urban settlements have been turned into pristine environments by invasive species. According to Shreshta (2018), the alien species do have negative impacts on human intervened sectors like agricultural production, regeneration of forests, grazing of livestock, native vegetation, human health and habitats. Scientists had reported the invasions biologically caused by invasive plant species as one of the serious threats to biological diversity. Biological invasions are regarded as one of the many factors that results in environmental degradation around the world. A habitat is made vulnerable to the native flora by the invasive plants as they delimit the physical and biological factors that supports their growth and stimulations. This includes reducing the uptake of available resources such as light, water and nutrients and disrupting the biogeochemical cycles as well (Shrestha *et al.,* 2018).

Maesopsis eminii belongs to family Rhamnaceae, that has species which are tolerant to drought. It is a large tree that is fast growing. It is popularly reputed as a plantation tree. Native to Africa, it is a useful timber in the humid tropics and occurs in the rainforests. This is commonly used as shade trees in coffee plantations and *M. eminii* colonizes forest canopy openings, grasslands and empty niches and also occupies disturbed areas in forests (Joshi *et al*., 2015). *M. eminii* apart from India and Africa has also been noticed in Bangladesh, Puerto Rico, Malaysia, Rwanda and Indonesia.

With the mapping of the current and future distribution of the IAS species, it is possible to find out its distribution and adopt necessary management practices to eliminate them from suppressing the native species and spreading to newer areas. A prediction about climate change impact will throw light on the future spread by creating suitable habitats for the species. The objective of this work is thus to map the current distribution of *Maesopsis eminii* Engl. in Wayanad and map the predicted distribution of the species under RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5

CHAPTER 2

LITERATURE REVIEW

2.1 Climate change and biodiversity

The changes in climate have become a noticeable and pressing talk of our day, putting great strain on society and the environment. Significant changes in temperature have been observed, and these changes appear to be the result of higher quantities of greenhouse gases. Anthropogenic activities, according to the IPCC, have caused global temperatures to rise by 0.8 to 1 degree Celsius (IPCC, 2018). In the future, it will be common for the mid-latitudes to see extreme hotter days with the tropics experiencing the greatest rise. Around the globe it is possible for many regions to experience heavy rain showers as well. The aforementioned changes in climate can affect the biodiversity and ecosystem habitats brutally resulting in the extinction of species.

Climate change is already influencing the biodiversity of the world. Climate change is expected to result in a decrease in the number of species in their geographic ranges, as well as a decrease in their abundance (Raman *et al*., 2020). The major forces that degrade the structural and functional integrity of ecosystems include the rapid changes in the climate, fragmentation in habitats, alien species and its invasion, pollution caused by air, water and soil, habitat destruction, nature and its exploitation and human population explosion. Climate variables (temperature, precipitation, humidity, and so on) have a substantial effect on plant growth and development thus governing plant species distribution. Throughout history, climate systems have tended to shift organically (around 4.5 billion years) (Coban *et al*., 2020). Extreme environmental circumstances were formed as a result of these changes, causing species to become extinct or altering their natural environment. Human kind is more conscious of global climate emergency now than ever before (Coban *et al*., 2020).

2.2 Invasive alien species

Biological invasion is generally defined as the initiation and establishment of a foreign species having invasive nature outside of its normal scale, whereby it could flourish resulting in its rapid spread. Invasive plant species, according to the International Union for Conservation of Nature (IUCN), are plants that have established themselves in natural or semi-natural ecosystems or habitats, have become agents of change, and pose a threat to native biological diversity (IUCN, 1998). Invasive alien species (IAS) are species that endanger biodiversity by being introduced and/or spreading outside of their geographic distribution (CBD, 2010). According to CBD, IAS can damage many varieties of habitats and can be found in all phylogenetic groupings, including animals, plants, fungi, and microbes. While only a small fraction of species brought to changing environments become invasive, the detrimental consequences can be severe, and these contributions can accumulate over time. Human mobility and trade are the most common vectors for species transmission. If a species' new habitat is sufficiently comparable to its native range, it has a chance of surviving and reproducing. To become invading, a species must outcompete local creatures, expand through its new environment, rise in population density, and cause harm to ecosystems within its invaded area. To summarize, an alien species must arrive, live, and thrive in order to become invasive. Rapid reproduction and growth, great dispersal ability, phenotypic plasticity (ability to adjust physiologically to new situations), and the capacity to survive on a variety of food sources and in a wide range of environmental conditions are all common traits of IAS. The success or failure of a species' invasion elsewhere is a good indicator of invasiveness (CBD, 2010). Scientists had identified bio invasions caused by foreign species that is invasive in nature as one of many serious threats to biodiversity as well as one among the primary causes of habitat degradation across the globe. Invasive plants, both woody and herbaceous, have become increasingly common in forest ecosystems and rangelands. Some exotic plant species can have outpouring effects, such as changing composition of trees, ecological succession, ecological diversity reductions, and influence nitrogen, water and carbon cycles.

Both biological and environmental factors have an effect on the potential exotic plant species to take over and colonize natural ecosystems. The primary steps in the natural restoration of exotic plant species is seed germination. Density of light, temperature, and content of moisture all have an impact on the process. Studying seed characteristics and germination behavior is thus a crucial step toward developing guidelines and tactics for invasive plant species prevention and management (Mwendwa *et al*., 2020). Almost a sixth of the world's terrain is currently endangered to alien species seizure, together with key expanse of growing providence and intercontinental biodiversity hotspots (Lamsal *et al*., 2017).

2.3 Effects of biological invasion

Foreign born plant species that have been brought to a new geographic expanse, both intentionally as well ass accidentally, and have a negative influence on agriculture, horticulture, and wild ecosystems are known as invasive plant species. (Adhikari *et al*., 2019). By influencing the nitrogen cycle, raising acid content in the soil, arising competition with native flora, and delaying their regrowth, they disrupt the successive balance of species and its environment and jeopardize ecosystem function (Adhikari *et al*., 2019).

In the current environment of climate change, many invasive plant populations are evolving adaptations that could result in rapid community expansion in the future. As a result, Invasive Alien Plant Species (IAPS) has emerged as a severe danger to habitat and ecosystems, and climate change may expand its spread (Lamsal *et al*., 2017). Climate change exacerbates ecosystem vulnerabilities and losses through a variety of mechanisms, including the elimination of climatic barriers and the facilitation of the spread of invasive species. When compared to native plant species, invading plant species have a stronger potential to move their niche faster and are more likely to adapt to new environments (Adhikari *et al*., 2019).

IAPS' rapid rate of growth, widespread temperature or ecological resistance, low reproductive period, persistent production, low germination percentage, great dispersing, and rapid ability to reproduce asexually are among some of the unique qualities that emerge when they invade new areas (Lamsal *et al*., 2017). In contrast to native plants, which have a much longer residency duration, invasive plant species often have only a few decades or a few centuries in their invaded regions. Aside from the temporal constraint, founder effects (a reduction in the number of the populace and genetic variability) may also limit invasive plants' ability to evolve local adaptation quickly (Oduor *et al*., 2016). Furthermore, invading plant species benefit more than native plant species from carbon-di-oxide accumulation in the atmosphere and rising temperatures. As a result, comprehensive research of changes in the climate and ecological invasion is required for protracted management of exotic species. Invasive species research has attracted a lot of attention in recent decades, with many studies focusing on mapping the distribution of invasive species, estimating economic and ecological implications, and proposing efficient and cost-effective control strategies (Thapa *et al*.,2018).

2.4 Global biological invasion

In International governance, flora and fauna which have been established beyond their geomorphological habitat by humankind, have a documented ecological or socioeconomic consequence, and can support a self-replacing community are classified as invasive alien species (IAS) (IUCN, 1998). Species invasions are an environmental issue of enormous worldwide relevance because of their significant and costly global repercussions (Turbelin *et al.,* 2016). Invasive alien species (IAS) pose a significant threat to species diversity, commerce, and human life. The pace upon which IAS plantlets are transported, as well as the level of disturbance that facilitates IAS development, both have been shown to increase the risk of infestation in any given region. Economically advanced countries, particularly most with a high Population Density, today have much more IAS, the most comprehensive IAS mitigation initiatives, as well as the most understanding well about spread of intrusions on the planet. Prospective colonization trends, from the other side, are considerably distinct from todays. (Early *et al.,* 2016).

Today, more than at any other moment in human history, the concentrations and trends of emergence and interruptions are changing at a quicker pace over the world. As a consequence of worldwide trade, IAS are readily incorporated as fugitives or pollutants in commodities and shipping materials. The veterinary and horticultural industries are primary contributors of floral and faunal invasions, and often a primary avenue for both the introduction of insect pests and pathogens transmission, owing to the occasional breakout or transfer of foreign species further into wild. Invading key differentiators are passenger flight stowaways, which are a highly prevalent cause of IAS infestations. Shipping and port terminals also serve as invasion hardest hit areas. Disturbance encourages the formation of IAS. One of most prominent perturbation drivers on a global basis are agricultural extension, alterations in the makeup of indigenous populations as a consequence of climate change (biome shifts), and escalating catastrophes (Early *et al.*,2016).

2.5 Biological invasion- India

South Asia's terrain, ecotones, and climate regimes are all different when compared to that of other continental biogeographical aspects. In these areas, the impact of climate change on biodiversity is significant. The southwest monsoon and the Himalayan high mountains influence the climate here. Floods have occurred in the Bay of Bengal in recent decades as a result of extreme rainfall and a series of meteorological "lows" and "depressions." Low rainfall during the non-monsoon season causes moisture stress, and drought affects diverse places. Global climate change has changed the rainfall patterns and temperature regimes in India. From 1881 to 1997, the average yearly temperature increased by 0.57 °C. Furthermore, with a temperature increase of the average of 0.49 °C, the previous decade (2001–2010) was declared the warmest decade (IMD, 2015).

At moderate to high levels of climatic adaptability, almost 49% of India's entire geographical area was anticipated to be vulnerable to invasion (Adhikari *et al.*, 2015). A hotspot of alien plant invasion was defined as the confluence of human made biomes and ecosystem functions with 'extreme' climate zones adaptability. The bulk of India's ecologically sensitive areas, such as 'mega - diverse' and coastlines, are also invading top destinations, illustrating the country's sensitivity to species encroachment. Despite the great taxonomic variety, quick proliferation, and broad IAS allocation territory in India, the scientific and policymaking communities have not paid enough attention to the problem. The bulk of conserved regions in India are found in ecological hotspot zones, which have the greatest proportion of forest cover. As a result of ecological competition, changing farming, agricultural production, and urbanism, these biodiversity hotspots have lost a significant amount of forest cover in the last three decades. As a result of these perturbations, the environmental conditions become unbalanced, making these places open to invasion. The existence of 'empty niches,' i.e., unfilled openings for extra species in ecosystems, or the creation of new 'ecological opportunities' for occupancy by the IAS, could explain ecosystem sensitivity to invasion. The Andaman Islands, coastline forests, wetlands, mangrove environments, and other forest reserves in India are all invasion hotspots (Adhikari *et al.*, 2015).

2.6 Biological invasion- Kerala

Kerala is located in India's humid tropical high rainfall region and is classified as a "warm humid", the mean monthly maximum temperature and relative humidity are used to determine the climate zone. The southwest (June-September) and northeast (October-December) monsoon seasons have a significant impact on the regional climate (Jose *et al*., 2020). The Western Ghats (WG), one of the world's greatest biodiversity - rich regions, present, has a huge impact on Kerala's climate because it feeds a substantial amount of precipitation to Peninsular India. During the summer months, prolonged drought distress is common in Kerala. Studies have suggested a decrease in yearly rainfall in Kerala's southern districts, but the similar patterns may not seem to be occurring in the north of the country. In comparison to 1980s temperatures, the Kerala region is expected to experience a 1.5°C increase in mean surface temperature during the monsoon season throughout the decade 2040–2049 (Jose *et al.,* 2020).

With just a tropical warm climate and a long history of maritime trade between Europe, the Middle East, and other landmasses, Kerala State in southwest India has prepared the path for the advent of exotic species to the region at a preliminary phase. The preponderance of IAPs in Kerala are native to south America, which supports the hypothesis that invading species travel across latitudes. The current openness of global markets, which has increased in the types and quantity of items imported, has aided IAS invasion more than ever before. According to the risk assessment, ten are high risk, twelve are medium risk, ten are low risk, and the remaining six are of little danger. Despite its limited distribution, *Maesopsis eminii* is emerging as a medium-risk species in Wayanad (Sankaran *et al*., 2013).

2.7 Maesopsis eminii

Maesopsis eminii is one of Africa's most extensively spread tree species, according to a recent study (Epila *et al.,* 2017). *M. eminii* is an African tree that is known for being an early successional tree that spreads through animal dispersal.
M. eminii thrives beneath forest canopy openings and is commonly utilized as a shade tree in coffee plantations (Joshi *et al*., 2015). *Maesopsis eminii* was mostly found in tropical rainforest ecosystems with fertile Orthic Ferralsol soils. They're located in areas with more than 1000 mm of annual precipitation, and when the average annual temperature is 22–28°C. The presence of the species in Africa is explained by findings from provenance trials, functional features, and phenology. The Rhamnaceous family includes many drought-tolerant species, including *M. eminii* (Epila *et al*., 2017).

The species produces obovoid drupe fruits that range from purple-black as they mature. Flowers are bisexual and yellowish-green. This gregarious tree can grow to be 10-30 meters tall with a bole 20 meters wide at breast height and a diameter of 70-80 cm. The plant can germinate and thrive with a canopy disturbance of at least 300 square meters. Germination was aided by the presence of light and bare soil. Because it thrives in forest openings and peripheral woods and can thrive in poor soils and grows quicker than coniferous trees, it is commonly used in agroecology, nature conservation, commercial forestry, and forest restoration enhancement (Mwendwa *et al.,* 2020). Responsive immune reactions including intensive phloem load and cavitation induced by drought helped it colonize. Drought tolerance is demonstrated by *M. eminii* in part due to their hydraulic capacity, which is linked to their anatomy. This species is considered invasive due to its unusual traits, which include drought-deciduous leaves, the capacity to endure drought for up to six months, quick growth, and high light needs (Mwendwa *et al.,* 2020). Four species of *Maesopsis* found in tropical Africa are *M. berchemioides, M. eminii, M. stuhlmannii*, and *M. tessmannii*.

Maesopsis eminii can be found in rainforests, riverine forests, blended wetlands, and perennial woody forest-grassland transition zones, high forests and savannah, and lowland and submontane forests. *M. eminii* being a "pioneer species" can live for 150 years and are long-lived. The species can thrive well under moist and fertile soils. They prefer sandy loam soils whose pH varies from neutral to acidic in nature. There are many reasons to grow *M. eminii*, including its ability to provide excellent timber and crop shading (Joshi *et al.,* 2015). An extend of elevations and geographical ranges have been reported to be suitable for its growth. *M.eminii* does not proliferate naturally on slopes that are steep, but when planted on these they thrive well. The spread of *M. eminii* outside its natural habitat happened during the early 20 th century in East Africa where it was introduced to promote afforestation activities. *M. eminii* has also been reported in other parts of the world, including Australia, Philippines, Bangladesh, Brazil, Costa Rica, Fiji, India, Malaysia, Samoa, Solomon Islands, Hawaii, Puerto Rico, and Indonesia (Joshi *et al*., 2015).

This species can reach different heights (up to 40 m) relying on the climate and growing season. The wood is relatively brittle, having a density ranging between 0.56 and 0.27g cm^{-3}. Trees of the genus *M. eminii* produce conspicuous flowers in their early years to allure insect pollinating, resulting in the development of succulent fruits. Dormant seeds can survive for more than 200 days when they are rapidly dispersed. Additionally, *M. eminii,* which is normally semi-deciduous, becomes drought-deciduous in extreme drought. The taproot of ss*M. eminii* is combined with lateral roots that help it access space horizontally and vertically (Joshi *et al.,* 2015).

The occasionally dense canopies and towering trees make it difficult to discern the tree crowns, and estimated annual trends in yellowing leaves, blooming, ripening, and pollen dissemination are linked to periodic rainfall distribution. The wettest parts of the year experiences defoliation (Aug-Sept), that too very rarely. In large dry seasons, it grows from October to January. In large wet seasons, it peaks in December to February. Despite this, fruiting increases from January to April that too when the end of the short rainy season is near. Approximately simultaneously with fruiting (March-April), dispersal peaked (Mwendwa *et al*., 2020).

As a result of its rapid seed development and explosive growth rates, *M. eminii* has a character for being an exotic species, diminishing the woodland ecosystem's indigenous ground cover scrubs and herb flora, changing top morphology and biodiversity composition. Although *M. eminii* is not fire-resistant in environment and cannot develop in extensive grassy ecosystems, its robust initial growth consistently outperforms other native trees. (Mwendwa *et al*., 2020). The ability to predict future plant community dynamics in light of rapidly changing climates depends heavily on the ability to determine how native and alien seedlings germinate under natural conditions. As a result, light and water availability regimes will need to be considered in the management of *M. eminii* invasions. Early discovery during the rainy season, when the species starts growing at its greatest, and reducing forest openings and other disruptions that can generate optimum light factors could be used to control *M.eminii* (Mwendwa *et al.*, 2020). Based on the findings of the authors, eminii incurs encroachment through a combination of disturbance events, mainly forest openings and mismanagement of vegetation and suggests that to replacing *M. eminii* with other native under storey species to reduce its invasiveness.

2.8 Ecological modelling

Factors, including biotic interactions between species, contribute to understanding the mechanisms behind the invasion success of many plants (Akomolafe *et al.,* 2019). A species distribution model (SDM), which assesses and predicts the impacts of climate change on fauna and flora, is scientifically proven. Species distribution models can be used to predict the distribution of species based on their occurrence (presence-only orabsence/presence) data. To develop effective adaptation strategies to cope with climate change's impacts, ecological researchers must understand how species distribution factors influence the distribution of species (Thapa *et al*., 2018). Along with ecological niche models (ENMs), the maximum entropy (MaxEnt) model is a machine-learning technique that has excellent predictive skills using a minimal amount of species presence data. (Adhikari *et al*., 2019).

Globally, biodiversity and resource conservation are under threat from biological invasions. For an alien species to successfully settle into a new range, favorable climatic conditions are crucial. Biogeography research has benefited from a constant update of geographic information system technology (GIS) and rapid advances in relative statistical modelling and analysis (Zhang *et al*., 2018). Climate change and its effects on regional ecology and communities throughout the globe are widely predicted by species distribution models (Liu *et al*., 2017). Thapa *et al*., (2018) describe ecological niche modelling as a tool for modelling the geographical distribution of plants based on empirical data and for estimating how organisms may respond to climate change.

2.9 Importance of ecological modelling

Recent expertise in modelling has made it possible to determine areas where invasive plants have a high chance of occurring based on native distribution data (Akomolafe *et al*., 2019). With the help of machine learning methods, it is possible to determine the current distribution of species and their future spread under different climate change scenarios using the layers that are created by combining point data and digital bioclimatic data regarding different regions (Coban *et al*., 2020). A sufficient existing presence record for a species is essential for developing niche models (Zhang *et al*., 2018). There is no way to overstate how ecological factors affect habitat and species niche distributions. The occurrence records and geographic correlations among parameters were used to create these estimates (Liu *et al*., 2017).

A ecological niche model (ENM) identifies areas of a new climatically favorable environment for an invading species, and they are widely applied in understanding the spread of invasive species under current and future scenarios of climate change (Banerjee *et al*., 2019). Valverde (2011) refer to the ecological niche as the condition under which a species can survive with a viable population. With or without competition, niches help a species thrive.

Models based on ENM such as MaxEnt are widely used for estimating species distributions since they are mathematically rigorous, provide continuous probabilistic output, incorporate categorical environmental data, fit in low sample sizes, and can easily be interpreted. This allows replications that facilitate cross-validation, bootstrapping, and repeated sub-sampling for testing the robustness of the model (Choudhury *et al*., 2016). In MaxEnt, species occurrence probabilities are generated based on the comparison of the probability density of factors in the ecosystem across the known occurrence locations and randomly selected pseudo-absence points relative to selected background models (Banerjee *et al.*,2019).

2.10 Modelling studies in India

Panda (2018), examined plant invasions of two perennial exotic species that originated from South Asia and naturalized in India, namely, *Chromolaena odorata* and *Tridax procumbens*. The assessment of their invasion risks, as well as the mapping of suitable habitats, both contribute to faster plant invasion control. Predictions for the current condition were made and then projected for 2050 and 2100 under both scenarios of moderate and catastrophic climate change. Objects assessed included analysis of risk areas and habitat suitability, and range size shifts using the MaxEnt. As moisture availability will be critical to their expansion, both species should have limited distribution ranges in the future. The ability to withstand a a wide temperature and solar radiation range allowed *T. procumbens* to mitigate the changes in climate impacts more efficiently, in comparison with *C. odorata*. Despite their similarities in distributions, the study proposed multiple conservation strategies for each species to eliminate invasion risks.

Fand (2020) examined the South American tomato pinworms, *Tuta absoluta*, causing widespread tomato crop infestations in Maharashtra and Karnataka in Indian states. Since India had never reported the presence of this pest, it was assumed to be of exotic origin. Study results indicated that certain geographical areas may provide suitable habitat for *T. absoluta*'s spread and distribution in India. *T. absoluta*'s potential habitat distribution was modelled using the MaxEnt maximum entropy model. Using presence only information for 64 sites and climate data for the year 2000, the climate niche for *T. absoluta* was developed. In addition to this established relationship, future climatic conditions of 2050 were used to predict potential distribution changes. According to current and future climate conditions, the distribution could be estimated reasonably, with better discrimination between viable and unviable areas. The modelled habitat spread of *T. absoluta,* researchers and plant protectionists will find this information useful in developing effective management techniques against this invasive insect pest in light of the effects of climate change in the future.

A comparison of possible climate scenarios was conducted by Boral and Moktan, (2021) in the Darjeeling-Sikkim region of Eastern Himalaya to determine the distribution of *Swertia bimaculata* by modelling MaxEnt presence data for the years 2050 and 2070. “Area under the curve” (AUC) values and “true skill statistic”

(TSS) values were adopted to evaluate the models. As a result of the habitat assessment of the species, low and sporadic distributions were observed in the study area. Future climatic scenarios suggest, the possible range of these species would decrease significantly. The results of the modelling process revealed that species ranges are shifting upward along an altitudinal gradient.

MaxEnt was used by Purohit and Rawat, (2021) to estimate the distribution of the plant *Clerodendrum infortunatum* under climatic conditions of today and for future conditions under Representative Concentration Pathways (RCPs) 2.6 and 8.5 for 2050 and 2070 in Dehradun district, India. In India, this native shrub is used in traditional medicine due to its antioxidant, antimicrobial, anti-malaria, anthelmintic, and analgesic properties. According to the study, areas with high potential for *C. infortunatum* were found. By predicting the species' suitable habitat under climate change scenarios, decision-makers will be able to understand the species' distribution and prepare strategies to manage it scientifically.

Kumar (2014) looked at how MaxEnt was used to create a tentative, district boundaries of the invading danger by an exotic cotton mealybug *Phenacoccus solenopsis* in India. Data on occurrences at the district level, coupled with bioclimatic variables (averages between districts), were analyzed using MaxEnt. With an average test AUC, MaxEnt performed better than random. Documented occurrences closely matched predictions *P. solenopsis* in all nine cotton growing states, and also other districts were projected to have appropriate environments. across India.

2.11 Modelling studies in Kerala

Many plant species have reported a geographic shift in distribution due to climate change in the recent past. Despite this, climate change's consequences on biological diversity remains largely unknown. A significant step toward biodiversity restoration declines is the identification of the right species' habitat impacted by climate change (Pramanik *et al*., 2018).

A study by Pramanik *et al*., (2018) assessed the spread of medicinally important and eco-friendly but problematic *Garcinia indica* species in the Northwestern Western Ghats based on presence only data and 19 bioclimatic variables. By using the four RCP scenarios of 2.6, 4.5, 6.0, and 8.5, current and future species distributions and suitability have been predicted. Further findings indicate how the bioclimatic variables contribute to species spread in northern Western Ghats and suggest the model could be a useful tool for managing biodiversity, ecosystems, and species re-colonization in the face of climatic variability (Pramanik *et al.,* 2018).

The Western Ghats of India are plagued by recurrent forest fires. The MODIS Hotspot database and MaxEnt algorithm were analyzed by Renard (2012) to determine whether environmental variables influenced the incidence of wildfires in the Western Ghats and two concentric subzones with different features. For determining model goodness-of-fit, they divided factors such as topography, climate, and vegetation into several partitions based on hierarchical partitioning. In spite of these differences, spatial projections and model accuracy varied greatly across regions, with forests on the Ghats' eastern slopes being the most vulnerable to fires (Renard *et al*., 2012).

A study by Chetan (2014) investigated Hanuman langur, one of India's most well-known and well-studied nonhuman primates. *Semnopithecus entellus* was until recently, thought to be a single species. Recent macroscopic and microscopic research suggest that at least three species of Hanuman langurs exist. *S. entellus*,*S. hypoleucos* and *S. priam*. A mathematical ENM was used to confirm the validity of these species. With MaxEnt, 19 bioclimatic, 12 vegetative, and 6 hydrological layers have been modelled. This study provided the first ecological variables necessary to determine whether is the species is ecologically suitable and its distribution in the Indian peninsula (Chetan *et al*., 2014).

Priti (2016) investigated the present distribution of five species of *Myristicaceae* in the Western Ghats, India, predicted their possible occurrences and predicted the climate change's impact on the population of these animals for two different scenarios. There was a higher density in the Central Western Ghats for all of the five species selected. Model predictions indicate that suitable habitats for species living in non-swampy areas will increase overall. Developing effective conservation strategies for species that inhabit fragile ecosystems requires predicting how species distributions will change due to future global climate change (Priti *et al*., 2016).

2.12 Global conservation-alien species invasion

A major conservation issue in the tropics is the impact of IAS on native ecosystems. A range of human activities, including agriculture, deforestation for plantations of economically important plant species, timber logging, and the construction of roads and dams, have fragmented tropical rainforests (Joshi *et al*., 2015). Planning and targeting management and control strategies of alien species on fragmented landscapes can be aided by knowing the distribution and abundance patterns (Joshi *et al*.,2015). A clear knowledge on the ecology of possible invasive plant species and the factors influencing their establishment that are affected by the climatic similarity between native communities and imported ones are vital to preventing their future spread and establishment (Akomolafe *et al*., 2019).

The global community has responded to the impending threat of IAS by setting up “Aichi Biodiversity Target 9 of the Convention on Biological Diversity” (CBD, 2010) to ensure that by 2020, there should be measures in place to prevent the establishment and introduction of IAS by all signatories. To assist in achieving Target 9, different indicators and mapping initiatives have been established, although they are constrained by the geographic area covered by the reporting countries. To monitor progress towards this target, the “European Environment Agency “(EEA, 2012) promoted indicators, such as a map of the "worst" species of invasive species in Europe has been created since 1900 as invasive species in

Europe have increased, awareness of IAS has grown, and a list of the worst species has been compiled. Identifying sectors of society that require more attention involves analyzing patterns of species invasions and taking advantage of international and national legal mechanisms for the regulation of invasions. Visualization of current invasion patterns may facilitate this process. Maps of the distribution of IAS can be found in databases such as the "Early Detection and Distribution Mapping System" (EDDMapS, 2016), the "CABI Invasive Species Compendium" (CABI ISC, 2016) or "Delivering Alien Invasive Species Inventories for Europe" (DAISIE, 2016). "EEA" (2012) makes use of maps to report the number of 'worst' exotic species in each country.

As a measure of a country's readiness to combat the spread of already-established IAS, it must acknowledge IAS as a threat to its economy and environment, identify IAS that have already been introduced, and demonstrate a capability to implement IAS policies. An important part of developing proactive capacity is preventing new species from being introduced and controlling the ones that are already there. Frontier programs and projects for assessment, surveillance, and citizen participation are required to demonstrate preventative preparedness. It is important to tailor eradication and early-warning schemes to the local factors responsible for the origin and the development. Data about IAS and management skills across borders could assist regions with limited resources in establishing management priorities.

The state should expand its forest surveillance program to cover all of its forest divisions before developing proper control methods. The purpose of introducing alien plants to an urban area is to enhance or restore ecosystem services (ES). Nevertheless, in other cases, invasive species have expanded exceeding their targeted plantings, wreaking havoc on established ES. IAPs are viewed negatively by many urban residents, but many appreciate their role in providing emergency services. Even though most locals are not hostile to IAP control, it is not seen as a great importance in comparison to other environmental concerns. IAPs in citiesare perceived differently by people based on factors such as gender, profession, environmental responsibility, and culture (Potgieter *et al.*, 2018). IAS is commonly employed by local people to generate income and sustain themselves. Due to considerations about forest protection and biodiversity, their removal frequently presents a conflict of interest. The local use of specific IAS will have to be simultaneously checked and controlled to minimize conflict and accommodate both development and conservation needs over the short and medium term (Kannan *et al.*, 2016).

Sankaran (2013) suggested the following measures in order to prevent future IAP intrusions into woods: (i) All seedlings, pollen grains, and soil truly meant for transit into natural forests should indeed be properly inspected for IAP seedlings as well as other reproductive structures (saplings of forest vegetation, soil for infrastructure projects). (ii) All plant species should be quarantined and their seeds, seedlings, and propagules imported after a risk assessment are conducted.
(iii) Tourists locations ought to have water-filled dips at the approach point so that IAP pollens can be rinsed off of farming instruments and automobile wheels prior approaching forested regions.

IAPs can be contained most economically by establishing a surveillance system that detects them soon after they arrive and eradicates them while the population is declining, and the distribution is restricted (Shiferaw *et al*., 2018). The monitoring of seaports, touristic and pilgrim routes, as well as air terminals in forest areas for invasive species needs to be done with appropriate tools and methods (Sankaran *et al*., 2013). The inspection service and forest authorities must be taught how to assess IAS as a real danger to prevent intrusions and keep the population in check. Rather than immediately eradicating IAP, those areas that have already been infested by weeds the emphasis must be on avoiding their proliferation by: 1) preventing the movement of soil and plant components from contaminated to non-infested areas; and 2) manually or mechanically eradicating weeds (cutting or pulling) before they flower or fruit and burning them. Biological control and mechanical control could be complex, expensive, and inefficient in the long run-in large areas where alien weeds have been established. A restoration strategy should be employed in such situations. This can be achieved by pulling all weeds (including their roots/tubers) out of small areas at a time and subsequently planting a fast-growing native species in their place. These areas may also be treated with assisted regeneration (Sankaran *et al*., 2013).

An understanding of the current distribution and level of invasion of invasive exotic species is essential for the development of spatially differentiated management strategies. It can often be challenging to manage IAPS that are widely established because eradication is often not possible. Different management alternatives will need to be considered in planning processes across the invaded range, including how target species is currently distributed geographically and in abundance, the environmental niche of the invaded region, the areas within the invasion range likely to be negatively affected, and whether there are areas that should be protected from invasion. The management of IAPS is also influenced by two types of factors: (i) biological factors such as reproductive mode and propagule production influence reproduction, and (ii) dispersion agents and invading paths are examples of extrinsic environmental influences. It may be challenging and complicated to manage IAPS spatially if these factors are ignored (Shiferaw *et al*., 2018).

2.13 Conservation -Biological species invasion- India

IAS has been considered one of the most significant influential elements in the development of India's environmental assets (Mandal *et al.*, 2011). The area of India accounts for only 2.4% of the earth's land area, yet it hosts 8% of the world's species diversity. A whopping 60% of India's biological resource is derived from fungi and insects (Mandal *et al.*, 2011). Indian botanical diversity is immense, but the country has only been examined in a fraction of its geographic areas including roughly 45,000 wild plant species and roughly 90,000 wild animal species (MoEF, 2008). In India, exotic race includes 18,000 species of plants, four mammalian species, four avian species, and over 300 species of fish. (Mandal *et al.*, 2011).

It has yet to be determined exactly what India's economic costs are for the management of IAS. Currently, three imperatives stand out: designing policies with valid scientific justifications that support effective conservation efforts; implementing changes in policy as quickly as possible on the ground; as well as creating proper legal structures to support initiatives (Joshi *et al.,* 2015). Considering their ability to impact native biodiversity and landscape changes, IAS are a serious issue in the forests of Kerala that must be addressed immediately. Efforts to protect forests must include a variety of measures aimed at restoring habitats from IAS, eradicating IAS already established in forest areas, as well as preventing incursions of new IAS into forest areas. Managing invasive species is an essential part of biodiversity conservation and natural resource management, but it is a complex and challenging problem. Global trade, and unprecedented climate changes are all contributing to the challenge of managing biological invasions. In addition to enhancing the number of climatically suitable areas for IASs, their increased spread will also negatively impact livelihoods, the economy, and biodiversity in the future. In managing IAS in forests, it is important to avoid using synthetic herbicides, the use of which would be counterproductive owing to the impact they would have on native species. The Central and State Governments share the responsibility for plant protection in India. Pest control in India is handled via a non - linear and non, multi-departmental, interdisciplinary, and cross approach, which includes IAS management. IAS management is not coordinated by a single agency at the national level.

Although India needs a regional policy at a national and regional level, it lacks one. In addition to an initial assessment, the program progresses based on a survey (Mandal *et al.*, 2011). The assessment of invasive alien species at the national scale will present several challenges to researchers, which include: estimation of IAS distributions in conjunction with an approximation of their densities, development of simple models to quantify the impacts of invasions on fundamental ecosystem services, and development of methods to estimate the spread of IAS.

CHAPTER -3

MATERIALS AND METHODS

3.1 Study area -Wayanad district, Kerala

The Wayanad district (11°44′ N–11°97′ N and 75°77′ E–76°43′ E), is located in North-Eastern part of Kerala, India. The annual mean rainfall of the district is approximately 2322 mm and the average temperature for the last 5 years ranged from 18 to 29 °C (Jose and Nameer, 2020). Wayanad is a beautiful plateau that ranges from an altitude of 700 and 2100 m above the mean sea level. The entire district covers an area of about 2130 km^2. The total forest area under the districts is about 885.92 km^2. The district is also famous for pepper, cardamom, coffee, tea, spices, and other condiments grown there. (https:// wayanad. gov.in/ demography/). The current distribution of *M.eminii* in Wayanad district is sparse suggesting that it is in its initial stages of invasion.

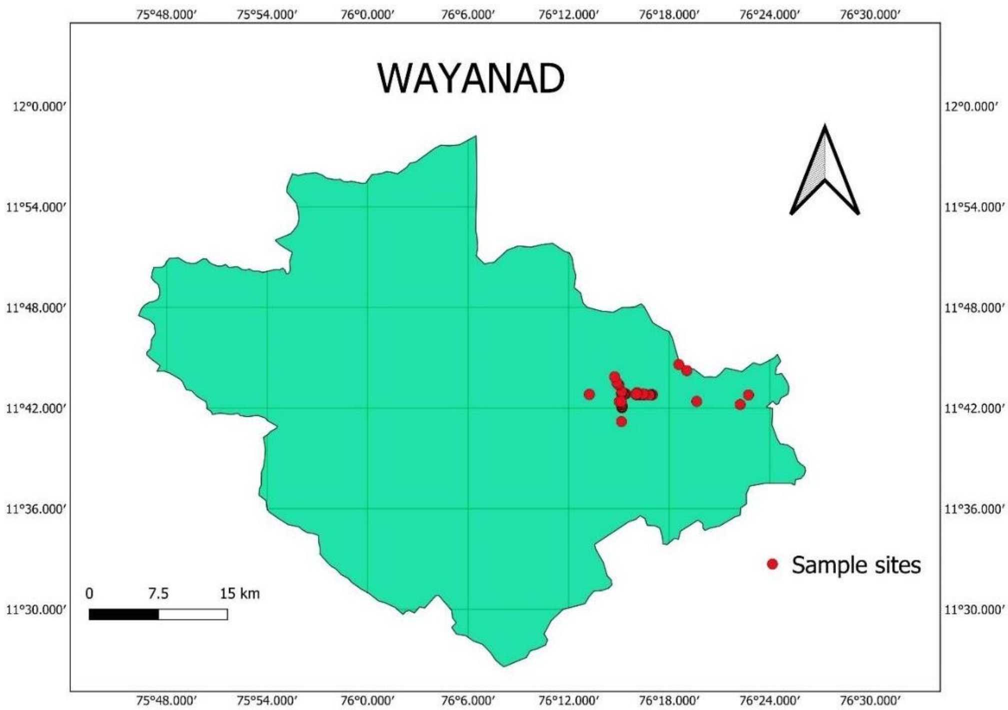


Fig 1: Study area of *Maesopsis eminii*, Wayanad district, Kerala showing occurrence data points

3.2 Occurrence points of *Measopsis eminii*

The primary data points of *M. eminii* was collected from the study area (March 2021), Wayanad district, Kerala through a field survey. The geographic location points of the invasive alien plant were tagged through a Garmin GPS device. The secondary data points were collected from Kerala Forest Research Institute, Thrisssur, Kerala. The occurrence points collected from both primary and secondary sources totalled to 84. The points were then uploaded and saved as .csv files in Microsoft Office Excel, 2019. The corresponding shape file was then derived from the occurrence points using ArcMap version 10.7.1 (Fig 1).

3.3 Environmental variables

The WorldClim database (http://www.worldclim.org/download) provided the bioclimatic variables for georeferenced presence locations. These 19 variables, which were derived from monthly rainfall and temperature values. The bioclimatic variables represent annual trends (mean annual temperature, annual precipitation) seasonality (annual range in temperature and precipitation) and extreme or limiting environmental factors (temperature of the coldest and warmest month, and precipitation of the wet and dry quarters). A quarter is a period of three months (1/4 of the year). They are coded as:

- Bio1 = Annual Mean Temperature
- Bio2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
- Bio3 = Isothermality (BIO2/BIO7) (×100)

- Bio4 = Temperature Seasonality (standard deviation ×100)
- Bio5 = Max Temperature of Warmest Month
- Bio6 = Min Temperature of Coldest Month
- Bio7 = Temperature Annual Range (BIO5-BIO6)
- Bio8 = Mean Temperature of Wettest Quarter
- Bio9 = Mean Temperature of Driest Quarter
- Bio10 = Mean Temperature of Warmest Quarter
- Bio11 = Mean Temperature of Coldest Quarter
- Bio12 = Annual Precipitation
- Bio13 = Precipitation of Wettest Month
- Bio14 = Precipitation of Driest Month
- Bio15 = Precipitation Seasonality (Coefficient of Variation)
- Bio16 = Precipitation of Wettest Quarter
- Bio17 = Precipitation of Driest Quarter
- Bio18 = Precipitation of Warmest Quarter
- Bio19 = Precipitation of Coldest Quarter

These bioclimatic variables correspond to a time period extending from 1970- 2000 using data from between 9000 and 60 000 weather stations (Hijmans *et al*., 2017). The resolution of the data downloaded were 30 arc seconds (approximately 1 km^2 at the equator). The latitude/longitude coordinate reference system was under the datum WGS84. The unit of temperature is '°C*100' and precipitation is 'mm'.

The climate datasets from the Climate Change, Agriculture and Food Security (CCAFS) website (www.ccafs-climate.org) was assessed to identify the species' future distribution under various climate scenarios. In its AR5 report (RCP2.6, RCP4.5, RCP6.0, and RCP8.5), the Intergovernmental Panel on Climate Change (IPCC) adopted four scenarios for greenhouse gas concentrations known as RCPs (representative concentration pathways). The environmental layers are all mapped at 30 arc seconds (1 km) per pixel. All the four scenarios viz., RCP2.6, RCP 4.5, RCP 6.0 and RCP 8.5 were used in evaluating the future spread of *M. eminii* in this study.

Table1: RCP scenarios and their characteristics

Sl.No	Representation concentration pathways	Radiative forcing	Temperature anomaly (⁰C)	CO_2 concentration (ppm)
1.	RCP 2.6	3.1 W m^{-2} then decline by 2100	0.3 ⁰C – 1.7 ⁰C	490
2.	RCP 4.5	4.5 W m^{-2} after 2100	1.1 ⁰C – 2.6 ⁰C	650
3.	RCP 6.0	6 W m^{-2} after 2100	1.4 ⁰C – 3.1 ⁰C	850
4.	RCP 8.5	8.5 W m^{-2} by 2100	2.6 ⁰C – 4.8 ⁰C	1370

Apart from the climatic variables, non-climatic variables were also used in the study. Land use and land cover changes, soil type, population density, normalized difference vegetation index, slope, distance from the road were the non-climatic variables. The non-climatic variables were selected based on literature survey done on the invasive nature of the species. Landcover, slope, elevation, were downloaded at one km resolution from www.earthenv.org (assessed on August 21, 2021). These data were downloaded at 1 km resolution. The global population data was assessed at 1 km resolution from https://sedac.ciesin.columbia.edu. Gridded Population of the World (GPW, v4.11)

(August 21, 2021), from NASA Socioeconomic data and Applications centre (SEDAC), based on counts consistent with national censuses and population registers, as raster data to facilitate data integration. The non-climatic layer for road network was obtained from the NASA Socioeconomic Data and Applications Center (SEDAC) Global Roads Open Access Data Set, (gROADSv1, https://sedac.ciesin.columbia.edu/ data/ set/ groads -global- roads- open- access-v1). The data was then derived using ArcMap version 10.7.1. The soil dataset was obtained from the Kerala soil health information system (https:// www. keralasoilfertility. net/). The vector map obtained was then georeferenced and rasterized using ArcMap 10.7.1.

All the variables assessed were at the same spatial scales of approximately 1 km resolution and were clipped and extracted to the study area, Wayanad Kerala using Spatial Analyst Toolbox in ArcMap version 10.7.1.

3.4 Variable selection and analysis

Autocorrelation among variables could cause inaccuracies before running the model (Sharma *et al*., 2018). Thus, to remove multicollinearity among variables, pairwise correlations were done and highly correlated variables were excluded. Pearson's correlation coefficient of $r > 0.7$ was chosen as the limit to determine the influence of multicollinearity and overfitting (Wei *et al.,* 2018).

3.5 Model selection

3.5.1 MAXIMUM ENTROPY SPECIES DISTRIBUTION MODELLING (MaxEnt)

MaxEnt is widely used for estimating species distributions since they are mathematically rigorous, provide continuous probabilistic output, incorporate categorical environmental data, fit in low sample sizes, and can easily be interpreted. MaxEnt allows replications that facilitate cross-validation, bootstrapping, and repeated sub-sampling for testing the robustness of the model (Choudhury *et al*., 2016). In MaxEnt, species occurrence probabilities are generated based on the comparison of the probability density of a random pseudo- absence point calculated using selected background models and environmental factors over known occurrence sites (Banerjee *et al.*, 2019).

MaxEnt version 3.4.4 was assessed from https:// biodiversityinformatics. amnh. org/ opensource /maxent/ . MaxEnt was used in predicting the current and future distribution of *M. eminii* and a habitat distribution map for the species was generated from the output received. The occurrence data pointsare to be fed as input in the '.csv' (Comma separated value) format and environmental layers in the '.asc' (American Standard Code for Information Interchange) formats.

3.6 Model optimization

Default settings, auto features were used in optimizing since this method is considered to achieve the greatest accuracy across different models. The replication run type in MaxEnt accounts for mainly three types- cross-validation, bootstrap and sub-sampling. The subsampling run type was employed in running the model. In subsampling, the presence data sets were repeatedly split into random training and testing data sets. Analysis of the contribution of both selected climatic and non-climatic variables was done for current distribution using the subsampling replication run type, where 25% of the data was set as test data and the remaining as training data. 10 subsampling replicates were used. To prevent the overfitting of the model, a regulation multiplier was employed. The values of each environmental variable on training presence and background data were randomly permuted to determine permutation importance.

3.7 Model validation

3.7.1 Threshold independent Receiver operating characteristics (ROC)

A ROC curve was plotted as a function of both the sensitivity (true positive percentage), or the fraction of recorded omissions that have been mistakenly forecasted, and the absence of omitted inaccuracy (1-significant interval), or false positive ratio. The analysis of the omission/commission graph can reveal the omission rate and predicted area at different threshold levels. The orange and blue shading surrounding the lines on the graph represented its variability. To be consistent with the definition of the cumulative output format, the omission rate should follow a straight line. The omission rate should be close to the predicted omission. The sensitivity vs. 1-specificity graph depicted the area under the Receiver Operating Characteristic (ROC) curve or the area under the curve (AUC). This allowed easy comparison of the performance of one model with another and a most useful tool to evaluate multiple MaxEnt models. 0.5 means that the model's performance was no better than random, while 1.0 means that the model's performance was better (Philips *et al*., 2006). The Jack-knife test of variable importance depicted the environment variable when taken alone, yielding the best results. (having the most useful information) and the environment variable which decreased the gain the most when it is omitted (having one of most data that really isn't available in another parameters).

3.7.2 True skill statistics (TSS)

A highly recommended measurement for accuracy of the model, True Skill Statistic (TSS), is a reformulation of Kappa which is defined as "sensitivity+ specificity – 1" considering both commission and omission. A value+1 indicates the model is best and values between zero and −1 indicate performance no better than random and are threshold depended (Jose and Nameer, 2020).

3.8 Threshold selection for the model

Thresholds are not set in stone; they are determined by the data utilised and the map's goal, and they differ depending on the species. Threshold numbers are provided by MaxEnt based on various statistical measures in the maxentResults.csv file included in the results. A "minimum training presence logistic threshold", a logistic threshold representing the 10-percentile training presence, and a logistic threshold representing equal training sensitivity and specificity are some of the most common thresholds used. The present study used a logistic threshold of 10 percentile training presence (Sharma *et al*., 2018). To distinguish appropriate from unsuitable locations, the outputs mappings of binary species distributions spread were created using a 10-percentile training presence threshold. A 10- percentile training presence criterion is widely used within MaxEnt for its ability to reliably and conservatively estimate species distributions in comparison with other thresholds. Even for locally confined and threatened species, it has been demonstrated to have the least amount of bias and the prediction accuracy (Liu *et al*., 2017).

3.9 Prediction of the current distribution of *M. eminii*

For the prediction of the current distribution of the species, the sample files and environmental layers were given as input in '.csv' and'. asc' file formats. Auto features with subsampling replication of 10 was allowed. 25% of the data was set as test data and the remaining as training data. Maximum iterations were set to 5000. A regularization multiplier of 2.5 was set and the others set as default.

3.10 Prediction of future distribution of *M. eminii*

Prediction of species distribution in the future could be done in MaxEnt by projecting the trained environment layers to another set of environment layers containing the future climatic data set. The projection layers had trained layers that were mutually compatible but different conditions. The name of the layers and the map projection were the same as that of the trained data. The environmental factors were used to train a model which corresponded to the current climatic conditions and were projected into a separate layer based on the future environmental data. Models of different RCPs were done using a single sampling technique with 10 replicates and 25 test percentage.

CHAPTER-4

RESULTS

Maesopsis eminii is considered to be an early successional tree that spreads through animal dispersion and are grown as shade plants in coffee plantations and flourish under forest canopy openings (Joshi *et al.*, 2015). The objective of the study is to map the current distribution of *M. eminii*. in Wayanad and map the predicted distribution n of the species under RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5.

The environmental variables needed to run the model was accessed through respective sites and were clipped and extracted by masking the study area of interest using the SDM toolbox in ArcMap 10.7.1. A total of 24 variables were analyzed for the study and the variables that contributed to the spread of the species were then selected to run the model and predict the current and future distributions. The variables were selected based on correlation analysis to remove multicollinearity using Pearsons correlation. The variables so obtained were then used as an input in Maxent to run the model.

4.1 Variable selection

The variables for predicting the potential distribution of *M. eminii* was retained after the statistical analysis of Pearsons Correlation coefficient ($r > 0.7$) done in ArcMap version 10.7.1. ESRI. Eleven variables out of the 24 variables were selected to run the model (Fig 2). The highlighted variables showed high correlation and the variables with reduced correlation was selected for the potential distribution of the species, thus improving the accuracy of the model through reducing the overfitting of the model. Here, Bio 1 (annual mean temperature) was correlated with Bio 10 (Mean temperature of the warmest quarter, Bio11 (Mean temperature of the coldest quarter), Bio 5(Maximum temperature of the warmest month), Bio 6(minimum temperature of the coldest month), Bio 8(Mean temperature of the wettest quarter), Bio 9 (Mean temperature of the driest quarter). Bio 1 was selected among the other variables due to its significant contribution to the spread of the species. Bio 12(Annual precipitation) was cross-correlated with Bio 13(Precipitation of the wettest month), Bio 14 (Precipitation of driest month), Bio 15(Precipitation seasonality), Bio 16(Precipitation of wettest quarter), Bio17(Precipitation of the driest quarter), Bio 18Precipitation of the warmest quarter), Bio 19(Precipitation of coldest quarter). Bio 12 was again selected amidst its significance over other variables. The reduced correlated variables from the correlation analysis yielded BIO1(Annual mean temperature), Bio 12(Annual mean precipitation), Bio 19 (Precipitation of the coldest quarter), Bio 18 (Precipitation of the warmest quarter), aspect, Normalized difference vegetation index (NDVI), Land use and landcover change (LULC), slope, soil type, distance from road and elevation.

	aspect	bio1	bio10	bio11	bio12	bio13	bio14	bio15	bio16	bio17	bio18	bio19	bio2	bio3	bio4	bio5	bio6	bio7	bio8	bio9	dis road	elevation	landcover	ndvi	populatn	slope	soil
aspect	1																										
bio1	0.113351	1																									
bio10	0.128495	0.998172	1																								
bio11	0.093472	0.997199	0.990916	1																							
bio12	-0.28296	-0.58767	-0.63509	-0.52589	1																						
bio13	-0.29073	-0.4283	-0.48157	-0.35985	0.982417	1																					
bio14	-0.17733	-0.95008	-0.96396	-0.92623	0.794531	0.66816	1																				
bio15	-0.27099	-0.04997	-0.10897	0.024541	0.831591	0.920303	0.327063	1																			
bio16	-0.28628	-0.55043	-0.59943	-0.4868	0.998913	0.990005	0.765583	0.856426	1																		
bio17	-0.23876	-0.80575	-0.83931	-0.75989	0.94738	0.875503	0.937453	0.624814	0.932727	1																	
bio18	-0.25018	0.008964	-0.0497	0.082158	0.789228	0.887255	0.274167	0.985191	0.81601	0.58334	1																
bio19	-0.27958	-0.39844	-0.44823	-0.33558	0.914245	0.935764	0.610529	0.865977	0.923427	0.829972	0.870457	1															
bio2	-0.00221	-0.754	-0.69934	-0.77999	0.040048	0.30222	-0.09912	0.34071	0.20802	-0.28367	-0.94903	-0.08036	1														
bio3	0.015248	0.56649	0.491191	0.603641	-0.42368	-0.65538	0.440963	-0.68329	-0.57725	0.615204	0.89151	-0.31946	0.865576	1													
bio4	-0.02733	-0.06685	0.022642	-0.11375	0.66378	0.881459	-0.81452	0.899103	0.789313	-0.90711	-0.60584	0.676999	0.626859	0.848097	1												
bio5	0.16001	0.982984	0.992254	0.966594	-0.72548	-0.58613	-0.98665	-0.23058	-0.69361	-0.89948	-0.1715	-0.54812	-0.60884	0.389192	0.140404	1											
bio6	0.055696	0.978174	0.964108	0.990647	-0.41022	-0.23432	-0.87238	0.155344	-0.36825	-0.66694	0.214721	-0.20626	0.790885	0.609611	-0.12192	0.923743	1										
bio7	0.281891	0.583409	0.63096	0.521715	-0.99336	-0.97789	-0.78317	-0.83158	-0.99298	-0.94576	-0.79866	-0.93769	0.975024	0.955113	0.745673	0.722354	0.402407	1									
bio8	0.125695	0.998777	0.999716	0.992498	-0.62459	-0.47024	-0.96144	-0.09746	-0.58876	-0.88296	-0.03941	-0.44237	-0.81423	0.994959	0.895344	0.990402	0.966902	0.821488	1								
bio9	0.116729	0.999873	0.998902	0.996053	-0.59891	-0.44071	-0.95441	-0.0633	-0.56198	-0.8134	-0.00375	-0.4086	-0.70012	0.485063	0.828622	0.985894	0.975383	0.942077	0.999209	1							
dis road	-0.2059	-0.81083	-0.82567	-0.78798	0.694478	0.59097	0.840072	0.300882	0.67157	0.81699	0.270605	0.578539	0.992819	0.867552	-0.19826	-0.84826	-0.73277	-0.70447	0.823121	0.812592	1						
elevation	-0.08946	-0.99503	-0.98885	-0.99853	0.515478	0.348419	0.920568	-0.03598	0.476084	0.750196	-0.09625	0.320994	0.736419	-0.53112	0.028146	-0.96286	-0.99087	0.71239	0.989603	0.99889	0.773526	1					
landcover	0.006956	0.03012	0.047672	0.008321	-0.25896	-0.28117	-0.12999	-0.29628	-0.26418	-0.21195	-0.30425	-0.26554	0.185567	-0.08877	-0.245	0.08245	-0.02694	0.245702	0.043766	0.033774	-0.08564	-0.0123	1				
ndvi	-0.21324	0.192419	0.180025	0.208305	0.046605	0.101164	-0.17286	0.206623	0.062084	-0.06971	0.17931	0.088851	-0.46426	0.392253	-0.22073	0.147943	0.239069	-0.07803	0.181699	0.188056	-0.11362	-0.21045	0.184987	1			
populatn	-0.13497	-0.89457	-0.90428	-0.88081	0.646217	0.511938	0.914907	0.170963	0.613951	0.812708	0.131876	0.454281	-0.82158	0.573667	-0.18325	-0.91039	-0.84532	-0.64976	-0.89793	0.897149	0.762354	0.886278	-0.11876	-0.25336	1		
slope	-0.10314	-0.12362	-0.12555	-0.11836	0.116006	0.107211	0.12162	0.08274	0.114641	0.13908	0.076046	0.105074	0.639285	-0.49244	-0.00104	-0.13156	-0.10441	-0.12593	-0.12849	-0.12333	0.079871	0.10826	-0.07634	-0.01287	0.073318	1	
soil	0.130822	0.148733	0.189874	0.094297	-0.64985	-0.6966	-0.33109	-0.72681	-0.66378	-0.52883	-0.68635	-0.63195	0.4076	-0.17194	-0.06352	0.273867	0.00389	0.647561	0.182019	0.157311	-0.28545	-0.09456	0.176397	-0.13197	-0.21426	-0.10083	1

Fig 2: The correlation matrix showing highly correlated and reduced correlated variable

Additionally, the variability of each chosen non-collinear bioclimatic variable with respect to different RCP scenarios also analyzed using the mean value of bioclimatic variables in the study area, which were calculated in R. The variables selected using the multicollinearity test were reaffirmed using its climatic variability and represented.

Table 2: Climatic variability analysis of selected non-collinear bioclimatic variables among different RCP scenarios for the time periods 2050 and 2070 in Wayanad district of Kerala

Variable	Current	RCP 2.6		RCP 4.5		RCP 6		RCP 8.5	
		2050	2070	2050	2070	2050	2070	2050	2070
Bio 1	12.61	138.54	138.55	138.55	138.55	138.55	138.56	138.56	138.56
Aspect	85.76	85.78	86.39	85.78	85.78	85.78	85.78	85.78	85.78
Bio 12	174.27	174.27	1715.85	166.98	170.86	171.27	603.59	173.21	174.54
Bio 18	150.44	182.45	175.71	177.80	183.12	172.94	136.35	176.69	176.26
Bio 19	409.7	64.27	68.59	117.17	380.64	111.40	479.19	88.35	129.28
Elevation	481.41	481.48	481.48	481.48	481.48	481.48	481.48	481.48	481.48
Slope	49.07	49.07	49.07	49.07	49.07	49.07	49.07	49.07	49.07

4.2 Variable contribution to the potential distribution of *Measopsis eminii*

4.2.1 Selected variables and their percentage contributions

The most significant variables that contributed to the potential spread of the species were found through Pearsons correlation coefficient test and among the variables selected the most promising variables that had significant contribution to the presence of the species was noted from the MaxEnt output results. From table (3), it is evident that Bio 18 has the highest contribution to the potential spread of the species with 64.8 %, Bio 19 contributed 14.6 %, Bio 12 contributed 9.7%, NDVI – 5%, aspect contributed 3.4%, distance from road contributed 1.5%. Soil type (0.4%), elevation (0.3%), Bio 1 (0.1%) had less than 1 % contribution while landcover had 0 % contribution in deciding the presence of *M. eminii*.

Table 3: Variables and their significant percentage contribution in the current distribution of *Maesopsis eminii*

Variable	Name of the variable	Percent Contribution	Permutation Importance
Bio 18	Precipitation of warmest quarter	64.8	73.4
Bio 19	Precipitation of coldest quarter	14.6	2.6
Bio 12	Annual precipitation	9.7	8.1
NDVI	Normalized difference vegetation index	5	4.1
Aspect	Aspect	3.4	2.5
Distance from road	Distance from road	1.5	6
Soil type	Soil type	0.4	0.1
Elevation	Elevation	0.3	1.6
Bio 1	Annual mean temperature	0.2	1.7
Slope	Slope	0.1	0
LULC	Land use and landcover change	0	0

4.2.2 Variables and their response curves

The response curves from the MaxEnt output (Fig.3) showed howeach environmental variable was affecting the distribution of *M. eminii*. The curves shown below are logistic prediction changes as each environmental variable was varied, keeping all other environmental variables at their average sample value. Using only the variable in question, the curves below show the MaxEnt model. The graphs illustrate how expected appropriateness varies depending on the selected variable as well as based on correlations between those variable and other factors.

4.2.2.1 Bio1- annual mean temperature

The occurrence of M. *eminii* was noted to be higher when temperature was between 21-22^0 C, and tend to decrease to 30-50% at 22-26^{0}C.

4.2.2.2 Bio 18- Precipitation of the warmest quarter

The presence of M. *eminii* was found to be highest between 220-280mm and no occupancy was noted between 300-400mm.

4.2.2.3 Bio 12- Annual precipitation

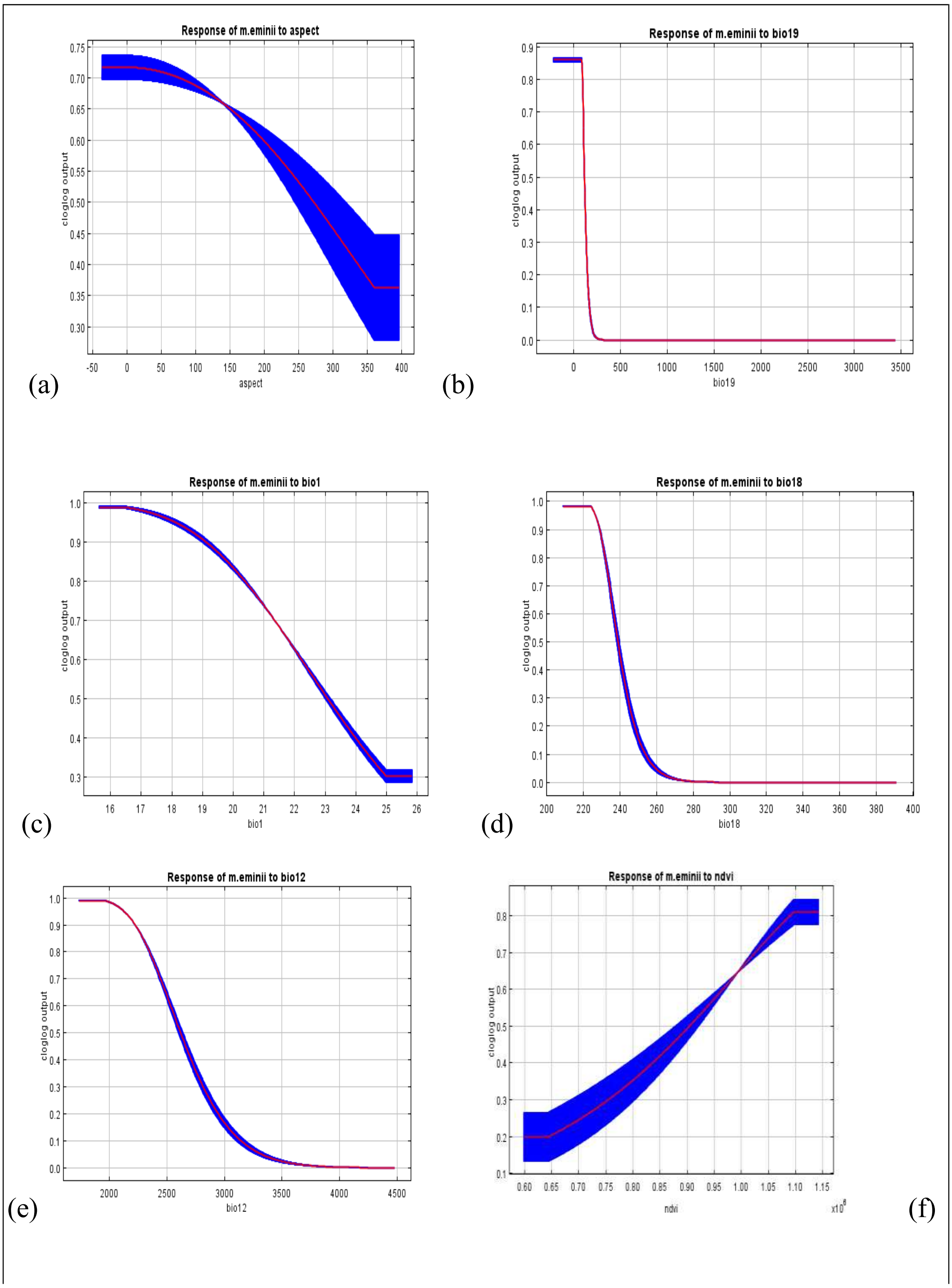
80% of the species was found to be highest between 2000-4000mm.

4.2.2.4 Bio 19- Precipitation of the coldest quarter

The presence of the species was found to be very less under Bio 19 and over 90% of the species was found to be under 0- 100 mm.

4.2.2.5 Static and dynamic variable

Static variables like slope, aspect and elevation had importance with more species falling under 0-100m, 600-100m and 50-90m respectively. Dynamic variables like landcover, distance from road, Normalized difference vegetation index and soil type also has significant contribution to the spread of the species.



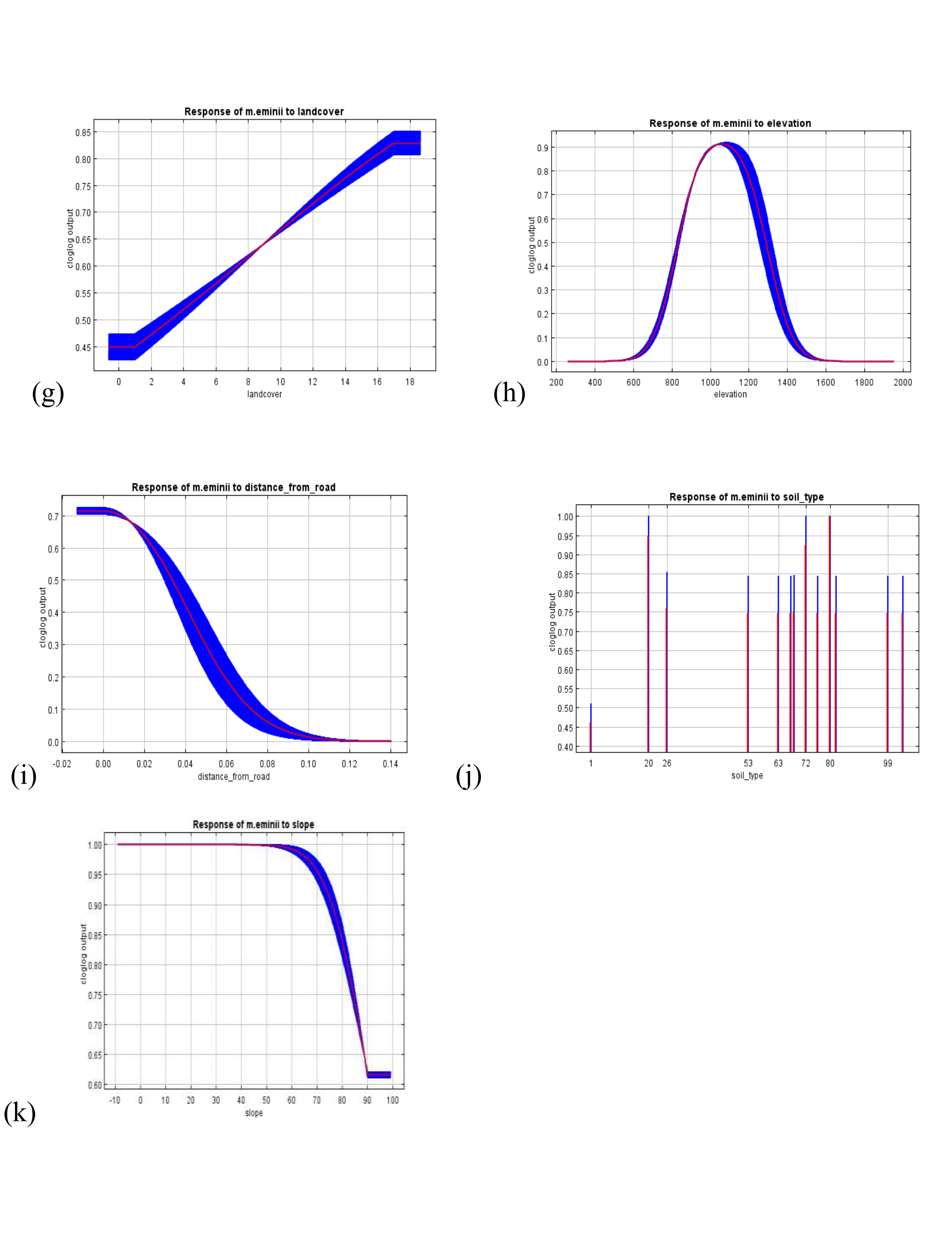


Fig.3: The response curves of variables in current potential distribution of *Measopsis eminii* to (a)aspect (b)Bio 19 (c)Bio (d)Bio 18 (e)Bio 12 (f)NDVI (g)landcover (h)elevation (i)distance from road (j)soil type (k)slope

4.2.3 Variable sensitivity -Jackknife test

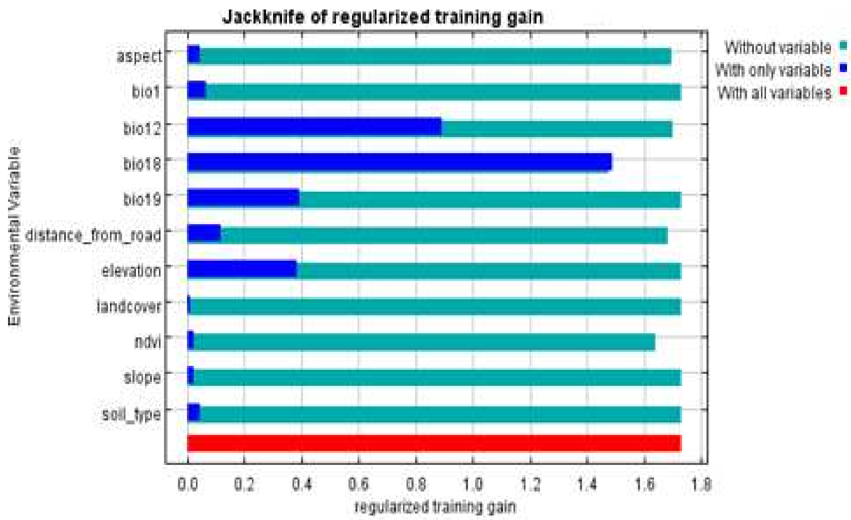


Fig 4: The Jackknife test for the regularized train for *Maesopsis eminii*

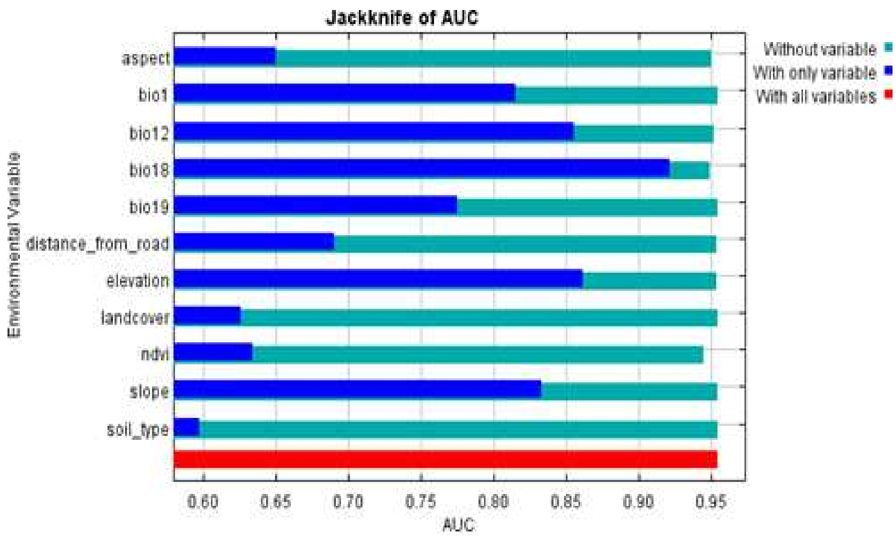


Fig 5: Jackknife test of AUC for *Maesopsis eminii*

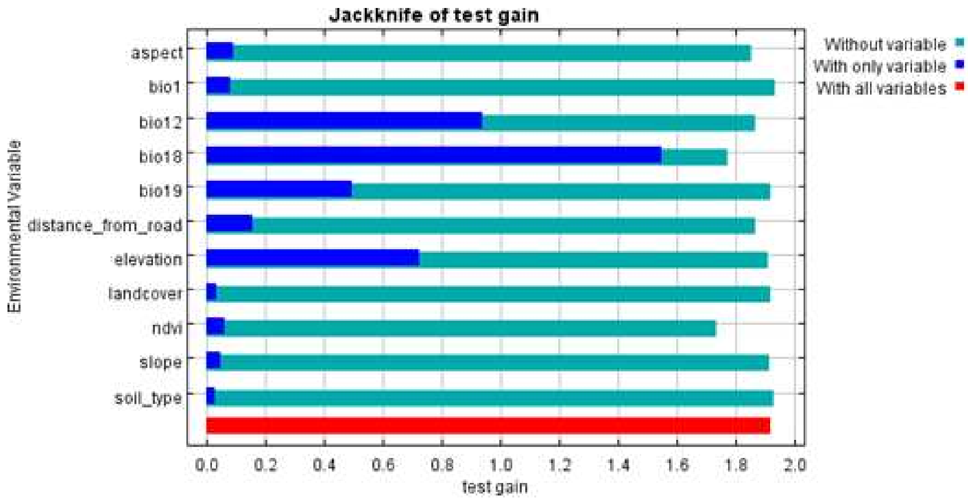


Fig 6: Jackknife of test gain for *Maesopsis eminii*

Jackknife is run to get an estimate of which variable is most important. If MaxEnt uses only landcover, it achieves almost no gain, so the variable is not (by itself) much important for estimating the distribution of *M. eminii*. On the other hand, Bio 18 allows a reasonably good fit to the training data Fig (4). Moving on to the lighter blue bars, it appears that no variable offers a significant quantity of important information that is not already present in the other variables, as deleting each variable did not result in a significant reduction in training gain. Two more Jackknife plots, use either test gain (fig 5) or AUC (fig 6) in place of training gain. The AUC plot (fig (5)) shows that Bio 18 is the most effective single variable for predicting the distribution of the occurrence data. The relative importance of Bio 18 also increases in the test gain plot, when compared against the training gain plot.

4.2 Validation of the Model

The model was then validated for their accuracies by understanding the Area under the curve (AUC) in Receiver operating characteristics (ROC), True Skill statistics (TSS), and Sensitivity and specificity as given in table(4)

Table 4: Accuracy matrix and their values for the current distribution of *Maesopsis eminii*

Accuracy matrix	**Values**
Overall accuracy	0.91
TSS	0.84
Teat AUC	0.95
AUC standard deviation	0.02
Sensitivity	0.92
Specificity	0.91

On average, omissions in the test samples are in line with the projected omission rate, which is the omission rate for the test data generated from the MaxEnt distribution. A straight line is the expected omission rate for the cumulative output format. Sometimes the test omission line is significantly lower than the predicted omission line for a variety of reasons. There is frequently a problem when test and training data are not independent, as when they are derived from the same spatially correlated presence data.

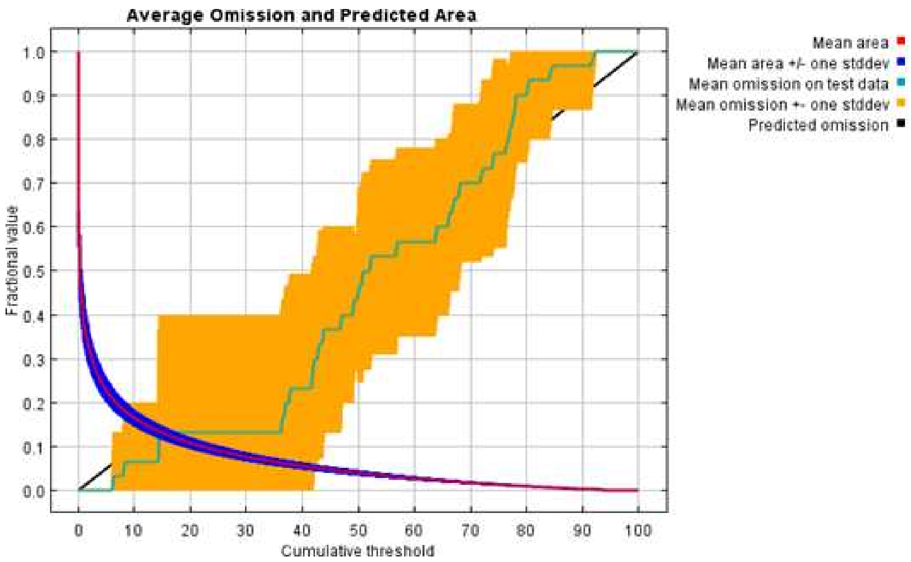


Fig 7: Average omission and predictive area for the current distribution of *Maesopsis eminii*

The receiver operating characteristic (ROC) curve is averaged over the replicate runs. The specificity is defined using the predicted area. The average test AUC for the replicate runs is 0.954, and the standard deviation is 0.024.

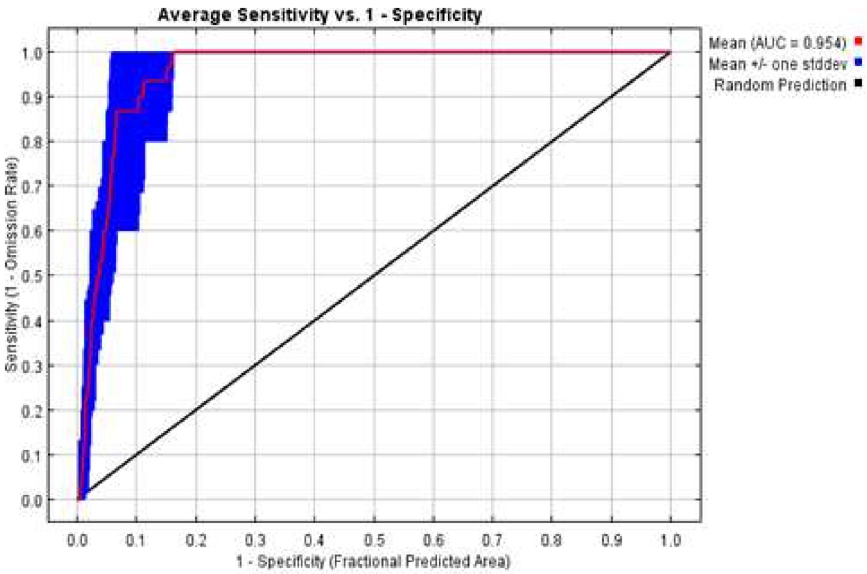


Fig 8: Receiver operating characteristics for the present distribution of *M.eminii*

4.4 Current potential distribution of *Maesopsis eminii* in Wayanad district, Kerala

The average ASCII files that were obtained from the MaxEnt output was reclassified into a binary raster to show potentially suitable and unsuitable areas for the spread of the species based on the 10-percentile clog log threshold selected. It was observed that the unsuitable habitat of the species covered an area of 2033km^2 the suitable area covered by the species accounted for 142 km^2 (6%). The current average ASCII files were again reclassified in ArcMap 10.7.1 to find the highly suitable, moderately suitable, moderately unsuitable and highly unsuitable areas for the spread of the species at equal intervals (Fig 10). The highly unsuitable area covered 1872 km^2, moderately unsuitable area covered 141 km^2, the moderately suitable area covered 95 km^2 and the highly suitable area covered 67 km^2.

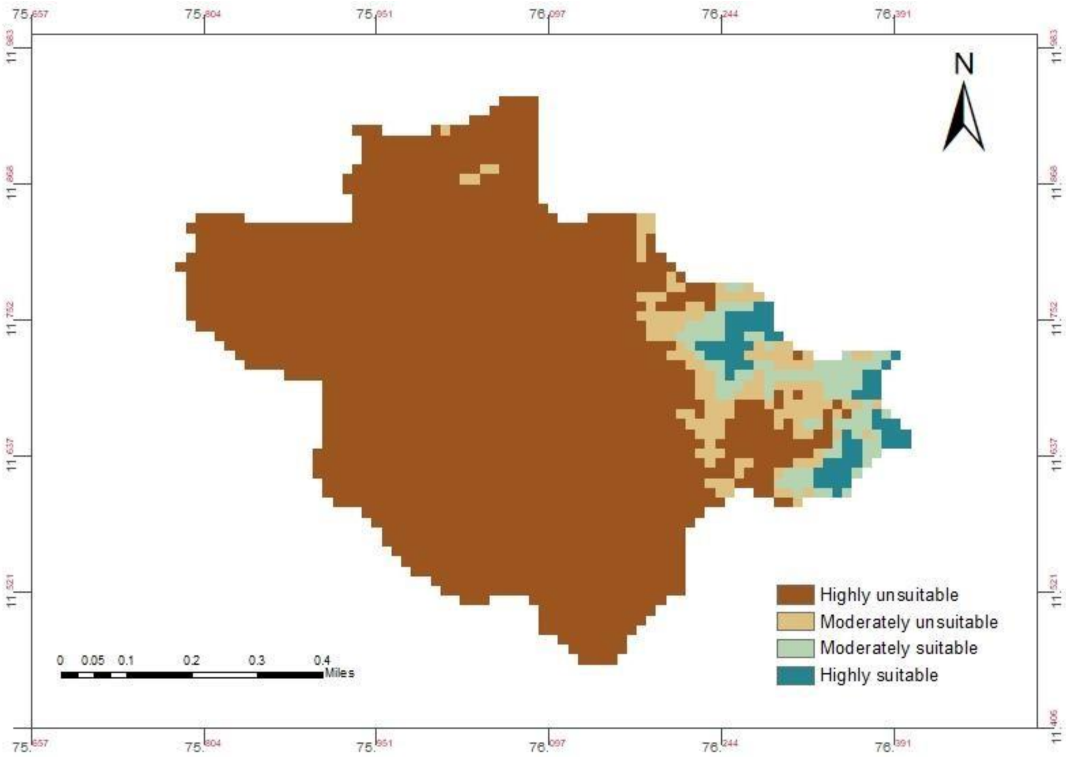


Fig 9: Map showing the potential suitability distribution of *Maesopsis eminii*, Wayanad district, Kerala

4.5 The future distributional spread of *Maesopsis eminii* under climate change scenarios 2050 and 2070 in Wayanad, Kerala

4.5.1 Significance of variables in the future spread of the species under various RCP scenarios

From table (3) it can be concluded that Bio 18 has the highest contribution to the potential spread of the species with 64.8 % followed by Bio 19 (14.6 %), Bio 12 (9.7%), NDVI (5%), aspect (3.4%) and distance from road (1.5%) while others had less than 1 % contribution to the presence of the species. For future prediction of the spread of the species, dynamic variables from the current were dropped keeping the static variables and bioclimatic variables that significantly contributed to the potential spread. It can be observed from table (5) and fig (11) that under RCP 2.6, Bio 12 has the highest contribution for the years 2050 and 2070 with 46.2% and 51.2 % respectively. Under RCP 4.5, Bio 18 and Bio 19 has a significant contribution with 44.2 and 28.3 % for the years 2050 and 2070. Under RCP 6, Bio18 and Bio12 had significant contributions for the years 2050 and 2070 with 55.7 and 79.2% respectively. For RCP 8.5 Bio 18 has a significant contribution for the years 2050 and 2070 respectively with 41.8 and 41.7 %.

Table 5: Variable contribution to the future distribution of *Maesopsis eminii* under different RCP scenarios

Variable	Name of the variable	RCP 2.6		RCP 4.5		RCP 6		RCP 8.5	
		2050	2070	2050	2070	2050	2070	2050	2070
Bio 12	Annual precipitation	46.2	51.3	34.2	27.2	21.9	79.2	38.5	36
Bio 18	Precipitation of warmest quarter	31	29.1	44.2	25.7	55.7	0.4	41.8	43.7
Aspect	Aspect	8.4	6.2	7.8	6.8	8.5	7	7.3	6.2
Bio 1	Annual temperature	7.8	4.8	4.3	4	5.2	2.4	3.3	5.9
Elevation	Elevation	6.2	8.2	9.2	7.6	8.3	1.4	8.9	7.9
Slope	Slope	0.4	0.3	0.3	0.2	0.3	0.4	0.2	0.3

Bio 19	Precipitation of coldest quarter	0.1	0.1	0	28.3	0	9.2	0	0

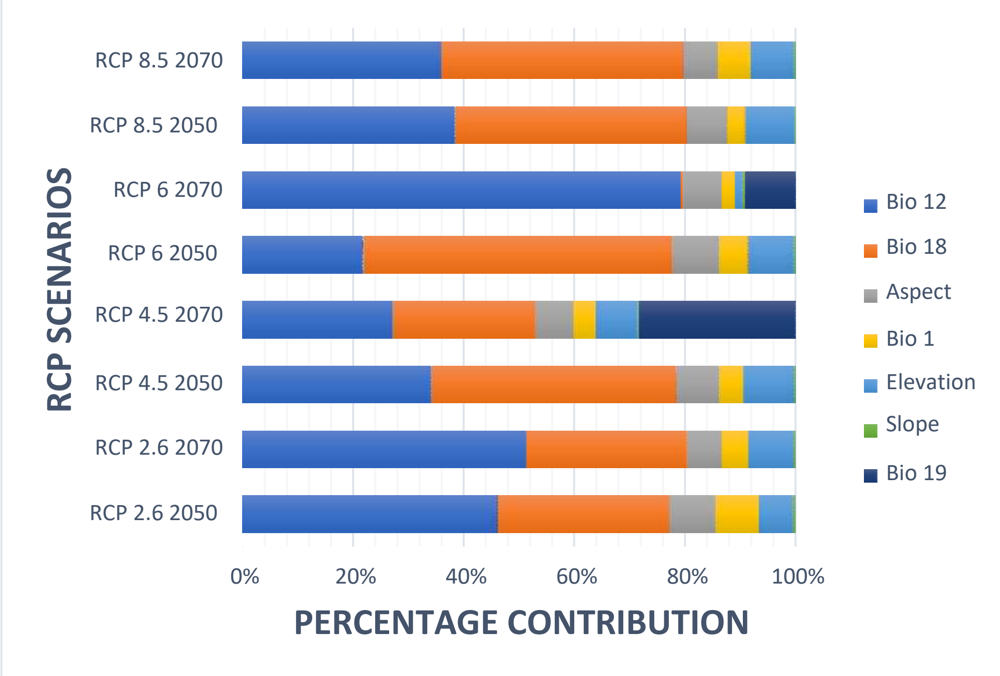


Fig 10: Graph representing variable contribution to the future spread of the species plotted against RCP scenarios

4.5.2 Validation of the model for future distribution

Table 6: Accuracy matrix and their values for future distribution of *Maesopsis eminii* under RCP scenarios

MODEL	TSS Value	Overall Accuracy	Sensitivity	Specificity	Test AUC	AUC standard deviation
RCP 2.6 2050	0.83	0.83	1	0.83	0.92	0.02
RCP 2.6 2070	0.83	0.83	1	0.83	0.94	0.02
RCP 4.5 2050	0.65	0.85	0.8	0.85	0.93	0.02
RCP 4.5 2070	0.71	0.84	0.86	0.84	0.93	0.03
RCP 6 2050	0.70	0.83	0.86	0.83	0.92	0.02
RCP 6 2070	0.70	0.84	0.86	0.84	0.95	0.01
RCP 8.5 2050	0.70	0.83	0.86	0.83	0.93	0.01
RCP 8.5 2070	0.70	0.84	0.86	0.84	0.94	0.01

For the validation of the model, TSS, overall accuracy, sensitivity, and specificity were calculated using codes in RStudio. Test AUC and AUC standard deviation were calculated using maxent.

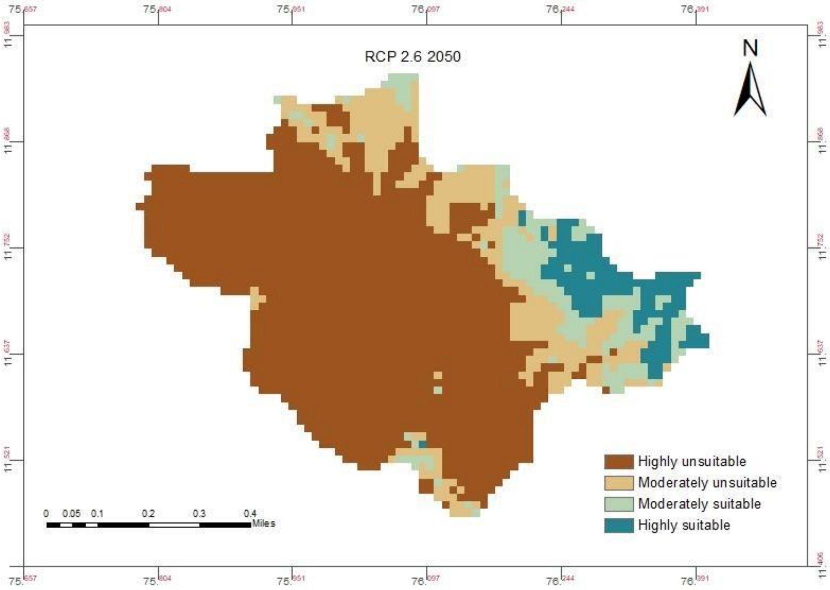
4.5.3 Distribution of *Maesopsis eminii* for the years 2050 and 2070 under RCP 2.6

The results of modelling of species distribution under the RCP 2.6 for the years 2050 and 2070 is given in fig 12 (a and b) and table 6. Under RCP 2.6 2050, the highly unsuitable region for the spread of the species covers a total area of 1493 km^2. The moderately unsuitable region spreads over an area of 345 km^2. the moderately suitable region covers an area of 185 km^2 and the highly suitable region covers an area of 152 km^2.

Compared to 2050, by 2070 the highly unsuitable area increased covering an area of 1719 km^2, the moderately unsuitable, moderately suitable and highly suitable area decreased 214 km^2, 125 km^2, 103km respectively.

For the year 2050, the western part of the district is predicted to have a highly unsuitable region of spread for the species. The eastern part, covering the Wayanad wildlife sanctuary is seen to have the high to low regions of spread of the species. The southern part of the district, near Vythiri, may also have patches of high to moderate spread. Similarly, for the year 2070, the eastern part of the district covering the wildlife sanctuary might see patches of moderate to high spread of the species and the northern part will see a moderate spread of the species.

(a)



(b)

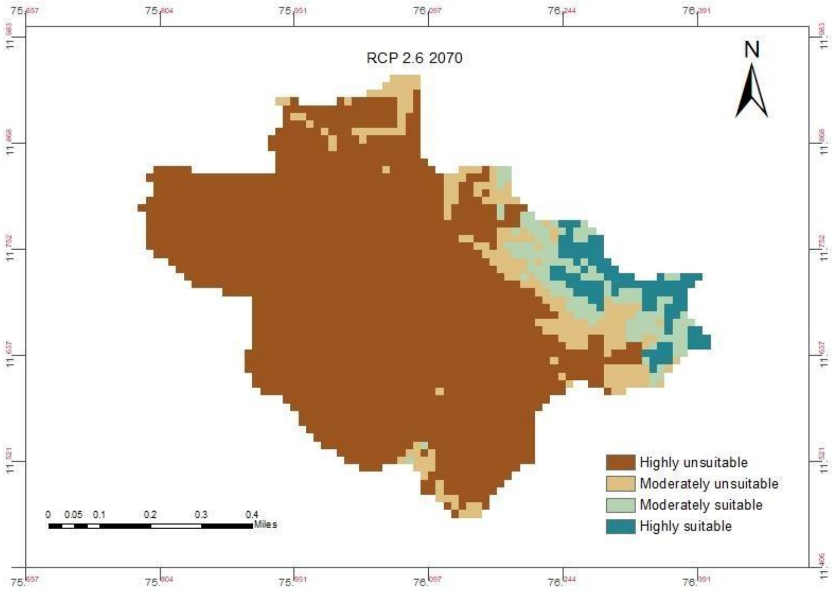
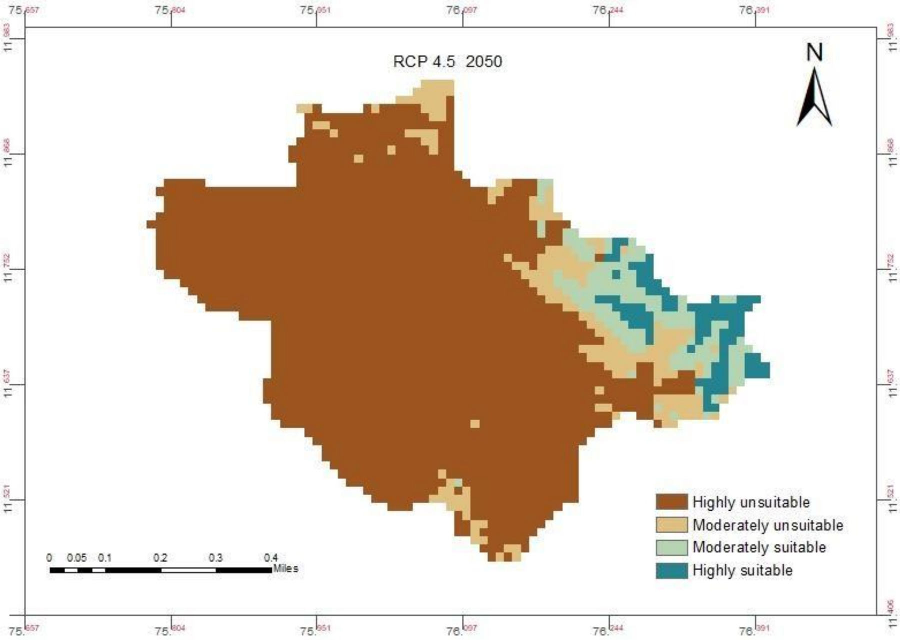


Fig11: Map showing the future distribution of *Maesopsis eminii* under RCP 2.6 for the years(a) 2050 and (b) 2070

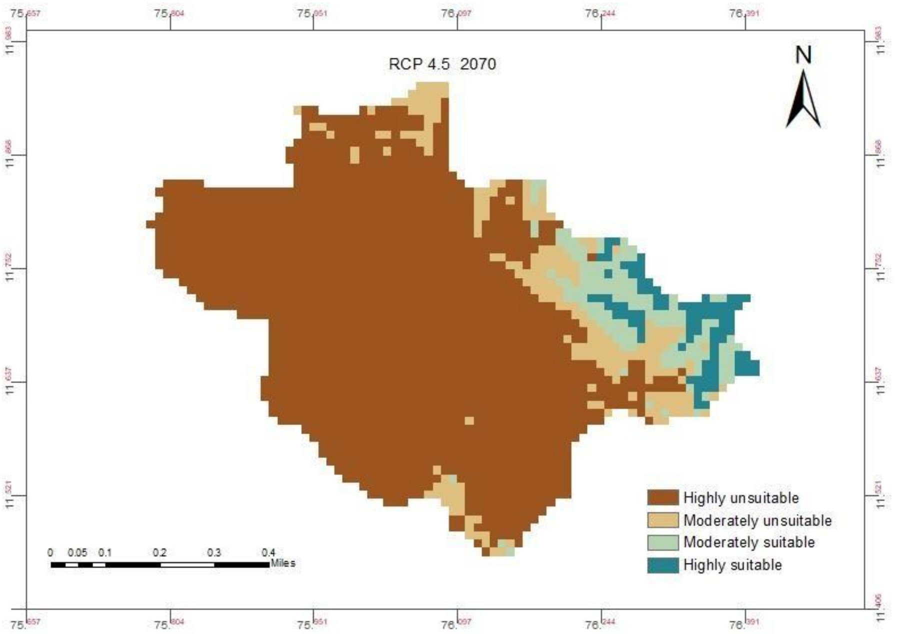
4.5.4 Distribution of *Maesopsis eminii* for the years 2050 and 2070 under RCP 4.5

Under RCP 4.5, the highly unsuitable region covers an area of 1755km^2, the moderately unsuitable region covers an area of 193km^2, the moderately suitable region covers an area of 134km^2, the highly suitable region covers an area of 93km^2. The eastern part of the district, covering the wildlife sanctuary will have the high potential spread of the species, region in and around Sulthan Bathery, in the eastern region will see moderate to low spread of the species and the western part of the district will have very low potential spread. The Thirunelly region, towards the north and Vythiri towards the south will have low potential spread.

Compared to 2050, in 2070 the highly unsuitable region will decrease covering an area of 1726km^2, the moderately unsuitable region will increase with an area of 222km^2. The moderately suitable region will increase with an area of 137km^2 and the highly suitable region will decrease covering an area of 90km^2. The eastern part of the district, covering the wildlife sanctuary will have the high potential spread of the species, region in and around Sulthan Bathery, in the eastern region will see moderate to low spread of the species and the western part of the district will have very low potential spread. The Thirunelly region, towards the north and Vythiri towards the south will have low potential spread.



(a)



(b)

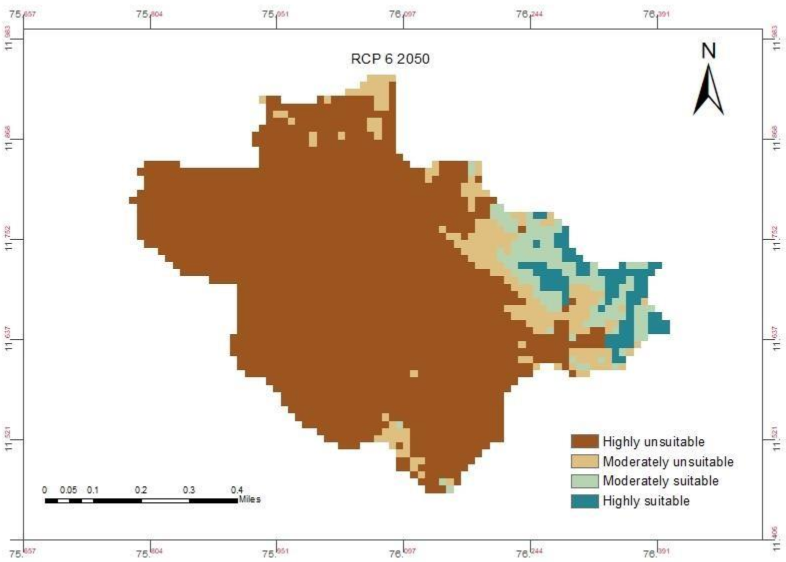
Fig12: Map showing the future distribution of *Maesopsis eminii* under RCP 4.5 for the years(a) 2050 and (b) 2070

4.5.5 Distribution of *Maesopsis eminii* for the years 2050 and 2070 under RCP 6

Under RCP 6, for the year 2050, the highly suitable range of the species will cover an area of 1765km^2, the moderately unsuitable range of the species will cover an area of 196km^2, the moderately suitable range will cover an area of 125km^2 and the highly suitable area will be 89 km^2.

Compared to 2050, by 2070 the highly and moderately unsuitable regions covered by the species will be decreased and have an area of 1746km^2 and 184km^2. The moderately suitable and highly suitable areas will be increased and have 140km^2 and 105km^2 respectively. For both 2050 and 2070, the eastern part of the district, covering the wildlife sanctuary will have the high potential spread of the species, region in and around Sulthan Bathery, in the eastern region will see moderate to low spread of the species and western part of the district will have very low potential spread. The Thirunelly region, towards the north and Vythiri towards the south will have moderate to low potential spread.

(a)



(b)

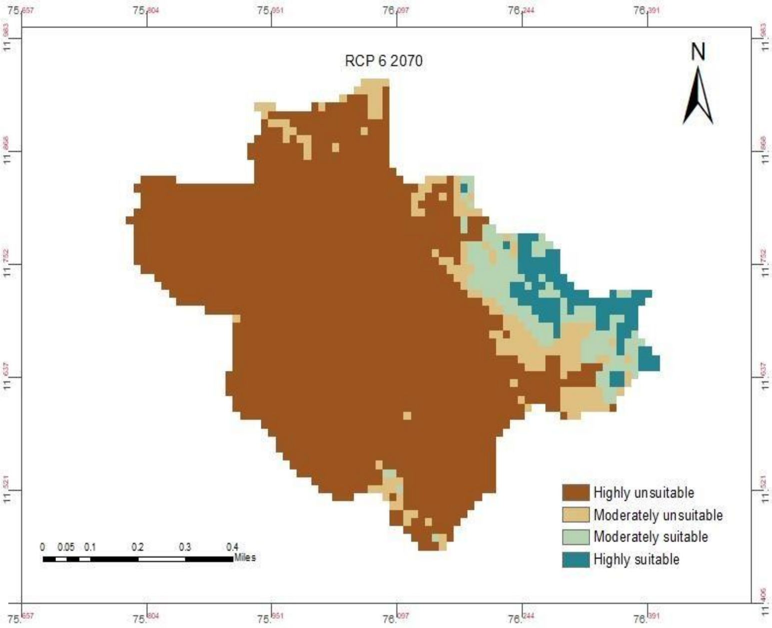
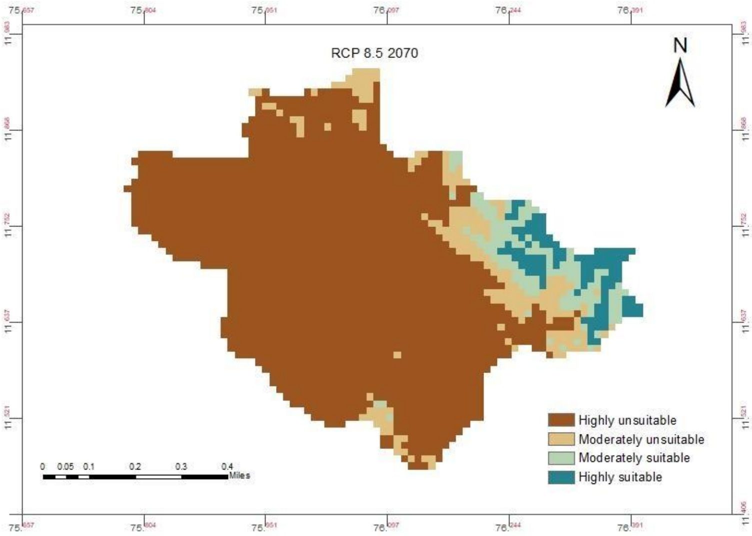


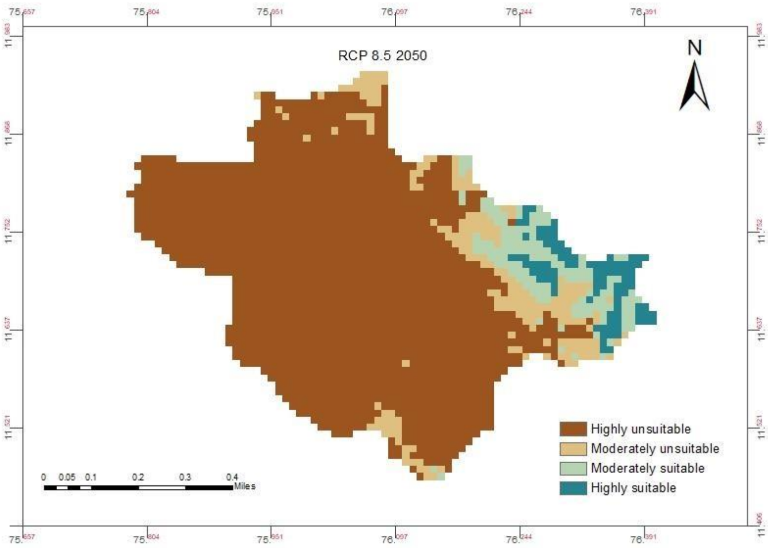
Fig13: Map showing the future distribution of *Maesopsis eminii* under RCP 6 for the years(a) 2050 and (b) 2070

4.5.6 Distribution of *Maesopsis eminii* for the years 2050 and 2070 under RCP 8.5

The spread of the species under RCP 8.5 for the year 2050, under the highly unsuitable region, will have an area of 1737km^2. The moderately unsuitable region will have an area of 205km^2. The moderately and highly suitable regions covered will have an area of 138 km^2 and 95 km^2. Compared to 2050, the year 2070 under the same RCP will notice an increase in the highly unsuitable and suitable regions with an area of 1744 km^2 and 104 km^2. The moderately unsuitable region will have an area of 201 km^2 and the moderately suitable region will have an area of 126 km^2, decreasing with that of 2050. For both 2050 and 2070, the eastern part of the district, covering the wildlife sanctuary will have the high potential spread of the species, region in and around Sulthan Bathery, in the eastern region will see moderate to low spread of the species and western part of the district will have very low potential spread. The Thirunelly region, towards the north and Vythiri towards the south will have moderate to low potential spread.

(a)





(b)

Fig14: Map showing the future distribution of *Maesopsis eminii* under RCP 8.5 for the years(a) 2050 and (b) 2070

Table 7: Table representing the habitat suitability of *Maesopsis eminii* under RCP scenarios

Scenario	Highly Unsuitable (km²)	Moderately Unsuitable (km²)	Moderately Suitable (km²)	Highly Suitable (km²)
Present	1872	141	95	67
FUTURE				
RCP 2.6 2050	1493	345	185	152
RCP 2.6 2070	1719	214	125	103
RCP 4.5 2050	1755	193	134	93
RCP 4.5 2070	1726	222	137	90
RCP 6 2050	1765	196	125	89
RCP 6 2070	1746	184	140	105
RCP 8.5 2050	1737	205	138	95
RCP 8.5 2070	1744	201	126	104

From table (7), it is seen for the year 2050, RCP 2.6 will have a high potential distribution of species covering an area of 152 km^2 and RCP 6 will have the least potential with an area of 89 km^2. For the year 2070, RCP 6 will have a high potential distribution of species covering an area of 105 km^2 and RCP 4.5 will have the lowest potential with an area of 90 km^2.

4.5.7 Range expansion

Range expansion was calculated by converting the average ASCII files to binary rasters in ArcMap 10.7.1. The binary rasters were then subjected to calculations in the raster calculator. The current average ASCII were given values 5 representing non-suitable and 10 representing suitable habitat. The corresponding binary values for the future was given as 1 for suitable and 0 for unsuitable. (10-1) in raster calculator gives no change. (10-0) gives loss, contraction in habitat. (5-1) gives gain- range expansion and (5-0) gives no occupancy.

Table 8: Table representing the change in the distribution of the species under RCP scenarios

Scenario	Range expansion (sq.km)	No Occupancy (sq.km)	No change (sq.km)	Range contraction (sq.km)
RCP 2.6 2050	70	1944	142	19
RCP 2.6 2070	86	1914	141	20
RCP 4.5 2050	83	1931	144	17

RCP 4.5 2070	83	1931	144	17
RCP 6 2050	69	1945	144	17
RCP 6 2070	104	1910	141	20
RCP 8.5 2050	89	1925	144	17
RCP 8.5 2070	86	1928	144	17

From table (8), it can be observed that for the year 2050 RCP 8.5 will have the highest range expansion with 89 km^2 and for the year 2070, RCP will have the highest range expansion with 104 km^2.

CHAPTER 5

DISCUSSION

The effects of climate change are being spread in all sectors. The existence of life is being questioned and several species have become extinct due to the devastating incidents that happened to nature. Sensitive species have perished and some have gone extinct when the habitat is changed drastically due to extreme climatic events. Several other species changed their habitat to appropriate spaces or showed adaptive mechanisms. Among avian species, changes in distribution are widely seen since they are sensitive to small climatic shifts and due to their migration.

Maesopsis eminii belongs to family Rhamnaceae, that has species which are tolerant to drought. It is an angiosperm and a large tree that is fast growing. It is popularly reputed as a plantation tree. Native to Africa, it is a useful timber in the humid tropics and occurs in the rainforests. This is commonly used as shade trees in coffee plantations and *M.eminii* colonizes forest canopy openings, grasslands and empty niches and also occupies disturbed areas in forests (Joshi *et al*., 2015). *M. eminii* apart from India and Africa has also been noticed in Bangladesh, Puerto Rico, Malaysia, Rwanda and Indonesia.

Thus, the present study examines the current distribution patterns of the *M. eminii* based on climatic and non-climatic variables and also the distribution is being projected for the years 2050 and 2070 under four Representative Concentration Pathways (RCP).

MaxEnt software was used to study the distributional changes of *M. eminii* by relating the presence data points to the climatic conditions prevailing there. The study used the occurrence data points both primary and secondary and climate data from 1970-2000 for current conditions and the years 2050 and 2070, the climate was predicted by using data accessed from CCAF of 30-second resolution under four different Representative Concentration Pathways (RCPs). In this chapter the results obtained are discussed and analyzed in detail.

5.1 Variable selection and analysis

Autocorrelation among variables could cause inaccuracies before running the model. (Sharma *et al*., 2018). Thus, to remove multicollinearity among variables, pairwise correlations were done and highly correlated variables were excluded with a Pearson's correlation coefficient (r). Pearson's correlation coefficient of $r > 0.7$ was chosen to limit the influence of multicollinearity and overfitting (Wei et al, 2018). The non-bioclimatic variables that were selected included aspect, elevation, NDVI, slope, population density, LULC, soil type.

Climatic variables are well known for high correlation among each other. For the interpretation of the contribution of each input variable to the species distribution model, the autocorrelation of the input has to be reduced by removing highly correlated variables. The inclusion of these variables will not affect the quality of the prediction, but can seriously limit the inference of the contribution of any correlated variable. From fig (2) the highlighted variables showing high correlation and the variables with reduced correlation were selected for the potential distribution of the species, thus improving the accuracy of the model thereby reducing the overfitting of the model. Bio 1 (annual mean temperature) was correlated with Bio 10 (Mean temperature of the warmest quarter, Bio11 (Mean temperature of the coldest quarter), Bio 5 (Maximum temperature of the warmest month), Bio 6 (minimum temperature of the coldest month), Bio 8 (Mean temperature of the wettest quarter), Bio 9 (Mean temperature of the driest quarter). Bio 1 was selected among the other variables due to its significant contribution to the spread of the species. Bio 12 (Annual precipitation) was cross-correlated with Bio 13 (Precipitation of the wettest month), Bio 14 (Precipitation of driest month), Bio 15 (Precipitation seasonality), Bio 16 (Precipitation of wettest quarter), Bio17

(Precipitation of the driest quarter), Bio 18 (Precipitation of the warmest quarter), Bio 19 (Precipitation of coldest quarter). Bio 12 was again selected amidst its significance over other variables. The analysis yielded Bio 1 (Annual mean temperature), Bio 12 (Annual mean precipitation), Bio 19 (Precipitation of the coldest quarter), Bio 18 (Precipitation of the warmest quarter), aspect, Normalized difference vegetation index (NDVI), Land use and landcover change (LULC), slope, soil type, distance from road and elevation.

5.2 Variable contribution to the model

To determine which variable is the most essential, the Jackknife test was employed. Each variable was eliminated one at a time, and a model was built using the variables that remained. Initially, the model was built separately for each variable. Subsequently a model was created using all variables (Fig 5). Bio 18 had a reasonably good fit to the training data. Moving on to the lighter blue bars, it appears that no variable offers a significant quantity of important information that is not already present in the other variables, as deleting each variable did not result in a significant reduction in training gain. Two more jackknife plots, use either test gain or AUC in place of training gain. Comparing the three jackknife plots can be very informative. The AUC plot (fig 7) shows that Bio 18 is the most effective single variable for predicting the spread of the species that was set aside for testing when predictive performance is measured using AUC, even though it was hardly used by the model built using all variables. The relative importance of Bio 18 also increases in the test gain plot, when compared against the training gain plot.

The response curves show a MaxEnt model that solely uses the appropriate variable. These graphs show how anticipated appropriateness is dependent on the selected variable as well as on dependencies generated by correlations between the selected variable and other factors. If there are high correlations between variables, they may be easier to interpret.

5.3 Validation of the model

The average test AUC value measures the predictive accuracy which is threshold independent. In the case of presence only data, higher the AUC shows that the model distinguishes between presence and background locations. The model having a higher AUC is more accurate. Also in Fig.7, it is seen that the omission on test samples is a very good match to the predicted omission rate. In the ROC curve (Fig.8), the mean (red line) is above the random prediction line which shows the model is better in predicting the presences.

5.4 Change in the habitat of *M. eminii*

Along with the anthropogenic pressure which promotes bio invasion, climate change amplifies the wide distribution of the invasive species (Adhikari et al. 2015; Panda et al. 2018).

From the results it can be concluded that for the year 2050, RCP 2.6 is more significant because the high suitability and moderate suitability areas are much higher under this greenhouse emission scenarios compared to other scenarios for the year. The scenario will also see high range contraction for the year 2050. The high suitability area or higher potential of the species will see an increase of 55% from the current. Highly moderate suitability will see an increase of 48% and the range contraction will see an increase of 0.8% from the current respectively. The reason RCP 2.6 will be experiencing the high percentage of habitat suitability for both high and moderate potential (High suitability and high moderate suitability) and range contraction is due to the high significant percent contribution of Bio 1(annual mean temperature) with 7.8%. Bio 1 has also showed significant mean fluctuation from the current. According to Epila., 2018, *M. eminii* thrives well at a habit which experiences temperature of 22-28 ^{0}C. RCP 2.6, 2050 showed notably less variance in mean fluctuations from the current for Bio 18 (Precipitation of the annual quarter). Bio 12 (annual mean precipitation) had no variability in mean fluctuation. Kidanganadu, Chetalayam and Muthanga regions of the district will see the high and moderate potential and high range expansion of *M. eminii*

For the year 2070, the intermediate scenario RCP 6 will have greater significance as high moderate suitability, high suitability, high range expansion and contraction was predicted under this scenario for *M. eminii.* The high moderate suitability for the species will see an increase of 32%, high suitability area will see an increase of 36%, range contraction and extraction will see an increase of 4% & 0.8% respectively from the current potential distribution of the species. The reason RCP 6 will have significance is because Bio 12 (annual mean precipitation) has high significant contribution (79.2%) and high variability in mean under RCP 6 2070 (Mwenda *et al*., 2019). Also, Bio 18 (precipitation of warmest quarter) showed low significant contribution (0.4%) and had significant mean fluctuations. For RCP 6 Bio 1 (annual mean temperature) had the lowest significant contribution (2.4%) and mean variance fluctuations were comparatively less. Kidanganadu, Chetalayam, Muthanga, Vythiri regions under the district will experience more presence of *M. eminii* for the year 2070.

5.5. Conservation strategies

From this study, it was clear that climate warming causes the range expansion of the invasive species. It could completely refurbish the ecosystem, its composition, phenology and also creates an ecosystem imbalance especially, inthe protected areas. The results of this study can act as a precautionary note in a situation where there is a lack of information base in invasive species distribution and ecology. With this result, management measures can be focused on the areas of predicted habitat suitability. To tackle the aggressive growth of the invasive species *M. eminii* there should be a short term and long-term management action plan implementation. The distribution modelling can aid in the risk assessment measures and thus the eradication procedures. Besides the distribution modelling, to prevent the profuse growth and colonization of the invasive species, species traits, dispersal pathways and the mechanism of the natural filters should be better understood. The invasive nature of *M. eminii* is mainly because of their drought tolerance, high growth rate and light demand (Epila *et al*., 2018). As climate changes rapidly, knowledge of native and introduced species' germination trends becomes increasingly important. To predict future plant community dynamics, it is essential to study alien species under natural conditions. Taking into account the future light and water availability regimes is imperative to minimize the impact of the *M. eminii* invasion. This can be accomplished by detecting the species during the wet season when it germinates most rapidly, minimizing forest gaps and other disturbances that might provide favorable light conditions for *M. eminii* (Mwenda *et al*., 2019).

CHAPTER-6

SUMMARY

Climate change has become more evident with its adverse effects becoming devastating in the 21 st century. The natural environment and humans have become more vulnerable to the effects of climate change. The biodiversity and climate change are more interlinked as the latter's distribution range, dispersal rates, growth seasons are noticed to have declined due to climate change, both natural and anthropogenic which have even resulted in the species getting extinct. This has also given rise to the spread of the invasive species which inhibits the growth of the native species adding up more to the reasons for extinction of the native species. Climate change can trigger the spread of invasive species and this study is proof in-ground standing the statement.

Maesopsis eminii, found in the South African savannahs were introduced into India as shade trees in coffee plantations and also for its timber. The climate conditions that prevailed has promoted the invasiveness of the species. This study aims in predicting the current and future species distributions of *Maesopsis eminii* in the Wayanad district, Kerala for the RCP scenarios for the years 2050 and2070. The selected RCPs include RCP 2.6, RCP4.5, RCP 6, RCP 8.5.

The primary data points were collected from the study area, Wayanad district Kerala and secondary data points were collected from KFRI, Thrissur. The environmental and climatic variables that promoted the spread of the species were evaluated and a total of 24 variables were assessed. These variables were then clipped and extracted by masking them to the area of interest using the shapefile in ArcMap 10.7.1. The variables were then subjected to Correlation analysis for multicollinearity and overfitting of the model. Highly reduced variables were estimated and the output was received in .csv form at in Microsoft Excel.

- 11 variables were selected as input to MaxEnt modelling of the current potential distribution of the species.
- For current distribution, Bio 18 yielded the highest contribution with 64.8 %, followed by Bio 19 with 14.6%, Bio 12 9.7%, Bio 0.1%. These bioclimatic variables along with static variables were subjected to MaxEnt modelling of future distribution of species.
- The validation of the model for current and future yielded high values of AUC under ROC and TSS which revealed high accuracy rates for the model
- The habitat potential of the species was calculated under the selected RCP scenarios which revealed high suitability potential for the species for the year 2050 is under RCP 2.6 with an area of 152 km^2 and least under RCP 6 with 89 km^2.
- For the year 2070, the high suitability potential was under RCP 6 with an area of 105 km^2 and the lowest under RCP 4.5 with an area of 90 km^2.
- Range expansion revealed that for the year 2050, RCP 8.5 will have higher expansion with 89km^2 . RCP 6 will have higher expansion under 2070 with an area of 104 km^2.
- Range contraction was also analysed which revealed that RCP 2.6 with 19 km^2 will see high contraction for the year 2050 and in 20170, RCPs 2.6 and 6 will see the same value of contraction with 20 km^2 respectively.

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IMPACT OF PROJECTED CLIMATE CHANGE ON THE SPREAD AND DISTRIBUTION OF THE INVASIVE ALIEN SPECIES *Maesopsis eminii* Engl. IN WAYANAD DISTRICT OF KERALA

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ABSTRACT

The 21 st century has witnessed an adverse increase in the impacts due to climate change. It has affected both societal and environmental regimes. Scientists has drawn conclusions to the impacts of climate change on the increase in the impacts caused due to invasive alien species invasion on the natural biodiversity. Biodiversity are known to be declining in large extends due to biological invasions. Climate change is one of the factors that triggers the spread of invasive alien species thereby affecting the growth of the native species. An early understanding of the effect of climate change on species distributions can provide critical information for conservation planning. *Maesopsis eminii* is a medium risk invasive alien species that has been noticed to be spreading across the Wayanad district, Kerala. Currently the species is at its initial stages of spreading which could fasten as the climatic factors triggers its rate of dispersal and growth. The goal of the study was to use ecological niche modelling, MaxEnt which uses presence only records along with the environmental variables to quantify the effect of climate change on the spread of the species. A high accuracy obtained from Area Under Curve (AUC) and True Skill Statistics (TSS) suggested that it is a good prediction model. The maximum entropy (MaxEnt) model was used to predict the current as well as the future distribution of the species. The future spread of the species was modelled under the four climate change scenarios RCP 2.6, RCP 4.5, RCP 6, RCP 8.5 for the years 2050 and 2070. The model also predicted suitable areas for the species which varies under the RCPs. The habitat potential of the species was calculated under the selected RCP scenarios which revealed high suitability potential for the species for the year 2050 is under RCP 2.6 and RCP 6 for 2070. The study could be used up by policy makers and conservatists to adopt necessary steps to delieniate the spread of *Maesopsis eminii* in the future.