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# ECOLOGICAL FORECASTING OF *MELIA DUBIA* CAV.: A CASE STUDY FROM KERALA

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Agroforestry and block plantations are increasingly recognised in Kerala as sustainable land-use strategies that integrate trees into farming systems, providing ecological and economic benefits. Among the tree species promoted in the region, *Melia dubia* (Malabar Neem) has gained popularity due to its fast growth and commercial potential. However, identifying suitable areas for its cultivation is essential to ensure plantation success, especially in Kerala's diverse agro-climatic settings and fragmented landholdings. Ecological Niche Modelling (ENM) serves as a valuable tool for predicting the potential distribution of species based on environmental variables, aiding in species-site matching and guiding plantation planning. In this study, the Maximum Entropy (MaxEnt) model (v. 3.4.3) with a regularisation multiplier of one was used to delineate the ecological niche of *M. dubia* in Kerala. The model output indicates that *M. dubia* is highly suitable in 2.57% of area in Kerala, and moderately suitable in 3.33%, and low suitable in 7.43%. District-wise, Palakkad (1.09%), Wayanad (0.57%), and Thrissur (0.53%) show higher suitability compared to other districts. Dedicated and adaptive tree management practices can help improve plantation outcomes in marginally suitable areas. The results demonstrate that ENM can significantly contribute to upscaling agroforestry by enabling accurate site recommendations, minimising failure risks, and supporting strategic expansion of tree-based systems in Kerala.

Keywords: MaxEnt, niche, tree cultivation, agroforestry, Kerala

## INTRODUCTION

Ecological Niche Modelling (ENM) is a widely adopted approach in ecological research to estimate the suitable habitat range of a species under current and future environmental conditions. It enables identification of climatically favorable zones and helps assess habitat stability across different climate change scenarios (Adhikari et al. 2018, Adhikari et al. 2019). While often used interchangeably with Species Distribution Modelling (SDM), ENM specifically aims to estimate the fundamental ecological niche of a species—based on abiotic factors—whereas SDM focuses on mapping observed species distributions in geographic space, incorporating presence-absence data and dispersal limitations (Melo-Merino et al. 2020). Over the years, ENM has played a significant role in biodiversity conservation, especially in projecting the potential spread or decline of species. For instance, Rajpoot et al. (2020) conducted niche modelling for *Boswellia serrata*, highlighting its limited potential range in natural habitats and the need for long-term conservation strategies. Similarly, ENM has been employed in studies involving both flora and fauna to support conservation planning for endangered species (Majumdar et al. 2019, Mipun et al. 2019, Pradhan et al. 2020). Beyond conservation, ENM holds promising applications in agroforestry and farm forestry systems, where matching species with ecologically appropriate sites is vital for productivity and sustainability. Accurate identification of niche suitability can guide farmers and planners in selecting tree species best adapted to specific climatic and geographic conditions. In China, ENM was used to determine the climate niches of ten tree species and assess potential distribution

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shifts due to climate change (Ranjitkar et al. 2016). Likewise, Wang et al. (2017) employed the BiodiversityR package to define persistent suitability zones for *Xanthoceras sorbifolium* in China. In Nepal, MaxEnt modelling indicated that only 24% of the national area was favorable for *Alnus nepalensis*, demonstrating the model's potential in guiding plantation strategies (Rana et al. 2018).

In the context of Kerala, where agroforestry is increasingly promoted for its ecological and livelihood benefits, the use of ENM offers a strategic advantage. The state of Kerala has rich biodiversity owing to its edapho-climatic conditions. Thus, the crops grown here are highly heterogeneous with each crop or plant having their own micro-niches, which are conducive for better growth and yield. Added to these favorable concrete traits is the strong appetite for new crops and the search for new plant resources with the aim of diversifying or innovating crops by educated farmers. Additionally, reviewing the tree plantations and agroforestry practices in the state of Kerala, it is evident that the choice of tree species has always changed with time. For instance, trees like *Eucalyptus, Acacia mangium* and *Albizzia falcataria* were introduced in the state and later these species were forsaken for alternative species. There is increased interest among the stakeholders to take up indigenous tree species cultivation.

*Melia dubia* has gained attention and has expanded its scope because of its notable attributes. It is fast growing tree with straight stem without much branches and less shade effect, making it an ideal choice for agroforestry practice (Handa et al. 2020, Chavan et al. 2022). In India, *M. dubia* is cultivated as a short-rotation species, typically harvested after 6–10 years. It can grow up to 40 feet in height within just 2 years of planting, and a 10-year-old plantation yields up to 40 tons of biomass per acre. These features make it a commercially viable timber tree, for agroforestry plantation or any other plantations, which can yield maximum in shortest period. Despite the limitations in wood density for structural usage in short rotation duration, it is suitable for packaging industries, matchsticks, mini furniture and musical instruments, among others. (Gupta et al. 2019). *Melia dubia* is identified as an alternative species for multiple uses. With more than 20% of the total geographical area under forest and tree cover in India, the wood demand of the country is met from the import as well as the wood sourced from Trees Outside Forests (TOF) like the plantations and agroforestry. Forest-related legislatives and policies directly emphasised on conservation of the forest resources and encourage the wood industries to meet their own raw material needs. The National Agroforestry Policy of India evidently states that agroforestry has to be promoted for meeting the increasing raw material demand of wood-based industries (GOI 2014).

Environmentally, *M. dubia* enhances soil quality, biodiversity and acts as a carbon sink, making it suitable for reforestation and afforestation projects. Its adaptability to diverse climatic conditions and resistance to pests and diseases add to its appeal, providing a reliable option for farmers across varying climates in India. The increasing global demand for eco-friendly and sustainable products has boosted the popularity of *M. dubia*, aligning with the growing emphasis on sustainable forestry and achieving the Sustainable Developmental Goals like SDG 1 (No Poverty), SDG 5 (Gender Equality), SDG 7 (Affordable and Clean Energy) and SDG 12 (Responsible Consumption and Production). Advances in silvicultural practices and research which have improved cultivation methods, yield and quality, was further supported by extension services and knowledge dissemination by agricultural universities and research institutions (van Noordwijk et al. 2018, Arunachalam & Ramanan 2021). Together, these factors have contributed to the steady expansion of *M. dubia* cultivation in Kerala (Binu 2019), highlighting a strategic convergence of economic viability, environmental sustainability and enabling policy frameworks. The species' fast growth, suitability for intercropping, and rising demand in timber-based industries have made it an attractive choice for farmers and stakeholders alike. However, to ensure that this expansion is both sustainable and regionally appropriate, it is essential to identify and prioritise ecologically suitable areas for cultivation. In this context, ecological niche modelling emerges as a valuable tool, offering spatial insights into habitats that align with the species' ecological requirements. By facilitating site-specific promotion, such modelling not only enhances productivity and resource use efficiency but also helps in maintaining ecological integrity, thereby striking a balance between economic development and environmental conservation.

## MATERIALS AND METHODS

### Scope of *Melia dubia*

This tree species has garnered sufficient attention and scientific evidence for its multipurpose usage like timber, fodder as well as fuelwood in tropical countries like India. Additionally, the fast-growing nature of the tree provide advantageous position from the carbon sequestration point of view and thus, we foresee a growing interest on the tree. It is also evident from the increasing number of publications on this tree species which was assessed using keyword search "*Melia dubia*" in Google Scholar database (Figure 1) [accessed on 31 December 2023]. Species occurrence records of *M. dubia* were gathered through field surveys across its natural range and supplemented with data from published literature. Based on dataset from the literature, we delineated the natural distribution range and conducted a systematic corridor survey. This approach facilitated targeted field observations, enabling comprehensive data collection and validation of spatial attributes within the designated region. All together 232 occurrence data were used in the analysis. In the present study, we used baseline and future climate scenarios to understand and predict the distribution of *M. dubia* in Kerala.

### Baseline scenario

The baseline climate scenario refers to the historical climate data that serves as a reference point against which future climatic changes are measured. This involves using observed climate data over a past period, commonly 30 years, to establish a 'normal' climate state. For this, 19 bioclimatic variables representing the current climatic conditions were used to delineate the niche of the *M. dubia* (Table 1). These variables represent annual trends in temperature and precipitation, encompassing aspects such as seasonality and climatic extremes. Such factors can place physiological limits on species, thereby influencing their spatial distribution (O'Donnell & Ignizio 2012). The bioclimatic variables for the present period are derived from long-term averages of monthly climate data, specifically minimum, mean and maximum temperatures, along with precipitation, covering the 30-year

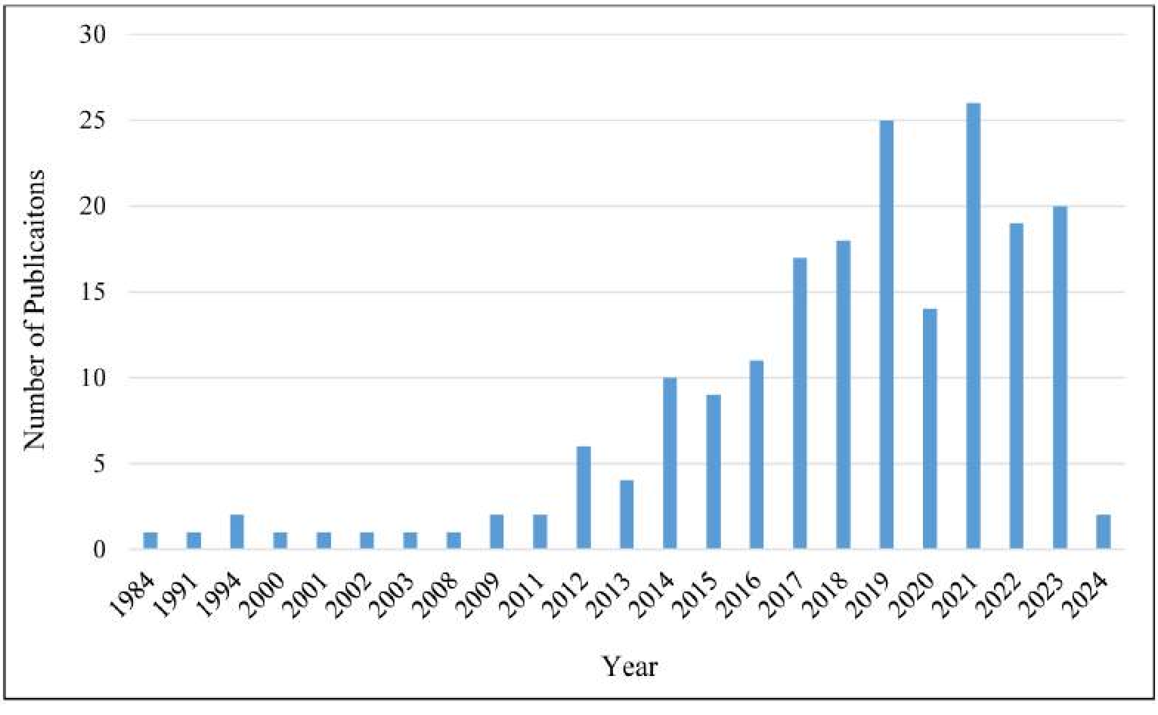



**Figure 1** Increasing number of publications on *Melia dubia* accessed from Google Scholar using the Publish or Perish software program (https://harzing.com/resources/publish-or-perish)

**Table 1** Overview of the 19 bioclimatic variables used

| Code | Variable Name |
|---|---|
| Temperature-related Variables | |
| BIO1 | Annual Mean Temperature (°C) |
| BIO2 | Mean Diurnal Range (°C) |
| BIO3 | Isothermality (%) |
| BIO4 | Temperature Seasonality (%) |
| BIO5 | Max Temperature of Warmest Month (°C) |
| BIO6 | Min Temperature of Coldest Month (°C) |
| BIO7 | Annual Temperature Range (°C) |
| BIO8 | Mean Temperature of Wettest Quarter (°C) |
| BIO9 | Mean Temperature of Driest Quarter (°C) |
| BIO10 | Mean Temperature of Warmest Quarter (°C) |
| BIO11 | Mean Temperature of Coldest Quarter (°C) |
| Precipitation-related Variables | |
| BIO12 | Annual Precipitation (mm) |
| BIO13 | Precipitation of Wettest Month (mm) |
| BIO14 | Precipitation of Driest Month (mm) |
| BIO15 | Precipitation Seasonality (%) |
| BIO16 | Precipitation of Wettest Quarter (mm) |
| BIO17 | Precipitation of Driest Quarter (mm) |
| BIO18 | Precipitation of Warmest Quarter (mm) |
| BIO19 | Precipitation of Coldest Quarter (mm) |

span from 1970 to 2000 (Fick & Hijmans 2017) which was accessed from WorldClim database (https://www.worldclim.org/).

## Future climate scenarios

Future climate scenarios are projections of how the climate might change based on different assumptions about future greenhouse gas emissions, land use changes, technological advancements, and global socio-economic factors (Hewitt et al. 2021). These scenarios are plausible representations of the future based on specific Shared Socioeconomic Pathways (SSPs) or Representative Concentration Pathways (RCPs). They range from low-emission scenarios that assume significant mitigation efforts and sustainable development (e.g., SSP1-2.6) to high-emission scenarios that reflect continued dependence on fossil fuels and higher levels of economic growth without equivalent sustainability efforts (e.g., SSP5-8.5).

For the present study, the selection of climate models was methodically undertaken to gauge the impacts of climate change on the distribution of *M. dubia* in Kerala. The selection process involved a review of the latest Intergovernmental Panel on Climate Change (IPCC) reports to identify climate models from the Coupled Model Intercomparison Project Phase 6 (CMIP6) that have been validated for the Indian subcontinent (Kaur et al. 2023). To encompass a spectrum of potential climate futures, a suite of Shared Socioeconomic Pathways (SSPs) was employed which are designed to reflect different magnitudes of climate change based on varying greenhouse gas emissions trajectories. SSPs provide a framework to explore how global society, demographics, and economics might change over the next century. Under this, we selected two model classes viz., CANEMS and HADGEM with different scenarios to assess the distribution of *M. dubia* in response to climate change in the year 2050. These scenarios included CANEMS SSP126, CANEMS SSP245, CANEMS SSP370, CANEMS SSP585, HADGEM KL126, HADGEM KL245, and HADGEM KL585. The models were chosen based on their capacity to simulate key climatic factors such as monsoon dynamics, temperature, and precipitation patterns (Rajpoot et al. 2020), which are important for the ecology of *M. dubia*.

The CANEMS model scenarios are based on the Shared Socioeconomic Pathways (SSPs) that represent different levels of greenhouse gas emissions and socioeconomic factors affecting climate change. CANEMS SSP126 scenario envisions a sustainable future with a low greenhouse gas concentration pathway, aiming at <2 °C above pre-industrial levels of global warming. CANEMS SSP245 predicts a middle-of-the-road pathway which emissions peak around mid-century, with some efforts toward sustainability without additional climate policies. CANEMS SSP370 predicts a scenario with more fragmented world concepts and regional rivalry, leading to higher emissions due to less cooperation and medium mitigation efforts. While CANEMS SSP585, the highest greenhouse gas emissions pathway, represents a future with unchecked emissions and rapid economic growth driven by fossil fuels. The HADGEM scenarios are projections from the Hadley Centre Global Environment Model, signified by KL alongside the SSP numbers, indicating a specific configuration of the model used. HADGEM KL126 corresponds to the SSP126 scenario but uses the HADGEM model configuration, representing the same sustainable, low-emission future. HADGEM KL245 uses the HADGEM model to simulate the SSP245 pathway, reflecting a moderate approach to emissions with some policy implementation toward sustainability. While HADGEM KL585 represent the SSP585 scenario, indicating a high-emission future with significant climate and ecological impacts (Jha & Jha 2021, Menezes et al. 2023).

## Ecological niche modelling

To model the ecological niche of *M. dubia*, we utilised MaxEnt software version 3.4.3. This tool predicts species distributions by correlating known occurrence points with environmental variables from the surrounding landscape (background). MaxEnt is widely recognised in ecological modelling for its robust performance and user-friendly graphical interface, which allows for automatic parameter tuning. Its consistent applicability and flexibility have made it a preferred choice in numerous peer-reviewed studies (Lantschner et al. 2019, Sillero & Barbosa 2021).

## Model parameterisation

For model calibration, we selected 10,000 background points and allowed up to 500 iterations, with a convergence threshold set at 0.00001. To manage model complexity, we incorporated hinge, product, linear, and quadratic feature types. The risk of overfitting was minimised by applying the default regularisation multiplier of 1. To evaluate the consistency of the model, MaxEnt was used to perform 20 replicate runs through cross-validation. Model accuracy was determined using the Area Under the Curve (AUC) metric. The significance of each bioclimatic variable was examined using multiple approaches: variable contribution analysis, the jackknife method, and response curves. Variable contribution analysis helped in estimating the relative influence of each predictor on model performance. The jackknife approach assessed how the inclusion or exclusion of individual variables affected the model's gain. Meanwhile, response curves provided insights into how each variable influence habitat suitability across different values along the climatic gradient.

## Model performance

The AUC is statistical measure that evaluates how well the model distinguishes between presence and absence, the performance of the model assessed based on it. The Receiver Operating Characteristic (ROC) curve is a graphical plot where the true positive rate (sensitivity) is plotted on the Y-axis against the false positive rate (1-specificity) on the X-axis at various threshold settings. The AUC value is the area under this ROC curve, with a range from 0 to 1. An AUC value of 0.5 suggests no discrimination (equivalent to random guessing), while a value of 1.0 indicates perfect discrimination, meaning the model perfectly separates presence and absence locations.

## Model thresholding

The current distribution of *M. dubia* was predicted based on the 'Cloglog' result which were transformed into binary maps for interpretation of climatic suitable and unsuitable areas with condition of applying threshold rule of 10-percentile training presence. The 'Cloglog' probabilities of species presence translates the continuous probabilities into binary maps indicating suitable or unsuitable habitats. While, the 10-percentile training presence threshold rule involves setting the threshold at a value for which 90% of the occurrence records used to train the model are predicted to be suitable. The rationale behind this approach is to minimise omission errors which occur when the model fails to predict an area as suitable where the species is known to be present. By using the 10-percentile threshold, researchers accept a certain level of commission error, i.e., predicting unsuitable areas as suitable, to reduce the risk of failing to identify areas that could potentially support the species. In the context of *M. dubia*, a species with economic and ecological importance, the application of the '10-percentile training presence threshold rule' ensures that the binary map reflects a comprehensive potential habitat. It is important, as the goal is to identify all areas that could support reforestation or cultivation efforts, ensuring that the suitability map is inclusive of all environments where *M. dubia* could potentially grow under current, as well as future, climate scenarios.

## Assessment of climatic novelty under future scenarios

The assessment of climatic novelty under future scenarios typically involves the analysis of how current climatic conditions might diverge from future conditions under various climate change scenarios. In the present study, climatic novelty under future scenarios was assessed using the Multivariate Environmental Similarity Surfaces (MESS) and most dissimilar variables (MoD) analysis of environmental variables within the Maxent framework (Rajpoot et al. 2020). The MESS analysis in MaxEnt involves comparing a set of environmental variables, e.g., temperature and precipitation under current conditions to the projected values of these variables under future climate scenarios. The result is a surface or map showing areas of similarity and dissimilarity. Areas with high dissimilarity scores indicate regions where the future climate is significantly different from the current climate, suggesting these areas may experience novel climatic conditions. While the MoD analysis is focused on identifying the environmental variables that contribute most to the dissimilarity between current and future conditions.

## Climatic niche characterisation

Climatic niche characterisation is a critical process in understanding the relationship between a species and the climatic variables that define its habitat. For *M. dubia*, this characterisation was performed through variable contribution analysis, jackknife test of variable importance, and analysis of response curves that assess the influence of various climatic variables on the species' distribution. The variable contribution analysis involves evaluating the individual contribution of each climatic variable to the predictive power of the niche model. In the context of MaxEnt modeling, variable contribution is quantified as the gain in model performance, i.e., increase in AUC value when the variable is included. By comparing the gains

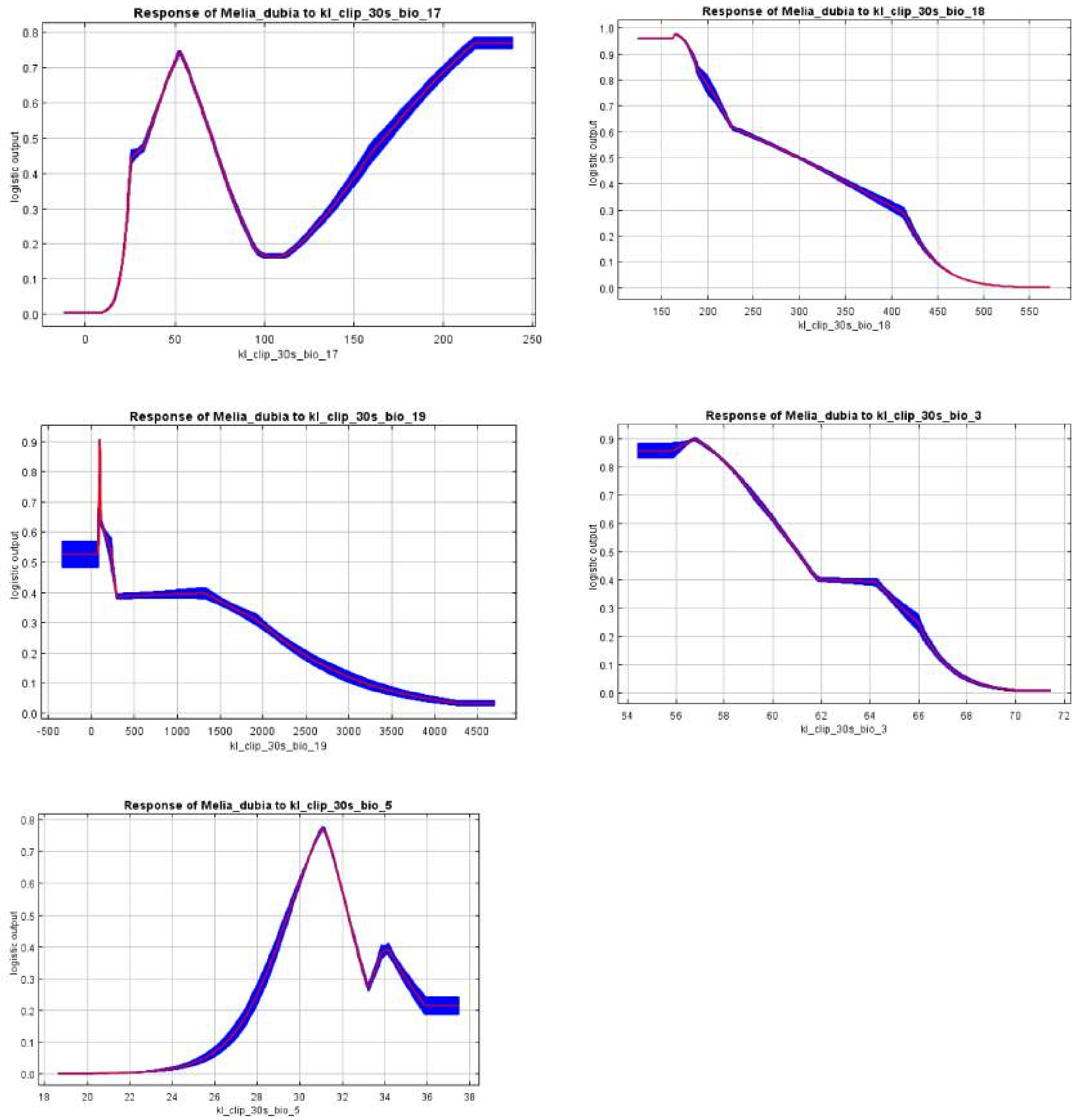



**Figure 2** The response curves illustrate how predicted suitability is influenced by individual variables, while also accounting for interactions with other correlated variables. The red line represents the average response across 20 replicate model runs, and the blue shaded area indicates the range of one standard deviation above and below the mean

across all variables, we can determine the climatic factors that are most significant in defining the distribution of *M. dubia*.

The jackknife test of variable importance is a resampling technique used to estimate the robustness and importance of each variable in the model independently. By systematically leaving out each variable from the model and then re-evaluating the model's performance, the jackknife test identifies variables that are unique predictors of the species' presence. A variable that causes a significant decrease in model performance when omitted is deemed to have high importance. Conversely, if model performance remains stable or improves when a variable is removed, that variable may be of lesser importance or redundant due to correlation with other variables.

The response curves depict the relationship between the probability of species presence and each climatic variable. They show how changes in a variable affect the likelihood of finding *M. dubia* in a particular area. For instance, a response curve might reveal that the probability of presence increases with temperature up to a certain point before declining, indicating an optimal temperature range for the species. These curves are crucial for identifying the thresholds and tolerances of *M. dubia* to different climatic conditions.

## RESULTS

### Model performance

The model demonstrated strong predictive ability, with mean training and test AUC values of 0.95 ± 0.052 SD and 0.94 ± 0.026 SD, respectively. These elevated AUC scores indicate robust and reliable model performance.

### Characterisation of the climate niche

The examination of variable importance and the corresponding response curves elucidates the climatic preferences of *M. dubia*, pinpointing critical climatic variables that delineate its niche. The species demonstrates a propensity for specific moisture conditions, favoring regions where the precipitation during the driest quarter ranges approximately between 220–250 mm. Similarly, its distribution is associated with the precipitation during the warmest quarter, which lies in the vicinity of 160–170 mm, and the precipitation of the coldest quarter, which spans a broader range of 100–200 mm. Additionally, the niche is characterised by a preference for isothermality, which measures the day-to-night temperature oscillation relative to the summer-to-winter oscillation, with an optimal range around 56–57%. The upper thermal limit of the species' niche is marked by the maximum temperature of the warmest month, which is around 31 °C. These climatic variables collectively sketch the essential contours of the climatic niche and inform the potential geographic distribution of *M. dubia* within Kerala (Figure 2).

The analysis of variable contribution showed that the precipitation of the driest quarter (19.4%) has the highest rank followed by precipitation of the warmest quarter (13%), precipitation of coldest quarter (12.8%), isothermality (12.8%) and maximum temperature of warmest month (12.2%). These variables account for >70% predicting the potential climatic niche of *M. dubia*. The jackknife analysis showed that the isothermality contributed for the highest model gain (0.45) when used in isolation, while the precipitation of the driest quarter decreased the gain predominately by 1.50 when omitted from the analysis (Table 2). This clearly indicates the influence of these variables on the distribution of the species compared to other variables (Figure 3).

The climatic niche of *M. dubia* is defined by a range of climatic parameters. The mean annual temperature conducive for the species is between 22–24 °C. During the warmest quarter, the suitable mean temperature lies between 25–27 °C, while the coldest quarter sees a mean temperature range of 21–23 °C. The species thrives in maximum temperatures of the warmest month ranging from 31–34 °C, with the minimum temperature of the coldest month falling between 16–18 °C. The temperature annual range that supports *M. dubia* is between 11.5 °C and 15.5 °C, with a mean diurnal range of 7.4–7.6 °C. Precipitation also plays a significant role, with annual figures ranging from 1100–2500 mm. The wettest month typically receives 700–800 mm of rainfall, while the driest month has 55–60 mm. Further delineating the precipitation profile, the wettest quarter contributes 1400–1600 mm, the driest quarter 230–250 mm, the warmest quarter 170–180 mm, and the coldest quarter 1000–1300 mm. These climate-related variables play a crucial role in identifying areas within the state that are currently suitable for the growth of *M. dubia*.

### Current distribution of climatically suitable areas

According to the MaxEnt model, about 2.56% of Kerala's total area is classified as highly suitable for *M. dubia*, with 3.33% identified as moderately suitable and 7.43% as having low suitability. District wise, Palakkad (1.09%), Wayanad (057%) and Thrissur (0.53%) have more suitability compared to the other districts of Kerala.

**Table 2** Summary of variable contribution analysis and jackknife test results for predictor importance

| Bioclimatic variable codes | Analysis of variable contributions | | Jackknife values of regularised training gain | |
|---|---|---|---|---|
| | Percent contribution | Permutation importance | Without variable | With only variable |
| kl_clip30s_bio_1 | 3.60 | 0.10 | 1.69 | 0.35 |
| kl_clip30s_bio_2 | 4.60 | 4.50 | 1.67 | 0.10 |
| kl_clip30s_bio_3 | 12.80 | 11.60 | 1.64 | 0.45 |
| kl_clip30s_bio_4 | 6.00 | 0.30 | 1.69 | 0.31 |
| kl_clip30s_bio_5 | 12.20 | 3.70 | 1.68 | 0.28 |
| kl_clip30s_bio_6 | 0.70 | - | 1.69 | 0.19 |
| kl_clip30s_bio_7 | 0.60 | 1.40 | 1.69 | 0.31 |
| kl_clip30s_bio_8 | 0.70 | 1.10 | 1.69 | 0.30 |
| kl_clip30s_bio_9 | - | - | 1.70 | 0.26 |
| kl_clip30s_bio_10 | 4.20 | 2.10 | 1.67 | 0.30 |
| kl_clip30s_bio_11 | 0.50 | 0.40 | 1.69 | 0.43 |
| kl_clip30s_bio_12 | 0.90 | 1.00 | 1.69 | 0.28 |
| kl_clip30s_bio_13 | 2.40 | 8.20 | 1.68 | 0.24 |
| kl_clip30s_bio_14 | 2.20 | 23.60 | 1.65 | 0.07 |
| kl_clip30s_bio_15 | 0.80 | - | 1.70 | 0.14 |
| kl_clip30s_bio_16 | 2.60 | 0.20 | 1.70 | 0.21 |
| kl_clip30s_bio_17 | 19.40 | 25.90 | 1.50 | 0.32 |
| kl_clip30s_bio_18 | 13.00 | 9.30 | 1.67 | 0.39 |
| kl_clip30s_bio_19 | 12.80 | 6.70 | 1.65 | 0.36 |

## Future distribution of novel climates

Results from the MESS analysis suggest that large portions of the current *M. dubia* range in Kerala are unlikely to experience novel climatic conditions in the future. However, regions projected to undergo climatic novelty are primarily associated with extreme values in annual mean temperature and the mean temperature during the coldest quarter (Figure 4).

## Future potential distribution areas

The climate models CanESM5 and HADGEM3-GC31-LL projected differing patterns in the future potential distribution of *M. dubia* across Kerala (Figure 5). The CanESM5 model indicated a notable expansion in climatically suitable zones, covering approximately 3% of the state's total area (Figure 6). In contrast, the HADGEM3-GC31-LL model also projected an increase in suitable habitat but within a narrower range of about 2–4% compared to present conditions (Figure 7). While the CanESM5 model showed a consistent rise in highly suitable areas over time, the HADGEM3-GC31-LL model reflected a more variable trend.

# DISCUSSION

As the MaxEnt model output indicated, 2.56% of the total geographical area of the Kerala state is highly suitable for the species studied—*M. dubia.* While assessing the impact of climate change, the outputs generated from such modelling exercises will play a crucial role in developing spatial maps. These maps will serve

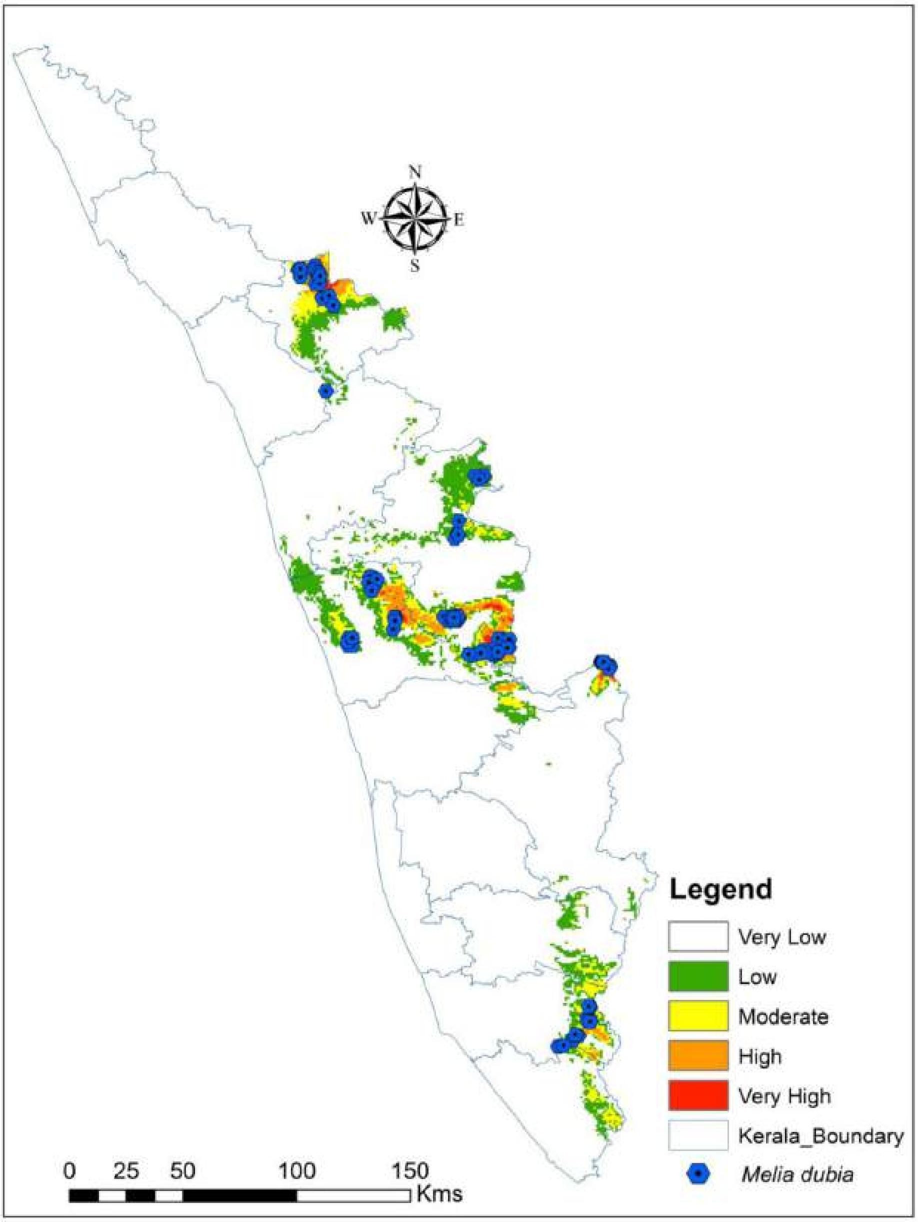



**Figure 3** The mapped occurrence points of *Melia dubia* are displayed over the modeled climatic suitability surface for the present period in Kerala. Distinct color zones indicate areas of climatic suitability, determined by applying the ten-percentile threshold to the average probability output from the model

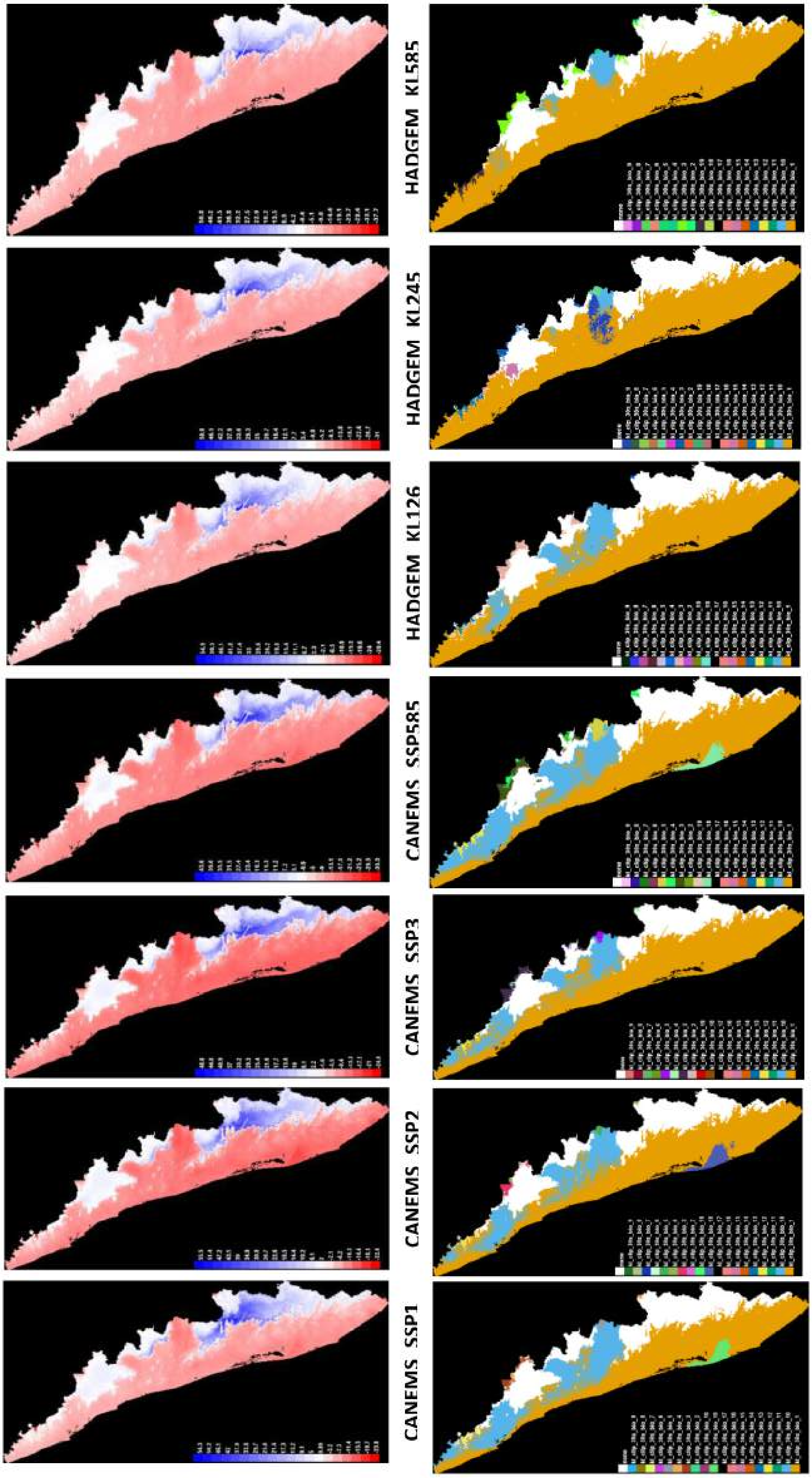



**Figure 4** Multivariate Environmental Similarity Surfaces (MESS) and most dissimilar variable (MoD) analysis of environmental variables. Pictures in first row (MESS) shows the areas in red having one or more environmental variables outside the range present in the training data. While the pictures in the second row (MoD) shows the most dissimilar variable, i.e., the one that is furthest outside its training range

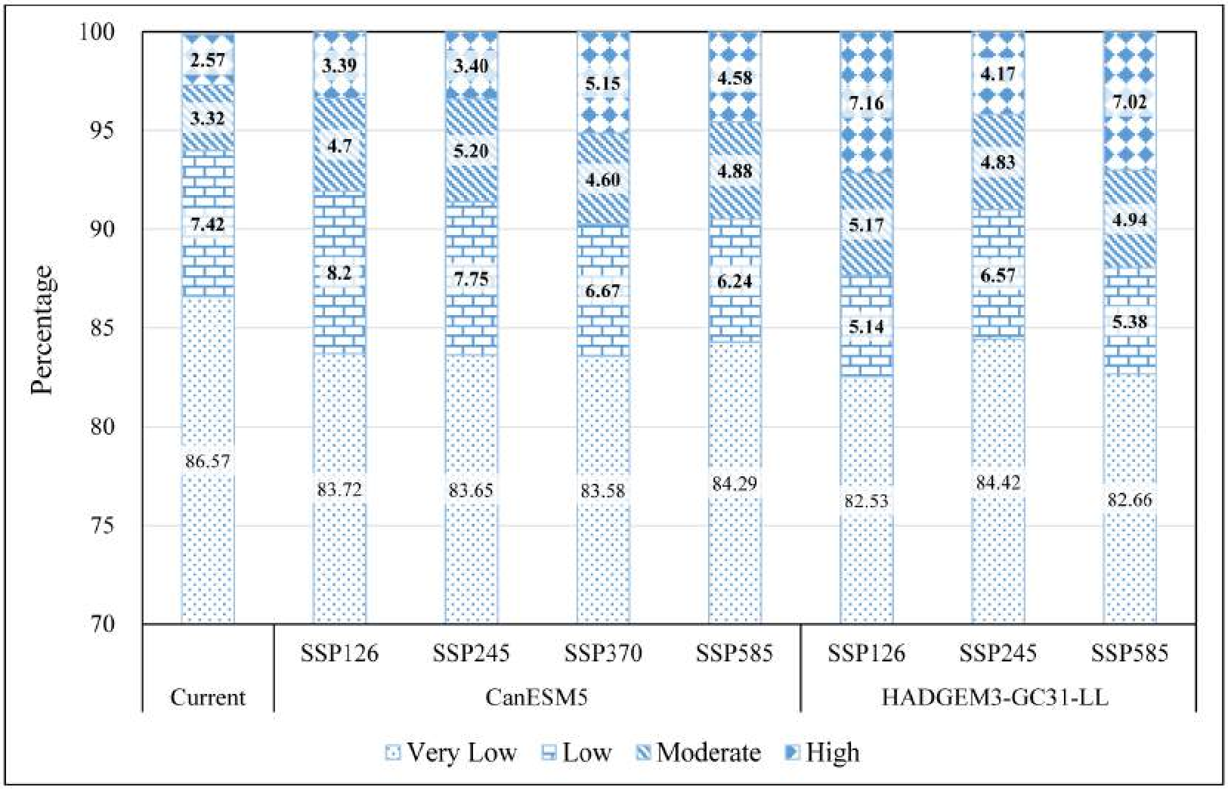



**Figure 5** Percentage Area statistics of the predicted shift in climatic ranges of *Melia dubia* in Kerala under different SSP of the two climate models namely CanESM5 and HADGEM3-GC31-LL

as valuable tools for identifying vulnerable areas, prioritising regions for intervention, and planning targeted strategies. As a result, they will support informed decision-making for both conservation initiatives and effective ecological restoration efforts (Adhikari et al. 2018, Adhikari et al. 2019). The result of the Multivariate Environmental Similarity Surfaces (MESS) analysis also indicates that the natural habitat of *M. dubia* might be impacted.

Earliest botanical and forestry literature mentions that *M. dubia* occurs in the tropical moist and dry deciduous forests of the Western Ghats (Champion & Seth 1968). Both these forest types are prevalent in region experiencing mean annual temperatures of 24–27 °C and 23.5–29 °C and a rainfall of about 1200–3000 mm and 750–1900 mm, respectively. This provides both the upper and lower thresholds for defining the climatic niche of *M. dubia*, helping to delineate the range of environmental conditions within which the species thrives. Also, the bioclimatic variable limits as indicated in the figure corroborate with temperature and precipitation thresholds of the tropical moist and dry deciduous forest. The plantation trails of *M. dubia* indicated that the irrigation requirement if the rainfall is less than 1000 mm $yr^{-1}$ (Ramanan et al. 2023). The MaxEnt models have indicated that there will be declining trend in the suitability of the site having precipitation of less than 400 mm during the warmest quarter, and less than 1000 mm during the coldest quarter.

The model tentatively indicates that 2.57% of the geographical area of the state may be suited for the *M. dubia* cultivation and the area is also projected to increase in future climatic scenario. This species is believed to be originated from the Western Ghats region and the model projections indicate the high adaptability of the species. The presence of multiple peaks in temperature response curve indicate that the species can thrive in more than one temperature range or else the species may have different populations that are adapted to different conditions, thus showing multiple preferred conditions. Given that there is ambiguity in the *Melia* species occurring in the North and North-eastern regions as separate species or ecotypes, there is need for niche differentiation or niche overlap works to be carried out for the whole country. This sort of work demonstrates that niche-based

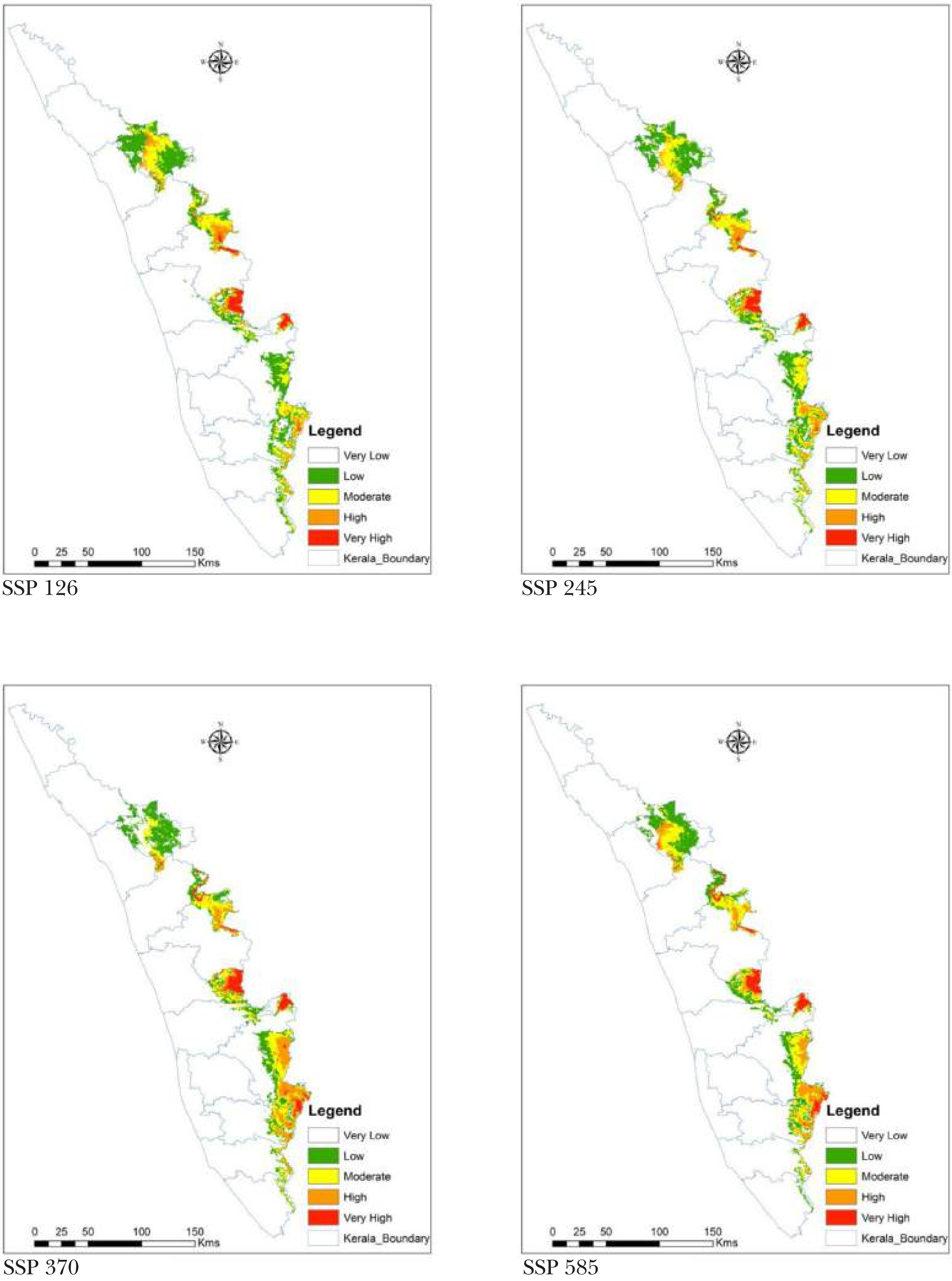
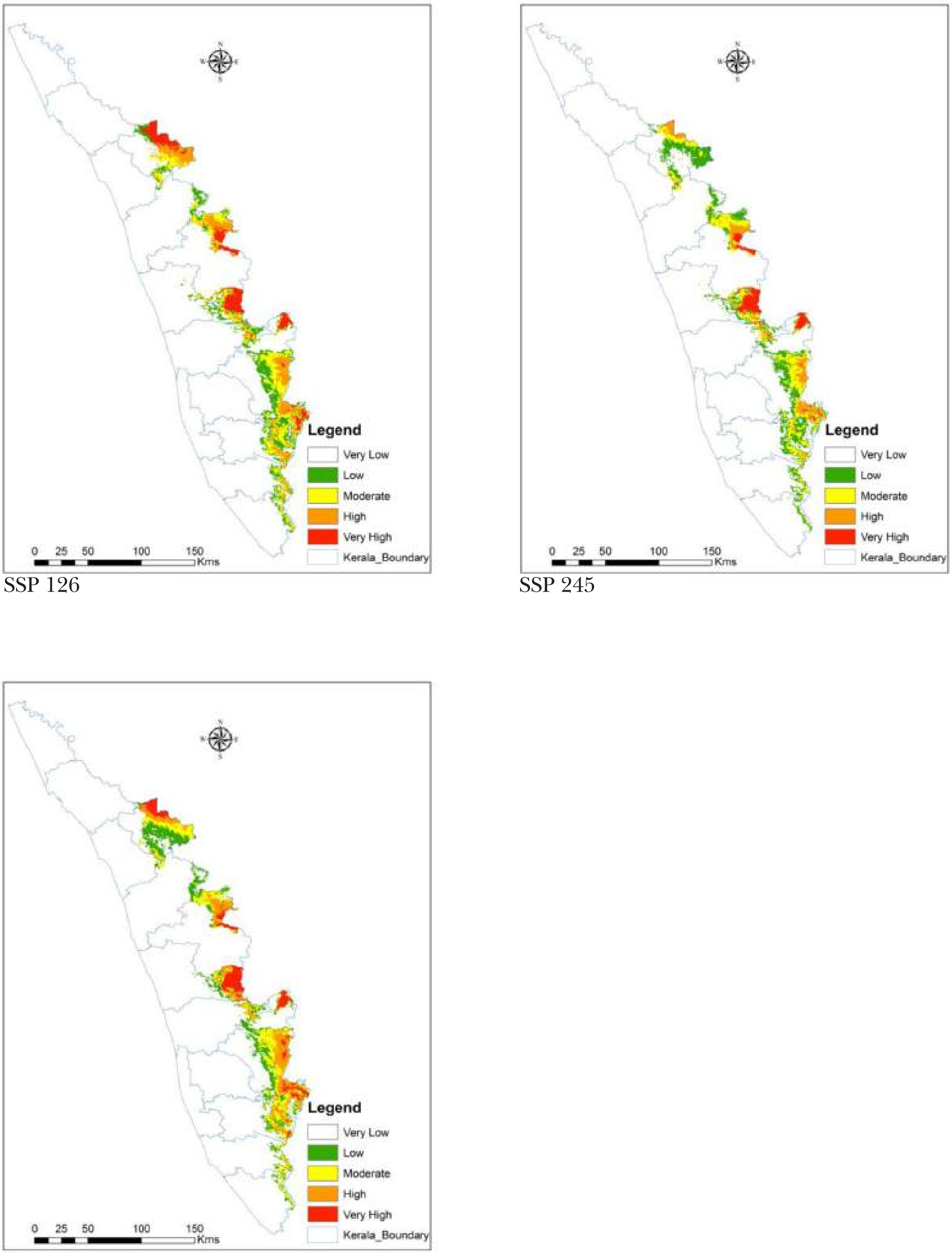



**Figure 6** Future potential distribution area extent of *Melia dubia* in Kerala predicted by different SSPs of the CanESM5 and HADGEM3-GC31-LL climate model




SSP 126

SSP 245

SSP 370

**Figure 7** Future potential distribution area extent of *Melia dubia* in Kerala predicted by different RCPs of the HADGEM3-GC31-LL climate model.

analyses can aid not only to identify suitable areas for cultivation of a particular species but also pertinently point out the suitable location of the germplasm/clones developed based on their native geographic distribution occurrence.

In agroforestry, niche modelling has been effectively applied to assess the suitability of individual tree species as well as combinations of woody perennials. A notable example is the ensemble-based modelling approach used in the creation of the "Suitability of Key Central American Agroforestry Species under Future Climates: An Atlas" (Sousa et al. 2017). This work provides a comprehensive spatial assessment of 54 important agroforestry tree species across seven Central American countries—Belize, Guatemala, El Salvador, Honduras, Nicaragua, Costa Rica and Panama. The atlas not only maps the current suitable areas for these species but also projects potential shifts in their distributions under future climate scenarios.

## CONCLUSIONS

Agroforestry is inherently the combination of different trees and crops together and therefore, collating the niche of different species together will aid in predicting the suitable geographic areas for different agroforestry models. As there is due possibility for extrapolating the climate change impact, there is way to predict the viability of different agroforestry models in the upcoming years (Ranjitkar et al. 2016). This sort of work can enable the policy makers to reframe the existing agroforestry policies and tree-marketing guidelines to suit a particular species. From the agroforestry perspective of farmer's field, it has always been that introduction of new tree species having better economic returns. For instance, Indian Sandalwood tree (*Santalum album*) is native to southern India, specifically the Deccan plateau. However, it is now cultivated in many parts of the country apart from its native distribution. There are a lot of speculations about the growth and yield from these new cultivation areas (Sandeep et al. 2020). In this regard, the ENM approach can tentatively provide a clear recommendation on species introduction. A similar sort of ENM work carried out in Nepal has provided inputs to the forest department to avoid *Alnus nepalensis* in the north-eastern part and to replace it with *Alnus nitida* in combination with cardamom or tea as intercrop (Rana et al. 2018). Given the Kerala agricultural landscape as well as economical dynamics, this species can be an apt choice for plantation sector and agroforestry provided the value-chain are developed in the state. Results from niche modelling when coupled with fuzzy logic model, have also been used to determine the optimal tree crop combination. This kind of results, however, need post-modelling data processing to make it more reliable and adaptable (Ranjitkar et al. 2021).

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