**IMPACT OF CLIMATE CHANGE ON THE DISTRIBUTION OF MONTANE SHOLA SPECIES (*Ficus drupacea*) IN THE SOUTHERN WESTERN GHATS**

by

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**(2015-20-005)**

**THESIS**

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## DECLARATION

I, Swathy Krishna G (2015-20-005) hereby declare that this thesis entitled "**Impact of Climate Change on the Distribution of Montane Shola Species (*Ficus drupacea*) in the Southern Western Ghats**" 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 title, of any other University or Society.

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Certified that this thesis entitled **“Impact of Climate Change on the Distribution of Montane Shola Species (*Ficus drupacea*) in the Southern Western Ghats”** is a record of research work done independently by Miss. Swathy Krishna G 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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## SYMBOLS AND ABBREVATIONS

| | |
|---|---|
| .asc | Action script communication |
| .csv | Comma separated values |
| \|r\| | Pearson correlation matrix |
| ◦C | Degree celsius |
| AR5 | Assessment Report 5 |
| AUC | Area under the curve |
| Bio1 | Annual mean temperature |
| Bio 2 | Mean diurnal range |
| Bio 3 | Isothermality |
| Bio 4 | Temperature seasonality |
| Bio 5 | Maximum temperature of warmest month |
| Bio 6 | Maximum temperature of 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 |
| CIAT | International Center for Tropical Agriculture |
| DMSP | Defence Meteorological Satellite Program |
| ENM | Ecological niche models |
| FAO | Food and Agriculture Organization |
| GCM | General Circulation Model |
| GHCN | Global Historical Climatology Network |
| GIS | Geographic Information System |
| H | Hinge |
| IMD | Indian Meteorological Department |
| IPCC | Intergovernmental Panel on Climate Change |
| IVI | Importance Value Index |
| $km^2$ | Square kilometre |
| L | Linear |
| LCCS | Land Cover Classification System |
| LP | Linear-Product |
| LQ | Linear-Quadratic |
| LT | Linear-Threshold |
| LH | Linear-Hinge |
| LPQ | Linear-Product-Quadratic |
| LQH | Linear-Quadratic-Hinge |
| LPH | Linear-Product-Hinge |
| LHT | Linear-Hinge-Threshold |

| | |
|---|---|
| LQT | Linear-Quadratic-Threshold |
| LPT | Linear-Product-Threshold |
| LPHT | Linear-Product-Hinge-Threshold |
| LPQT | Linear-Product-Quadratic-Threshold |
| LQHT | Linear-Quadratic-Hinge-Threshold |
| LPQH | Linear-Product-Quadratic-Hinge |
| LPQHT | Linear-Product-Quadratic-Hinge-Threshold |
| m | Metre |
| MaxEnt | Maximum Entropy Modelling |
| ppm | Parts per million |
| QGIS | Quantum GIS |
| $R^2$ | Coefficient of determination |
| RCPs | Representative Concentration Pathway |
| ROC | Receiver Operating Characteristic |
| SDM | Species Distribution Modelling |
| SRES | Special Report on Emission Scenarios |
| SRTM | Shuttle Radar Topography Mission |
| TSS | True Skill Statistics |
| UN | United Nations |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |
| $W/m^2$ | watt per square metre |
| WMO | World Meteorological Organization |

# INTRODUCTION

# CHAPTER 1
# INTRODUCTION

The world at present is facing a severe environmental threat. The impact and threat of climate change affect the ecosystem and its biodiversity. It is evident from recent decades the anthropogenic influence on the climate. Even though many changes happened, the notable difference is seen in the temperature which lead to the increase of greenhouse gases in the atmosphere. The world's majority of the valuable ecosystem has faced extinction due to global warming. There is likely a winnowing effect on the ecosystem by global warming. It is evident from the IPCC AR5 synthesis report that in the Northern Hemisphere the period from 1983 to 2012 was likely the warmest 30 year period of the last 1400 years. The globally averaged combined land and ocean surface temperature, from 1880 to 2012 showed a warming of 0.85 (0.65 to 1.06) degrees Celsius. So it is atmost important to find measures to mitigate the climate before it cost lives.

The effects of climate change affect both plant and animal species. Even though the difference has been observed over the years, the impact may cause physiological changes in these species. Climate change is co-related to environmental threats such as habitat loss and overharvesting, and it exacerbates species decline. This decline in species and ecosystem further accelerate climate change and creates a feedback loop that aggravates the situation. The effect of climate change is different in different species and is mainly observed in tree species. The changes may either result in their enhanced distribution or reduced distribution. Habitat change in the ecoregions will result in catastrophic species loss, depending on their response to warming. These results will explain whether the tree species have adapted to the changing climate scenario.

The average temperature of India has already increased by around 0.7 degrees Celsius during 1901 – 2018 due to greenhouse gas emissions, and it is expected to rise by approximately 4.4 degrees Celsius by the end of 2100. India has many global biodiversity hotspots with numerous endemic species of plants and animals. Among those regions, Western Ghats is considered one of the rich biodiversity hotspots in India. It is a significant global importance site that comprises areas of very high physical, aesthetic, and cultural values. Most of the forest area of Western Ghats has declined due to climate change and increase in agricultural land usage (Chandran et al., 2010; Chethana and Ganesh, 2013). Firstly, temperature rise and rainfall pattern variability significantly impact the potential distribution, range shifts of several species, and overall decline in the suitable habitats in the Western Ghats (Priti et al., 2016). The total forest cover area may reduce due to a deficit rainfall pattern (Ramachandran et al., 2017).

The shola forests are dense and floristically rich with many endemic and rare species. The trees form a continuous canopy not exceeding 10 – 15 m. Many tree species show a shift in their distribution patterns. *Ficus drupacea* Thunb commonly known as Mysore fig, is one such tree species affected by climate change. Ficus drupacea is a huge, spreading canopy tree that grows 10 to 15 metres tall in the cooler regions of its habitat. The plant usually starts out as an epiphyte, growing on another tree's limb; as it becomes older, it sends down aerial roots that swiftly form roots and become much thicker and more vigorous when they reach the ground. They provide the fig with nutrition, allowing it to grow quicker than the host tree. When powdered and applied to wounds, the roots are an efficient vulnerary. It is essential to study these changing patterns to ensure the conservation and protection of the species.

The change in the distribution of these species is studied using empirical models. Different environmental variables, represent the potential population distribution (GuilleraArroita et al., 2015; Elith et al., 2006; Elith and Leathwick, 2009; Franklin,2013). These models can predict the potential distribution with time and space in unsampled areas and future climatic conditions.

The main objective of this study is to understand the changes in the distribution of the selected species *viz., Ficus drupacea.* With the help of this result we can understand the impact of future climate under different climate scenarios on the species. This model can be used for other species in the shola forests thus enlightening our planet.

# REVIEW OF LITERATURE

# CHAPTER 2

# REVIEW OF LITERATURE

## 2.1 CLIMATE CHANGE AND KERALA

Kerala bounded by the Arabian sea at one side and the Western Ghats on the other has an equable and tropical climate that offers a pleasing atmosphere throughout the entire year. The coastal state has hot and humid weather during April-May and a pleasant, cold environment during December-January. There was proof that showed a decline of annual rainfall in the southern part of Kerala, whereas the trend was not similar in the northern part (Soman et al., 1988). During the monsoon season, an increase in the mean surface temperature (1.5ºC) was predicted in the decade 2040-2049 concerning the 1980s (Saseendran et al., 2000). Annual rainfall in the Western Ghats area in the Palakkad Gap varied with altitude and comparatively lower annual rain over these regions compared to the entire state (Raj and Azeez, 2009; 2010).

### 2.1.1 Climate in the Western Ghats

The Western Ghats, or Sahyadri, is a mountainous region along the Indian peninsula's western coast. The area is listed as a World Heritage Site with 39 significant properties, including reserve forests, wildlife sanctuaries and national parks (UNESCO, 2007). It is also considered one of the world's most important biodiversity hotspots (Molur et al., 2011; Myers et al., 2000). This area has recorded a considerable proportion (at least 325 species) of globally threatened species (Dahanukar et al., 2004; Nayar et al., 2014). Climate change and rising anthropogenic pressures have resulted in the loss of a large portion of this unique landscape's forest cover, and the remaining forest areas are also endangered (Raha and Hussain, 2016). The study area's average annual temperature varies from 20ºC to 24º C. The western mountainous regions of the site receive a lot of rain (2000–4000 mm/year) (IMD, 2016). However, as you get closer to the eastern foothills, the number of precipitation drops. Under future climatic conditions, the central and southern parts of the Western Ghats, specifically the South of Palghat Gap, are expected to provide the best habitat for mid-elevation evergreen forests (Priti et al., 2016). The Western Ghats are likely to see an extension of evergreen forests under the A2 and B2 scenarios of the Special Report on Emission Scenarios (SRES). Because of the unfragmented existence of the forest, there is no lack of seed-dispersing agents, tropical evergreens continue to thrive and grow. However, anthropogenic stresses and climate change affected the number of dispersal agents, causing the forest to disperse in the real world. Higher elevations are more likely to be affected by climate change, making mountainous forest types like those in the Western Ghats vulnerable to degradation. Such areas necessitate effective pest and fire control, scientifically correct harvesting, and anticipatory plantations (Chaturvedi et al., 2011).

## 2.2 IMPACT OF CLIMATE CHANGE ON FOREST TREES

The Shola forests of peninsular India are part of a larger group of tropical montane forests found in Asia, Africa, and America. In Kerala, shola forests are found along the crest of the Western Ghats, where the elevation exceeds 1800 metres. The altitudinal gradient is one of the ecological factors that influence the plant population's structure, composition, and diversity of the plant population in these forests, as it is in other tropical forest belts. Indeed, through morphological, phenological, and physiological changes in response to a broad range of environmental conditions prevailing along an altitudinal gradient, most tropical tree species can sustain a consistently high level of growth-related activity.

Long-distance gene flow is a capability of forest trees. Their genes travel across broad spatial scales at high enough rates to deal with habitat changes anticipated as climatic conditions change. Such a trait in forest trees promotes adaptive evolution by increasing genetic variation, which improves fitness. When bioclimatic envelopes change, region-specific populations are at risk of extinction and recolonization, with the latter causing dispersal of genetic diversity, to which region-specific populations react in a variety of ways. Adapting to changes in the environment is one option for certain communities, while the migration is another. Migration allows species to drift to more suitable areas over time with no development, but adaptation occurs due to evolutionary changes (Kremer et al., 2012). Even though high levels of genetic variation and increased gene flow are thought to facilitate adaptive changes in forest trees, the population's long life span and low mortality of existing trees limit their adaptability. Forest trees' adaptive rates to climate change are typically higher in communities subjected to frequent fires or storms and have higher mortality rates. Local demography is another crucial factor influencing forest tree adaptability to climate change (Kuparinen et al., 2010).

## 2.3SPECIES DISTRIBUTION AND CLIMATE CHANGE

Scholars have long recognized the strong correlation between individual species distributions and species richness, and the climate of that region. Although there is a clear link between environmental factors and species distribution, the impact of these factors is still unknown (Murray and Conner, 2009). The factors that influence species distribution remained an unsolved subject in ecology (Araujo and Guisan, 2006). Changed species distribution due to diminished viability owing to range loss will be one of the significant consequences of climate change. It affects the risks of species even in protected areas. Biodiversity hotspots face a substanial threat of reduction as they have a wide variety of species within their limit. Different species respond to climate change in a different manners. Most of the predictions suggest that there will be reduction and fragmentation because of distributional shifts resulting from climate change. Movement (if the species is mobile, it will track suitable environment niches), adaptation (if the species can adjust to changing conditions and has high physiological tolerances), and extirpation (when both movement and transportation fail) have been the three methods used by species to respond to climate change (Holt, 1990; Melillo et al., 1995).

According to Thomas (2010), the climate is one of the most critical factors of range boundaries. Aside from climatic variables, changes in land use and habitat, biotic interactions, and evolutionary adaptability all had a role in species distribution (Huntley et al., 2006; La Sorte and Thompson, 2007; Beale et al., 2008). For RCP 8.5, the maximum range loss of the montane grasslands is expected to be 63% by 2080. Because of climate change, the montane grasslands are predicted to lose more than 60% of their existing appropriate habitat. The model output reflects the facts that, under various climate change scenarios, protected areas of the Southern Western Ghats, such as the Eravikulam National Park, Parambikulam Tiger Reserve, and a portion of the Chinnar Wildlife Sanctuary, will provide some stable areas; however, the chances of large-scale local extinction of the species with high risk of habitat loss are irrefutable (Sony et al., 2018).

## 2.4 IMPORTANCE OF RANGE DISTRIBUTION STUDIES

For a better understanding of the ecological and evolutionary determinants of various spatial patterns of biodiversity (Rosenzweg, 1995; Ricklefs, 2004; Graham et al., 2006), as well as for conservation planning and forecasting, a broad understanding of species ecological and geographic distribution was required (Ferrier, 2002b; Funk and Richardson, 2002; Rushton et al., 2004). Climate change indicators were still in the early stages of development, and scientists and policymakers were eager to learn more about the biological effects of climate change and how to apply adaptive and mitigation strategies (Mace and Baillie, 2007; EEA, 2007).

## 2.5 SPECIES DISTRIBUTION MODELLING

### 2.5.1 Importance of species distribution modelling

To understand about the spatial configuration and characteristics of habitats that allowed for species continuity in landscapes (Araujo and Williams, 2000;

Ferrier et al., 2002b; Scotts and Drielsma; 2003), past species distribution (Hugall et al., 2002; Peterson et al., 2004), species distribution in future climatic conditions (Bakkenes et al., 2002; Skov and Svenning, 2004; Araujo et al., 2004; Thomas et al., 2004; Thuiller et al., 2005) and relationships between environmental parameters and species richness (Mac Nally and Fleishman, 2004), researchers used species distribution model. Conservationists used distribution models to estimate the most favourable locations for a species and to forecast the likelihood of occurrence in places where systematic surveys had not been conducted (Elith, 2002). The use of predictive modelling was utilized to investigate changing distributions. If a species' range was correctly mapped, environmental variables such as climate could be linked to its presence or absence (Crick, 2004).

The environmental parameters were determined using known species distributional information, resulting in identifying geographical regions with similar environments and the modelling of species distribution (Pearson and Dawson, 2003). Bio-geographical analysis techniques have been used to investigate the distribution of species abiotic niches in connection to environmental variables at the observed locations (Guisan and Thuiller, 2005). Watching the real future develop was the only method to test the hypotheses or scenarios of foretelling the future. To get around this problem, we could use prior environmental changes to see if species and ecosystems responded similarly to the models anticipated (Araujo et al., 2005).

Using the presence or absence of species in relation to environmental factors, the species distribution models attempt to predict species distribution. These models were frequently employed to analyze different ecological, evolutionary, and conservation reasons (Elith et al., 2006). Apart from this, these models could also be used to predict future species distributions under various climate change scenarios (Jeschke and Strayer, 2008; Sinclair et al., 2010), potential expansion of introduced species in newly colonized areas (Jimenez-Valverde et al., 2011; Jeschke and Strayer, 2008), and reserve planning (Thorn et al., 2009).

### 2.5.2 Process of Species Distribution Modelling

#### 2.5.2.1 Steps in species distribution modelling

There are various steps to do the modelling of species distribution. Different steps involved are: (1) current species data in the form of occurrence points (Peterson et al., 1998; Peterson and Stockwell, 2001b); (2) ecological niche models are created and tested using distributional data (Guisan and Zimmerman, 2000; Kobler and Adamic, 2000); (3) the shift in distribution is projected onto the landscape of interest using general circulation models of climate change; (4) distributional shifts are mapped onto the changed landscapes using ecological niche models of specific species. Models in the environmental space can estimate the suitable ecological niche by analyzing species responses to abiotic environmental factors (Soberon and Peterson, 2005) and using this information; the model can derive the probability of species present in any given area or trace the specific environmental conditions that suit the species (Elith et al., 2011).

#### 2.5.2.2 Methods for testing accuracy

There were several methods for modelling species distribution that differed in the steps of modelling: selecting the most appropriate predictor variables, defined functions for each variable, weight variable contributions, predictor-species interactions, and predicting geographic patterns of occurrence (Guisan and Zimmerman, 2000; Burgman et al., 2005; Wintle and Bardos, 2006). Individual algorithms made up the numerous rules in the models, and it was based on them that the landscapes within and outside the biological niche were recognized (Peterson, 2001a). Hierarchical portioning could evaluate alternative models and investigate the weight of evidence for various components contained in the model (Mac Nally, 2002). Testing climatic envelope models addressed concerns about future species distribution prediction accuracy under different climatic conditions (Akcakaya et al., 2006; Pearson et al., 2006; Araujo and Rahbek, 2006; Zimmer, 2007). The degree of environmental dimensions that defined the species distributional limitations determined the accuracy of model descriptions about the range of conditions suited for a species (Pearson et al., 2007). Models were built primarily on correlations between variables and distribution patterns, which did not identify the causal relationship due to autocorrelation among the variables (Bahn and McGill, 2007; Currie, 2007; Beale et al., 2008), but this method was limited due to the same data source being used for all the different models (Bahn and McGill, 2007; Currie, 2007; Beale et al., 2008), but this method was limited due to the same data source being used for all the Large geographical areas were evaluated to prevent misinterpretation of species dispersion responses. Thus, the connection of environmental variables with climatic variables was reduced (Maclean et al., 2008). It was used to resolve ambiguities caused by correlated predictors, but it could not detect spurious correlations among the environmental components used to determine the spatial distribution (Ashcroft et al., 2011). Generalized linear mixed models were used to increase the accuracy of species distribution range forecasts (Swanson et al., 2013).

#### 2.5.2.3 Advancements in species distribution modelling

Climate significantly impact species distribution on land, and niche modelling was founded on this concept. Even while the prediction power of models has improved, understanding the principles that underpin them has been difficult (Shipley, 1999). Although fewer studies were comparing future distribution shifts to previous distribution shifts, the climate envelope approach was widely employed to tackle this issue (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). The use of ecological niche modelling for predicting species distribution from environmental data was acknowledged (Pearson and Dawson, 2003). Advances in research and technology led to complicated mathematical general circulation models (GCMs), which influenced global climate and forecasted future climate by combining multiple greenhouse gas emission scenarios (Raper and Giorgi, 2005). The lack of data on species-specific physiological characteristics and processes, as well as the link between climatic and non-climatic factors, remained an issue (Kearney, 2006).

### 2.5.2.4 Species distribution studies

Environmental variables such as climatic conditions could be used to explain species richness and dispersion patterns (Kerr, 2001; Ricklefs, 2004; Ceballos and Ehrlich, 2006; Mittelbach, 2010). Using climatic data, several studies have been successful in predicting species distribution (Pearson et al., 2002; Bakkenes et al., 2002; Burns et al., 2003; Thuiller et al., 2005; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and Wang, 2006; McKenney et al., 2007; Peterson et al., 2008; Stankowski and Parker, 2010; Joyner et al., 2010; Beever et al., 2010). Since both used the same climate-space, it was anticipated in studies of future distribution predictions that changes in species range occurring under warmer conditions would be mirrored by changes in the colder extremities (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). Some studies predicted mass extinction of species over the next century (Peterson et al., 2002; Bakkenes et al., 2002; Thomas et al., 2004; Thuiller et al., 2005; Malcom et al., 2006), as well as redistribution of species range (Iverson and Prasad, 1998; Pearson et al., 2002; Burns et al., 2003; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and wang, 2006; McKenney et al., 2007; Peterson et al., 2008). As a result of the detrimental effects of climate change on biodiversity, several analytical tools have been developed to correlate quantifiable environmental variables with known species locations (Heikkinen et al., 2006; Elith et al., 2006; Guisan et al., 2007; Loiselle et al., 2008; Graham et al., 2008; Feeley and Silman, 2010; Beever et al., 2010). Range shifts or range extension could cause changes in distribution, and the impact of temperature dependence has been investigated (Maclean et al., 2008). Environmental variables explained species richness prediction at multiple levels (Coops et al., 2009; Hinsley et al., 2009; Hansen et al., 2011; BarMassada et al., 2012; Fitterer et al., 2012).

## 2.6 DATA USED FOR MODELLING

### 2.6.1 Type of data and performance of the model

The presence only models failed to get a general test of model accuracy when using withheld data for predicting species distribution due to biases in the geographic and environmental space (Bojorquez et al., 1995, Hijmans et al., 2000; Soberon et al., 2000; Kadmon et al., 2004). It was possible to assess the model's performance by introducing false data and comparing the accuracy of projected responses, or by modelling both presence and absence data and comparing fitted functions (Austin et al., 1995). When independent data was not utilized to develop the model, which was referred to as "test" data, and just "training" data was used to build the model, it had a higher prediction success rate (Fielding and Bell, 1997). For model performance testing, various test statistics or discrimination indexes were used (Fielding and Bell, 1997; Pearce and Ferrier, 2000). The predictive performance of the models was more focused on the evaluation step. Some known occurrences that were withheld (just presence data) from the model created by splitting the data set, k-fold partitioning, or bootstrapping were more focused in the evaluation step (Fielding and Bell, 1997; Hastie et al., 2001; Araujo et al., 2005).

The accuracy of the forecast was evaluated based on the correctness of the withheld data (Boyce et al., 2002; Hirzel and Guisan, 2002b). The generally used indices, such as Kappa and the area under the receiver operating characteristic curve (AUC), were not suited for evaluating poorly sampled regions (Boyce et al., 2002; Phillips et al., 2006). Because the model was statistically equivalent to a random prediction, predicting, a higher proportion of test localities (low omission rate) while not predicting a significant proportion of the study area would produce relevant forecasts. When data portioning was done for testing, the Chi-square test or upper-tailed binomial probability was utilized to examine the statistical significance of the model (Anderson et al., 2002). The anticipated model's performance was based on the available absence data (Loiselle et al., 2003). A 2-2 confusion matrix could be used to describe the frequency of correctly and wrongly predicting absences and presences, and tests were limited to presence-only models that did not require absence data (Anderson et al., 2003).

Absence data (which may occur owing to non-inclusion of data in the model) was proposed not to be included since false-positive predictions would be seen as failures when possible suitable habitat was modelled (Anderson et al., 2003;

Pearson and Dawson, 2003; Soberon and Peterson, 2005). The most systematic and straightforward method was to use a random or regionally stratified partition (Peterson and Shaw, 2003). However, the data was too tiny to partition into test and training data sets, and harmful data was complex (Anderson and Martinez-Meyer, 2004). When some studies were conducted with small samples, predictive performance was reduced (Stockwell and Peterson, 2002; Reese et al., 2005). Given the widespread usage of distribution models and the progress of data availability and modelling methodologies, extensive synthetic studies of high prediction capacity and accuracy of species distribution modelling methods for presence-only data were urgently needed (Elith et al., 2006). The validation of the model was improved by using an independent, well-structured presence-absence dataset (Elith et al., 2006). Many methods capable of capturing complicated answers have been developed due to advancements in machine learning and statistical disciplines, even when the data was quite noisy. Even though the study seemed promising, it did not acquire any attention in distribution modelling (Phillips et al., 2006, Leathwick et al., 2006). Resampling designs had biases in the spatial and environmental space (Elith et al., 2006). When there were just a few observed locale records available, a jack-knife approach may be utilized to assess predicting ability. The Jack-knife ('leave-one-out') strategy worked well for evaluating models with a modest number of occurrences. The model was built using the remaining n-1 localities after excluding each observed locality (n) once. The model's predictability was measured by the model's ability to predict a single locale from the training data (Pearson et al., 2007). Because absence data was infrequently accessible and challenging to detect in surveys, the modelling methodologies and validation relied on it (Pearson et al., 2007). Algar et al., (2009) found that temporal prediction was entirely accurate, but spatial autocorrelation may be used to eliminate biases using regression models.

### 2.6.2 Presence and absence records

The development of distribution modelling research had previously concentrated on the producing models based on presence/absence or abundance data, with systematic sampling methods utilized in the study areas (Austin and Cunningham, 1981; Hirzel and Guisan, 2002b; Cawsey et al., 2002). Previously, presence-only data were analyzed using envelope calculations or distance-based measures designed particularly for that purpose (Silverman, 1986; Busby, 1991; Walker and Cocks, 1991; Carpenter et al., 1993). In most presence/absence models, breeding areas were assumed to be saturated (Capen et al., 1986). As several methods in the species distribution modelling indicated, only presence data were evaluated (Nix, 1986; Carpenter et al., 1993).

When utilizing presence/absence models, there was a risk of two sorts of errors: false positives and false negatives (Fielding and Bell, 1997). Adaptation to model presence-only data from presence-absence methods (which used a binomial response for modelling) using background environment samples (data developed by selecting random points over the study area) or ‘non-use' or ‘pseudo absence' area (Stockwell and Peters, 1999; Boyce et al., 2002; Ferrier et al., 2002b; Zaniewski et al., 2002; Keating and Cherry, 2004; Pearce and Boyce, 2006). Because accurate absence data was rarely available due to poor sampling or missing species occurrences during surveys, methods that required both the data set used pseudo-absences instead of accurate absence data (Ferrier et al., 2002a; Engler et al., 2004), or some methods used background data for the entire study area (Ferrier et al., 2002a; Engler et al., 2004). (Hirzel et al., 2002b).

Species occurrence data were widely available and easier to obtain, thanks to high-resolution environment data layers developed with satellite imagery (Turner et al., 2003) and highly sophisticated climate data (Thornton et al., 1997; Hijmans et al., 2005). Even if a species was chance to be spotted at a site, it was difficult to corroborate the absence data because there was no wildlife-habitat correlation (MacKenzie et al., 2004; Gu and Swihart, 2004).

Modelling ecological niches were done using a various methodologies, the majority of which included both presence and absence records (Bourg et al., 2005). Predictions from each approach differed significantly, emphasizing the importance of method selection and cross-validation of results from diverse methods (Thuiller et al., 2004; Pearson et al., 2006). The majority of the species occurrence data had been acquired without any defined sampling methods. A large amount of these data came from presence-only records from museum or herbarium collections that were electronically available (Graham et al., 2004; Huettmann 2005; Soberon and Peterson, 2005). There were currently ways that employed the presence information of other community members to supplement the data regarding the modelled species, and this strategy was promising for rare species because the more comprehensive community information assisted in revealing the modelled relationships (Elith et al., 2006). The problem with this type of presence data was that the goal and methods used to collect it were rarely known, and we couldn't extrapolate the absence data with accuracy (Elith et al., 2006). Over the last decade, new approaches have emerged that rely just on presence data, eliminating the need for absence locations (Baldwin, 2009).

## 2.7 ASSESSMENT OF CLIMATIC CHANGES

Global climate models, regional climate models, dynamic and equilibrium vegetation models, species bioclimatic envelope models, and site-specific sensitivity analysis were utilized to estimate the impact of climate change on biodiversity (Sulzman et al.,1995). Equilibrium simulations using a step increase in $CO_2$ revealed rising temperatures in both hemispheres, but transient simulations showed both ups and downs in the temperature distribution (Sulzman et al., 1995). Regional models could be used in conjunction with more detailed Global Circulation Models (GCMs). The two major regional models that were commonly utilized were MM5 (Mesoscale Model version 5) and RAMS (Regional Atmospheric Modelling System) (Sulzman et al., 1995). Because the climate dynamics of the southern and northern hemispheres differed, models designed with a significant focus on one hemisphere would not produce excellent findings in the other (Grassl, 2000).

Regional models were more helpful determining local climate change than global models that relied on global forcings (Pitman et al., 2000). These models could depict changes in land use and their impact on cloud formation mechanisms.

However, not all regions had access to the results of these models. Dynamic vegetation models, forest gap models, biome envelope models, and species envelope models all used GCM and regional climate models to shed light on different elements of future climate change biogeography (Cramer et al., 2000).

GCMs, which modelled the global climate and provided projections at various resolutions, with differences in projected climate change values for each grid cell, were regarded as the entry points for climate change conservation assessments because only these models provided estimates of future climate change due to greenhouse gas emissions (Hannah et al., 2002). Results from transient (not equilibrium) simulations of CO2 growth and models completely connected with ocean and atmosphere to the regions of interest improved the evaluations (Hannah et al., 2002).

## 2.8 SPECIES DISTRIBUTION MODELLING TYPE

### 2.8.1 Maximum Entropy Modelling (MaxEnt)

For estimating the species distribution, MaxEnt uses the maximum entropy distribution, which was subjected to the constraint that the predicted value of each environment variable (interactions) in the estimated distribution matched its empirical average (Phillips et al., 2006). It approximated the most uniform distribution using background locations and data-derived constraints (Philips et al., 2004; Philips et al., 2006). If presence-only species data were used in this model, the complexity of the fitted functions might be chosen. Maximum entropy modelling (MaxEnt) performed better or equally well as other modelling strategies (Elith et al., 2006; Hernandez et al., 2006; Philips et al., 2006). MaxEnt had a higher success rate than other algorithms, and it was able to detect differences even with small sample sets (Pearson et al., 2007). When sample sizes were artificially reduced, the model performance suffered. MaxEnt models projected a greater range of appropriate circumstances, and the MaxEnt projection had the potential to anticipate excluded areas as well (Pearson et al., 2007).

MaxEnt had previously been used to investigate the distributional patterns of Geckos (Uroplatus spp.) for predicting species distribution (Pearson et al., 2007), American black bear (Ursus americanus) for assessing denning habitat (Baldwin and Bender, 2008), Bush dog (Speothos venaticus) for evaluating protection excellence (DeMatteo and Loiselle, 2008), and Little bustard (Tetrax (Thorn et al., 2009). MaxEnt can precisely create the model even with fewer location points, which is a valuable feature because there are often insufficient dependable locations available for mapping the species distribution (Baldwin, 2009).

# MATERIALS AND METHODS

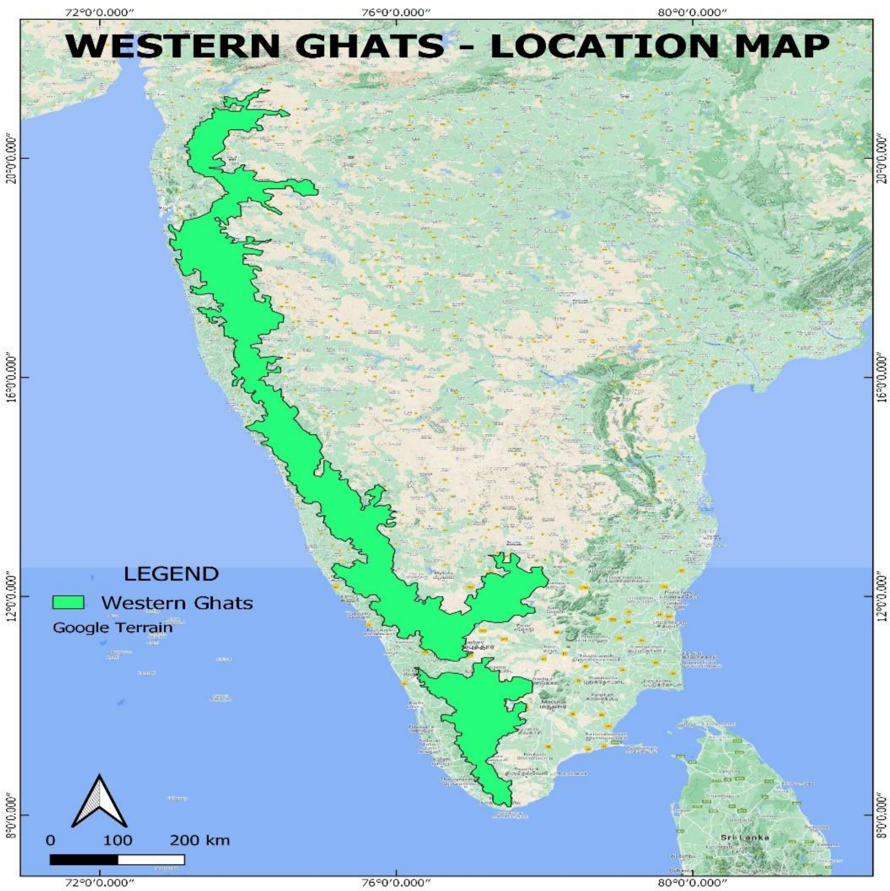
# CHAPTER 3

# MATERIALS AND METHODS

## 3.1 STUDY AREA

The area under study is the Southern Western Ghats. It is surrounded by montane shola forests covering the southern part of the Western Ghats in Karnataka, Kerala and Tamil Nadu. The selected species for the study is *Ficus drupacea* commonly known as Mysore fig. It is a montane shola species whose global distribution is seen in Australia, India, Myanmar etc. In India, it is found in Kerala, Karnataka, Tamil Nadu, and some parts of Maharashtra.

Fig 1: Map showing the Western Ghats

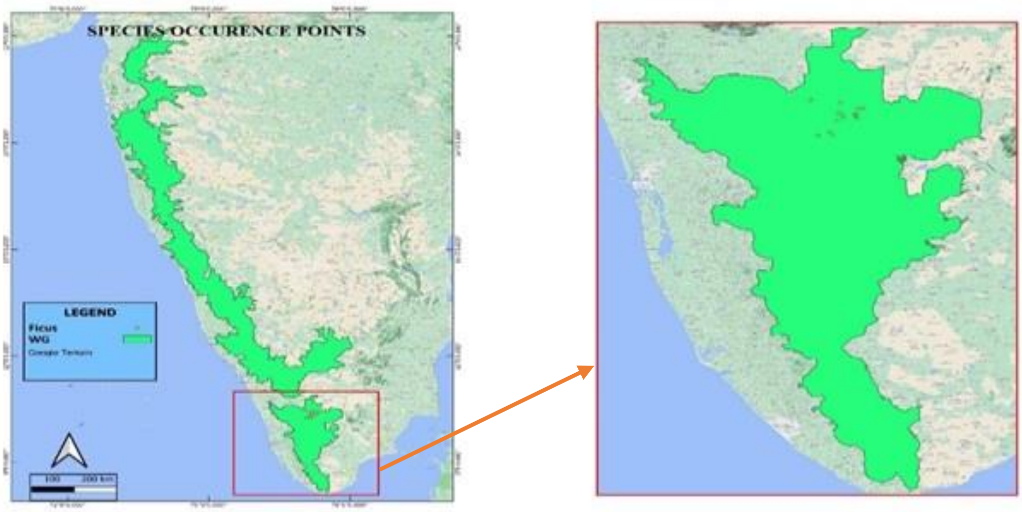


3.2 SPECIES SELECTION

The selection of species was made after analysing certain factors like the Importance Value Index (IVI), which explains the ecological importance of the species within the community and species with a maximum number of occurrence points to get a desirable output from the model.

Among 70 montane shola species available with location data, IVI was calculated, and species with the highest value were shortlisted. From the shortlisted species, *Ficus drupacea* was selected. *Ficus drupacea* is a terrestrial tree species of montane shola forest found at elevations up to 1000 m.

Fig 2: Map containing the occurrence points of *Ficus drupacea* in Southern Western Ghats




3.3 ENVIRONMENTAL VARIABLES

For each georeferenced presence location, bioclimatic variables from the WorldClim v1.4 database (http://www.worldclim.org/download) (Hijmans et al., 2005) were utilised for current and future scenarios. These variables were created by combining monthly rainfall and temperature data to produce 19 more valuable variables. Annual trends, seasonality, and extreme or limiting environmental circumstances are all represented by these variables. Those variables are given 19 different names as follows;

BIO1 = Annual Mean Temperature

BIO 2 = 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

Data from https://www.worldclim.com/bioclim

The temperature unit is '◦Cx10', and the precipitation unit is 'mm'. For both current and future conditions, 30 arc-seconds (0.86 km2 at the equator) data were employed. They were using the WGS84 datum in the latitude/longitude coordinate reference system. Monthly precipitation, minimum, mean, and maximum temperature were used to determine bioclimatic variables. Interpolating average monthly data from weather stations were used to create the data layers. This information had its own set of benefits and drawbacks. Climate is defined by the World Meteorological Organization (WMO) as the measurement of the mean and variability of actual amounts of particular variables (such as temperature, precipitation, or wind) throughout time, which can range from months to thousands or millions of years. Thirty years is the classical period.

The WorldClim interpolated climate layers were created using major climate databases compiled by the Global Historical Climatology Network (GHCN), the UN Food and Agriculture Organization (FAO), the World Meteorological Organization (WMO), the International Center for Tropical Agriculture (CIAT), R-HYdronet, and numerous other databases for Australia, New Zealand, and the Nordic European countries (Hutchinson and Xu, 2013). The same current bioclimatic layers and future bioclimatic layers corresponding to the climatic responses of Representative Concentration Pathways (RCPs) were used for ecological niche modelling the future prediction of distribution for the *Ficus drupacea* using the coupled model HadGEM2-AO of 30 seconds resolution, which is available in the WorldClim database. The four scenarios like the RCP 2.6, RCP 45, RCP 6 and RCP 8.5 were used.

Apart from the bioclimatic layers, altitude, aspect, slope and land cover were also used for the ecological niche modelling. The land cover data is sourced from SPOT VEGETATION, Defence Meteorological Satellite Program (DMSP) data under the name Land Cover Classification System (LCCS), having 85 per cent accuracy with Forest Survey of India Report at a resolution of 1km. The altitude data was obtained from Shuttle Radar Topography Mission (SRTM) at three arc-second or 90 meters.

Table 1. Different RCP's and their characteristics

| Name | Model used | Radiative forcing | CO2 equivalent (ppm) | Temperature anomaly (◦C) |
|---|---|---|---|---|
| RCP2.6 | IMAGE | 3.1 $W/m^2$ at mid-century, returning to 2.6 W/m2 by 2100 | 490 | 1.5 |
| RCP4.5 | MiniCAM | 4.5 $W/m^2$ post 2100 | 650 | 2.4 |
| RCP6 | AIM | 6 $W/m^2$ post 2100 | 850 | 3.0 |
| RCP8.5 | MESSAGE | 8.5 $W/m^2$ in 2100 | 1370 | 4.9 |

### 3.4 MAXIMUM ENTROPY SPECIES DISTRIBUTION MODELLING (MaxEnt)

The MaxEnt is a software that uses the principle of maximum entropy for species habitat modelling. The model expresses a probability distribution from a set of environmental (e.g., climatic) grids and georeferenced occurrence sites. Each grid cell has predicted the appropriateness of circumstances for the species. The result can be interpreted as the anticipated probability of presence (cloglog transform) or forecast local abundance (cloglog transform) depending on the assumptions made about the input data and biological sampling efforts that lead to occurrence records (raw exponential output).

A set of environmental or climate layers (or "coverages") for a group of grid cells in a landscape, as well as a set of sample locations where the species has been seen, are used to create species models. The model expresses each grid cell's appropriateness as a function of the environmental variables present in that grid cell. At a given grid cell, a high value of the process implies that the grid cell is projected to have favourable conditions for that species. The model that has been computed is a probability distribution across all grid cells. The distribution chosen has the maximum entropy, but it must have the same expectation for each characteristic (derived from the environmental layers) as the average across sample locations.

MaxEnt can be downloaded online freely (https://www.cs.princeton.edu/~schapire/MaxEnt/). The information must be entered into the software in the correct format. The bioclimatic layers should be in '.asc' format, and the species data should be in '.csv' format. Under the settings options, software was configured to acceptable levels based on our requirements for the run (Philips et al., 2004; 2006).

### 3.4.1 OPTIMISATION OF MODEL

#### 3.4.1.1 MODEL FEATURES

As per the requirement of the study, the primary step in optimising the model is to find a suitable combination of the model features. The default feature set in the MaxEnt software is the auto features. There are five features available in the model, and they can be applied in isolation and in combination too. The five model features are linear (L), quadratic (Q), product (P), threshold (T) and hinge(H). Different combinations of the features are: L, LP, LQ, LT, LH, LPQ, LQH, LPH, LHT, LQT, LPT, LPHT, LPQT, LQHT, LPQH and LPQHT.

All these combinations were run, and the best output that suits was analysed using the True Skill Statistics (TSS) and the best model feature identified was L.

#### 3.4.1.2 REPLICATION RUN TYPE AND REGULATION MULTIPLIER

In MaxEnt, the three replication run type used are cross-validate, bootstrap and subsampling. Cross-validation is a type of replication in which the occurrence data is randomly divided into several (k) groups (‘folds') of equal size, with one part left out, and the model is fitted to the other k-1 parts (combined), yielding predictions for the left-out part. Each portion was given the same treatment, and the findings were incorporated. Cross-validation had the advantage of using all of the data for validation, which was helpful when dealing with a small number of data sets. It made good use of the data in reporting the range and standard error. It also allowed for the simultaneous assessment of prediction uncertainty, which was helpful in model evaluation. However, because only a portion of the data was used for model fitting, retrieving test data statistically (spatially) independent of the training data proved problematic (Hijmans, 2012; Wenger and Olden, 2012). When applying spatially correlated folds, overestimating model performance and underestimating the standard error of predictions are possible. The statistical independence of the test and train data is lost when using the Bootstrap approach, and the AUC values are slightly exaggerated.

All these three run types were run and the best type was identified to be cross-validate.

The regulation multiplier is used to avoid the overfitting of the model (Philips, 2008). The model was run by trying different regulation multipliers which control the model complexity (Radosavljevic and Anderson, 2014). The default regulation multiplier is one and to identify the best model setting, varying values of regulation multiplier were incorporated, namely 1.5, 2, 2.5, 3, 3.5 and 4. Among this regulation multiplier, the model fitting was found to be high with the value 4.

The model settings were adequately tuned by assessing discriminatory ability to examine overfitting and, visual inspections of maps to conclude on output credibility (Radosavljevic and Anderson, 2014).

## 3.5 VARIABLE CONTRIBUTION AND OPTIMISATION

All bioclimatic variables, altitude, aspect, land cover and slope were analysed to determine the contribution of each variable to the modelling of distribution for the *Ficus drupacea*. This was done for the current distribution (no projections for the future), and the best sampling approach was chosen based on previous analysis. Ten subsampling replicates were utilised, with 25% of the data being kept for testing and the rest being used to develop the model. The results were formatted in logistic format to obtain the probability of occurrence in the range of 0-1. The enhanced regularised gain is added to the contribution of the associated variable in determining the percentage contribution, or deducted from it if the change in the absolute value of lambda is negative in each run of the training method. The values of each environmental variable on training presence and background data were randomly permuted to estimate permutation importance.

Trials were conducted using a single sample strategy with 13 replicates and a 25% test percentage to assess the model prediction accuracy. The MaxEnt output included attributes that defined the data's authenticity and how well the predicted model fit the data. Both omission curves and AUC curves described the model's accuracy (Fielding and Bell, 1997; Philips et al., 2006; Elith et al., 2011). The omission rate and anticipated area at different threshold levels were shown by analysing the omission/commission graph. The lines on the chart were shaded orange and blue to represent their variability. According to the definition of cumulative output format, the expected omission rate was a straight line. The expected omission rate should be similar to the actual omission rate. The area under the Receiver Operating Characteristic (ROC) curve, or area under the curve, as illustrated in the sensitivity vs 1-specificity graph (AUC). This made it simple to compare the performance of one model to that of another, and it was a valuable tool for evaluating numerous MaxEnt models. AUC values of 0.5 suggested that the model's performance was no better than random, whilst values of 1.0 indicated that the model performed better. The numerous models projected under different parameters were examined using these aspects of MaxEnt output. The best-fitted model based on the ROC curve and having a high AUC value was selected (Philips et al., 2006).

The procedure of model construction included a significant amount of variable optimisation. Even if all variables were related to the result, it was recommended to remove some with a bit of effect to boost the interpretability of the final model (epistemic sparsity) or to build a model with greater predictability (predictive sparsity) by reducing the variance (De Bin et al., 2015). To reduce autocorrelation, highly correlated variables should be removed when evaluating the contributions of each environmental variable to the species distribution model. Many climatic variables were strongly correlated, so integrating them all would not alter the validity of the MaxEnt model prediction. Still it would severely limit the contribution of other associated factors. If a highly correlated variable was included in the model, it disqualified any other associated variables from being included, even if they were significant in predicting species distribution (Brown, 2014). If there is a correlation, the response curves derived from the presence could be misleading. When there are a lot of factors that are highly associated, the per cent contributions should be used with caution. If the test and training data were spatially autocorrelated, the test omission line was significantly lower than the predicted omission line, indicating that the model was not well fitted. Because geographically auto correlated data will inflate the accuracy measurement for presence-only models (Veloz, 2009), spatially correlated variables have to be eliminated before the modelling procedure.

## 3.6 CURRENT DISTRIBUTION OF SPECIES

The correlation matrix (Pearson) and coefficients of determination ($R^2$) were used to analyse the bioclimatic variables (bio1-bio19) for the current conditions (1950-2000). The correlation values $|r| > 0.7$ and $|r| > 0.9$, as well as $R^2 > 0.9$, were used to categorise the variables. The variables with the highest percentage contribution were chosen, and important results based on the MaxEnt model output were utilised to make future predictions. The percentage contribution chart depicted each environment variable's proportionate contribution to the MaxEnt model. The increase in regularised gain was added to the contribution of the associated variable in each iteration of the training process, or deducted from it if the change in the absolute value of lambda was negative. They were dependent on the MaxEnt code's path to the solution, and the contribution values altered when it chose a different approach to obtain the same result. When there were a lot of highly linked factors, it was important to evaluate the results carefully. The MaxEnt model, not the path it took to get the value, determined the permutation relevance. The importance was determined by calculating the decrease in training AUC after randomly permuting the values of that variable in both the presence and background (training points). The greater the drop, the more dependent the model was on that variable. The environment variable had the highest gain when used in isolation (having the most useful information) and the environment variable that decreased the gain the most when it was omitted (having the most information that isn't present in the other variables), according to the Jack-knife test of variable importance. After removing the correlated variables, the selected variables were used in the subsequent modelling.

### 3.7 POTENTIAL DISTRIBUTION OF FICUS DRUPACEA

To estimate the probability distribution of the selected montane shola species in the future, the trained environment layers are projected to another available set of environmental layers including future climate data in the MaxEnt model. The projection layers should include training layers that are compatible but have varied circumstances. The names of the layers and map projection should be the same as the trained data. Based on future climatic data, a model was trained on environmental factors related to current climatic circumstances and projected into a distinct layer. Models of several RCPs, such as RCP 4.5, RCP 6.0, and RCP 8.5, were created using ten replicates and a test percentage of 25 for the 2050s and 2070s. The projection was carried out with the help of cross-validation replication.

# RESULTS

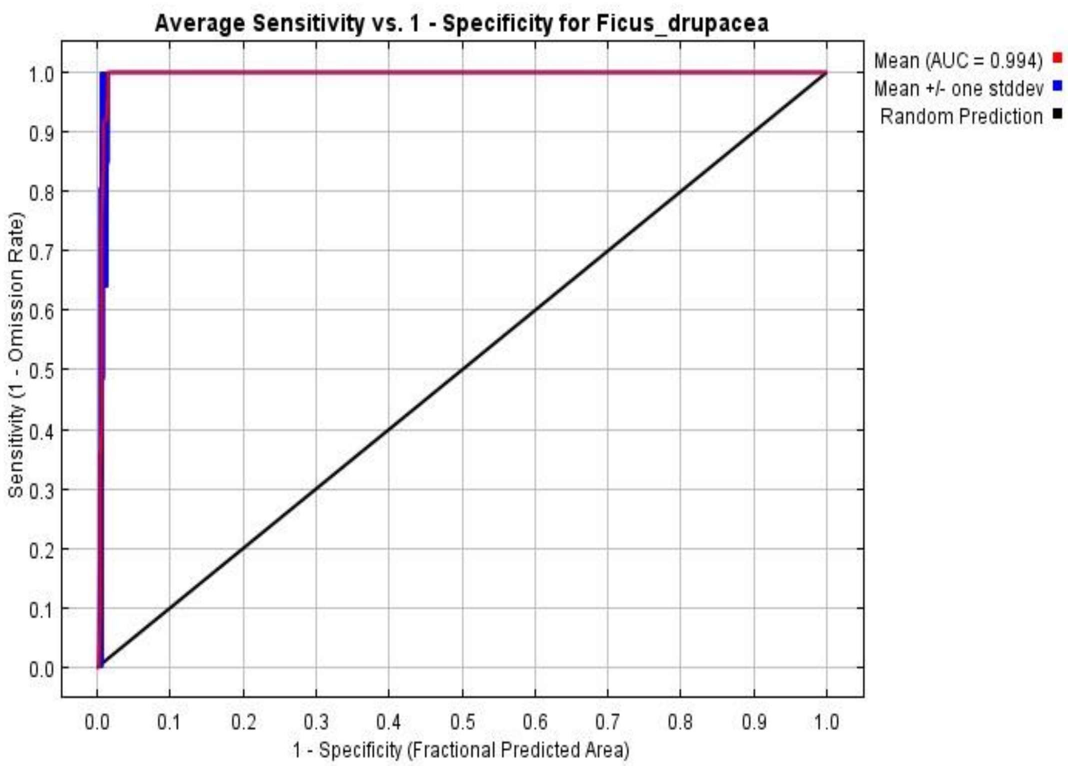
CHAPTER 4

RESULTS

## 4.1 VALIDATION OF MODEL

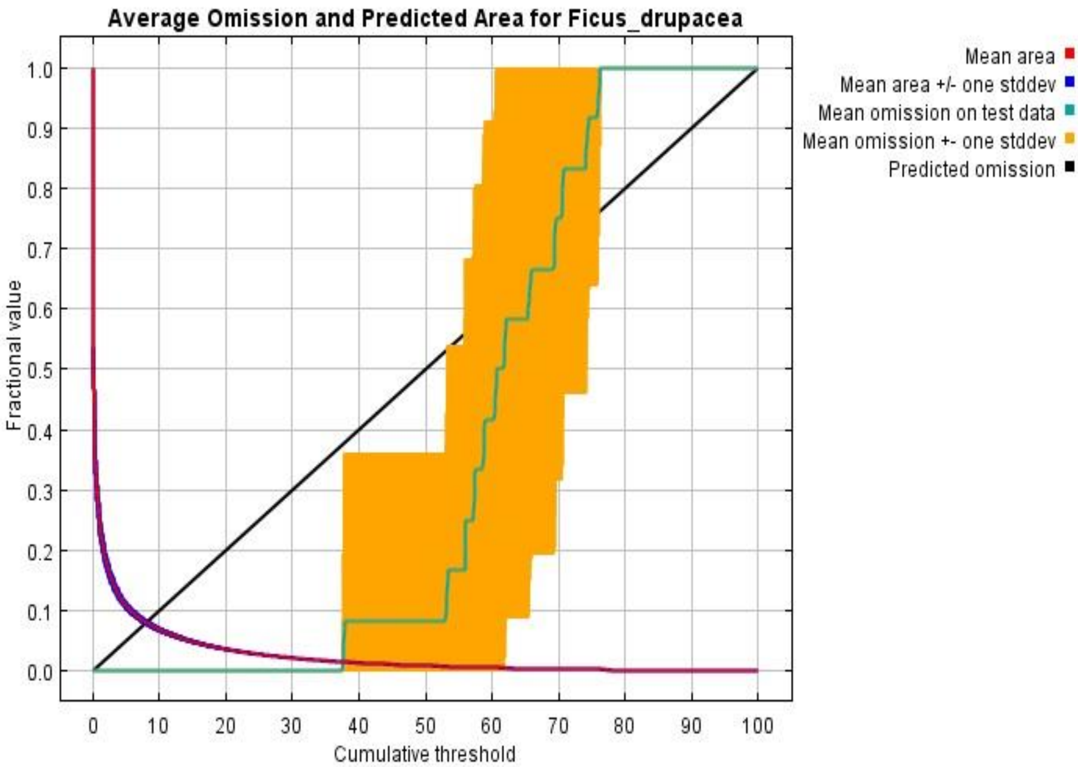
To test the accuracy of the model outputs, various methods are incorporated. Some of the ways are AUC, sensitivity, and specificity. The model is run as per the output of the ENM evaluate script in the R-studio. After the run, the finalized model outputs are assessed by visual inspection of graphs and maps.

Fig 3: Receiver Operating Characteristic (ROC) curve of the finalized model output in MaxEnt




The response curves from MaxEnt output demonstrated how each environmental variable affected *Ficus drupacea* distribution. The graphs above depict changes in logistic prediction as each environmental variable was modified while all other environmental variables remained at their average sample value. The average test AUC value is 0.994 with a standard deviation of 0.003. A model to be best, the AUC value should be 0.9 as it ranges from 0 to 1. The graph shows that the selected model is outstanding because of the curve curves from the origin to the top left of the plot.

Fig 4: Average omission curve and predicted area for *Ficus drupacea*




The above graph shows the test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs. The emission rate should be close to the expected omission because of the definition of the cumulative threshold.

4.2 ANALYSIS OF VARIABLE CONTRIBUTION

To select the suitable bioclimatic variables from the 19 variables, we need to find their correlation. Correlation also helps us to find the essential variables for the selected species. We use the Species Distribution Modelling (SDM) toolbox in

ArcGIS and create a correlation table to find the correlation. Analyzing the table based on the collinearity test and percentage contribution, the following variables were finalized for the selected species *Ficus drupacea*.

After the selection of the variables, each variable contributed differently to the species. Bio 3 (Isothermality) contributed 64.9%, slope contributed 23.7%, Bio 2 (Mean Diurnal Range) contributed 5.9% and Bio 19 (Precipitation of coldest quarter) contributed 2.9%. When put together, bio 14 (Precipitation of driest month) and Bio 18 (Precipitation of warmest quarter) contributed only 2.6%, which is negligible, and the contribution of land-cover and aspect in both current and future scenarios are nil. From this, it is clear that the most influencing variable in the distribution of the species is isothermality and the least contributed variable is the precipitation of the warmest quarter.

Table 2: Percentage contribution of the finalized bioclimatic variables and other factors in the distribution of *Ficus drupacea*.

| **Variable** | **Name of the variable** | **Per cent contribution** | **Permutation importance** |
|---|---|---|---|
| Bio 3 | Isothermality | 64.9 | 59 |
| Slope | Slope | 23.7 | 23.2 |
| Bio 2 | Mean Diurnal Range | 5.9 | 9.4 |
| Bio 19 | Precipitation of coldest quarter | 2.9 | 1.6 |
| Bio 14 | Precipitation of driest month | 2 | 0 |

| | | | |
|---|---|---|---|
| Bio 18 | Precipitation of warmest quarter | 0.6 | 6.9 |
| Aspect | Aspect | 0 | 0 |
| Land-cover | Land-cover | 0 | 0 |

Fig 5: Jackknife test gain of finalized bioclimatic variables and other factors obtained from MaxEnt output.

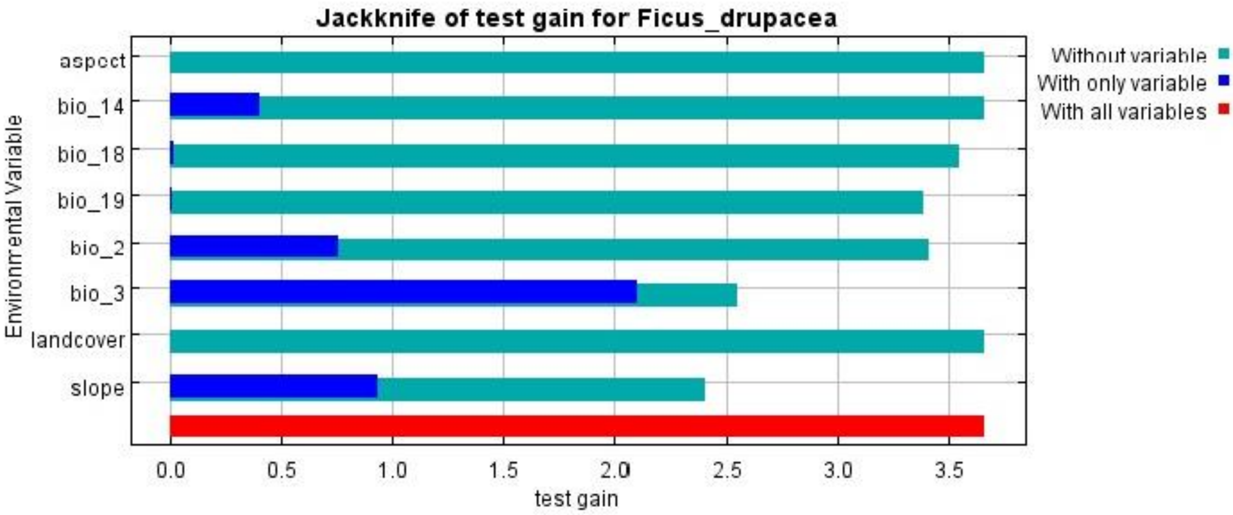
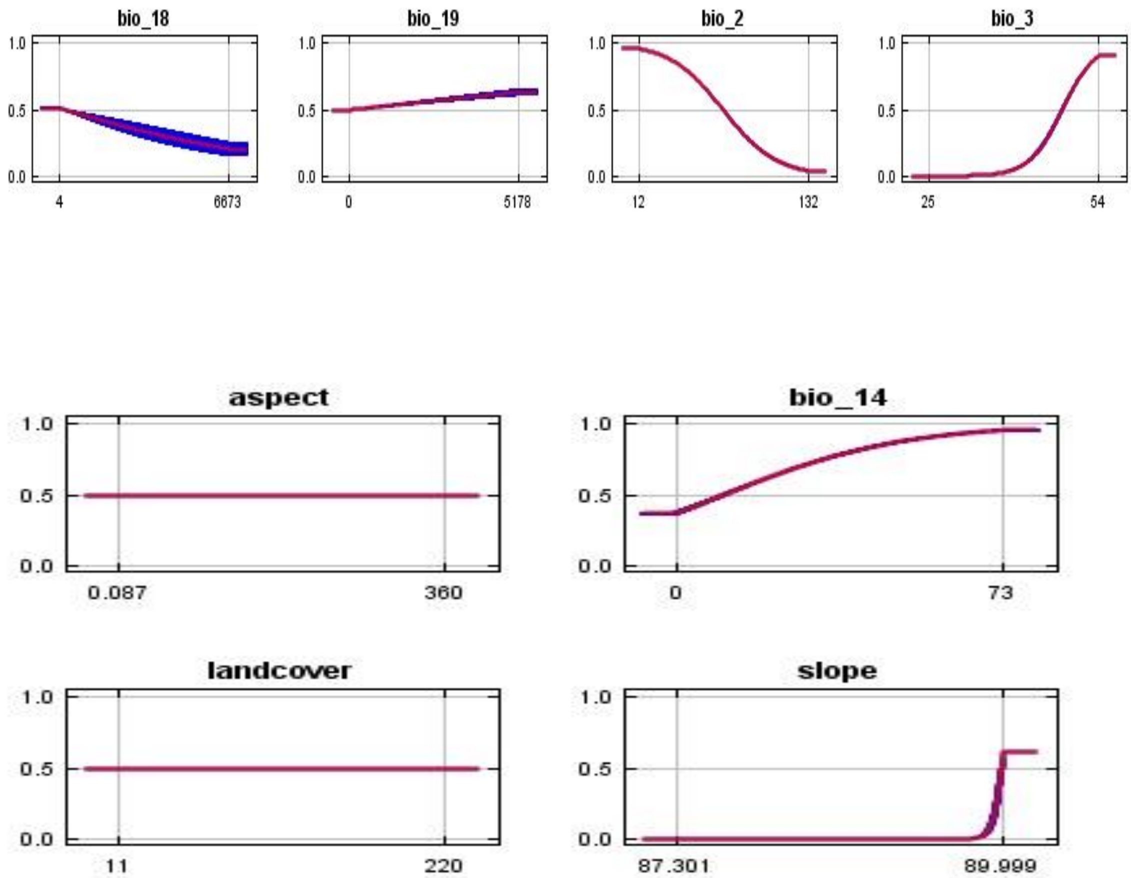



Fig 5 shows the jackknife test gain of the selected bioclimatic variables and other important factors. From the graph, it is evident that isothermality (Bio 3) is the bioclimatic variable that influences the distribution of species when taken into consideration. So from both the graph and the per cent contribution, it is clear that isothermality affects the distribution significantly.

Fig 6: Response curve showing the dependency of each selected variable to the potential distribution obtained from the MaxEnt model output.



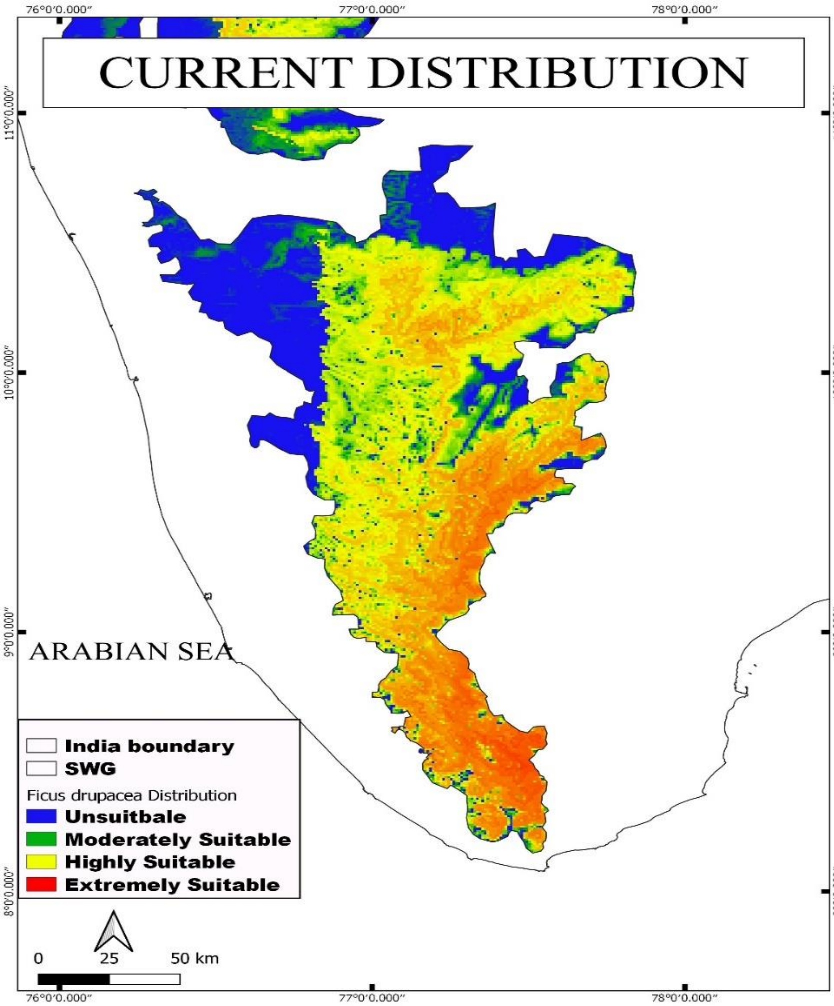

The above graph depicts the response curve of the selected variables to the potential distribution of *Ficus drupacea.* These response curves are in accordance with the per cent contribution table.

## 4.3 CLIMATE SPACE SUITABILITY FOR *Ficus drupacea* UNDERCURRENT AND FUTURE SCENARIOS

The MaxEnt model was run with all data including the species occurrence points, bioclimatic variables and current and future data. After receiving the output, the suitability area of *Ficus drupacea* under current and future scenarios were calculated using QGIS.

4.3.1 Climate Space Suitability Under Current Scenario

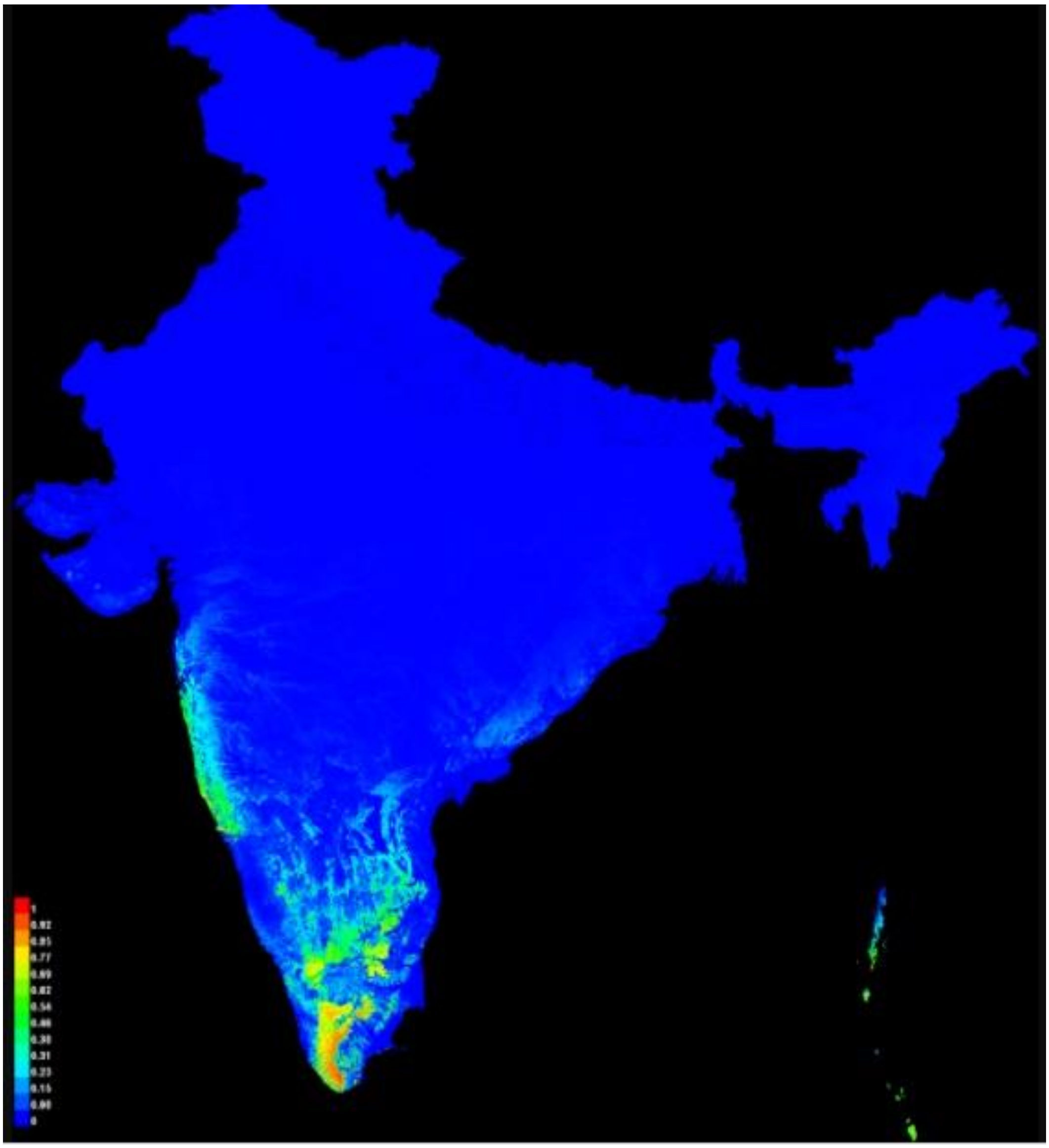
Fig 7: Distribution map showing the suitability areas under the current scenario




Under the current climate scenario in the Western Ghats, the highly suitable area available for the *Ficus drupacea* is 5312.845 km$^2$. These areas are found in the southern Western Ghats. The highly relevant areas under the current climate scenario are Idamalayar Reserve Forest, Kuttambhuzha, Neriamangalam, Adimali, Kodaikanal, Angamala Reserved Forest, Marayoor etc.

The extremely suitable area under the current climate scenario is 9426.397 km$^2$. The areas are found near Agasthyamalai, Kalakkad, Thenmala Reserve Forest, Konni Reserve Forest, Aruvappulam, Ranni Forest Division, Periyar National Park etc.

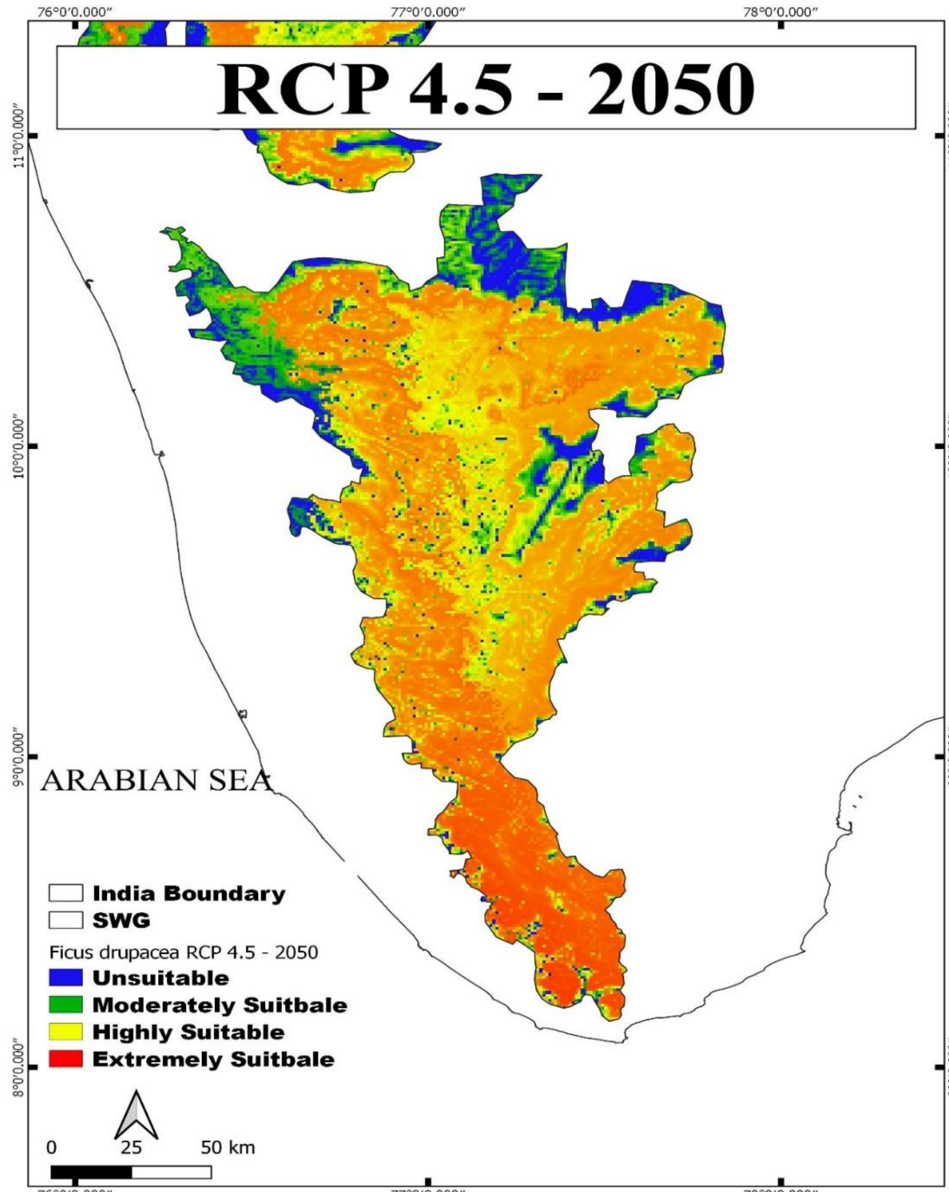
Fig 8: Map showing the distribution of suitability areas under the current scenario



4.3.2 Climate Space Suitability Under RCP 4.5

4.3.2.1 RCP 4.5 - 2050

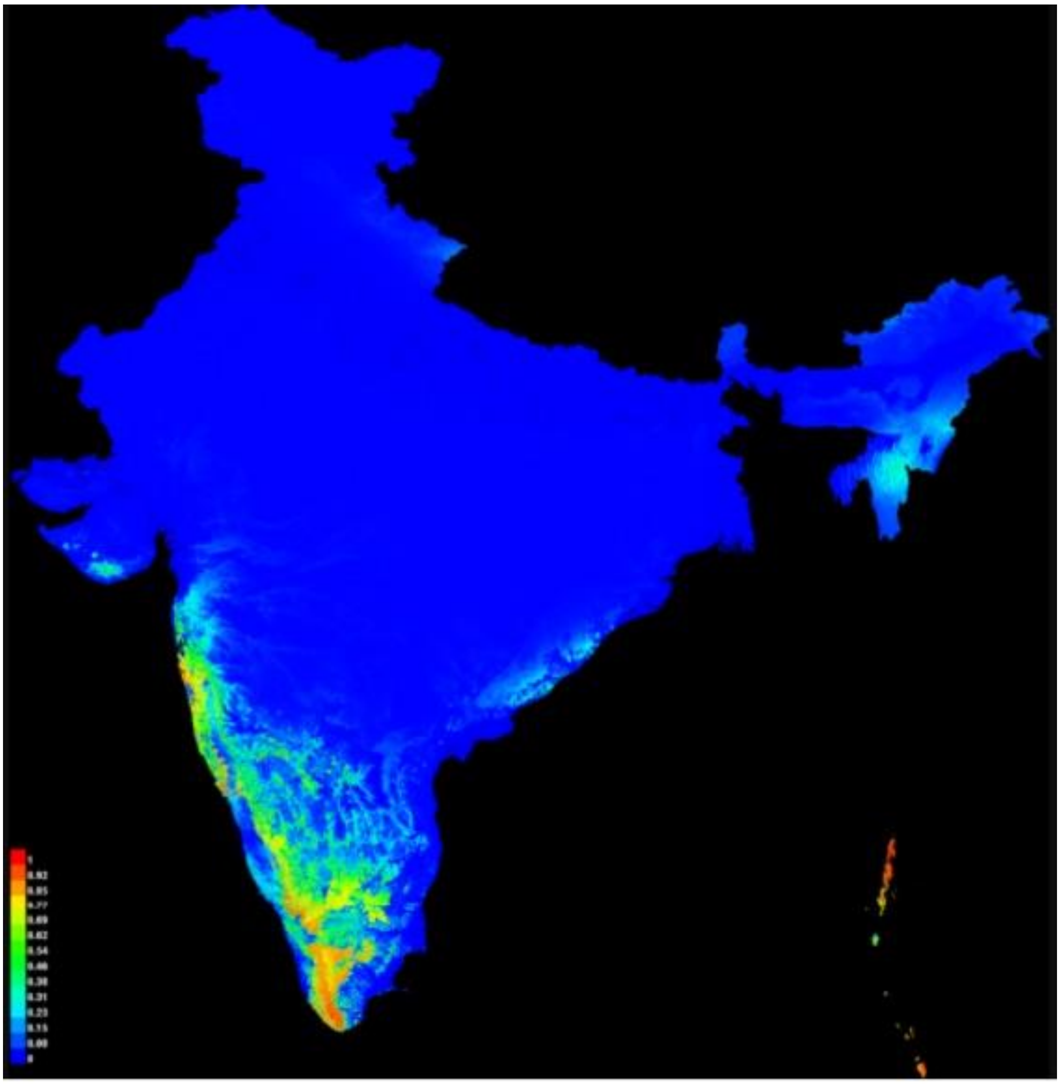
Fig 9: Distribution map showing the suitability area under the RCP 4.5 for the year 2050



The above figure shows the suitability areas of the distribution of the species *Ficus drupacea* under the RCP 4.5 for the year 2050. From the map, we can say that the highly suitable site available is 3033.212 km$^2$. The areas of highly appropriate distribution are Adimali, Kuttambhuzha, Neriamangalam etc.

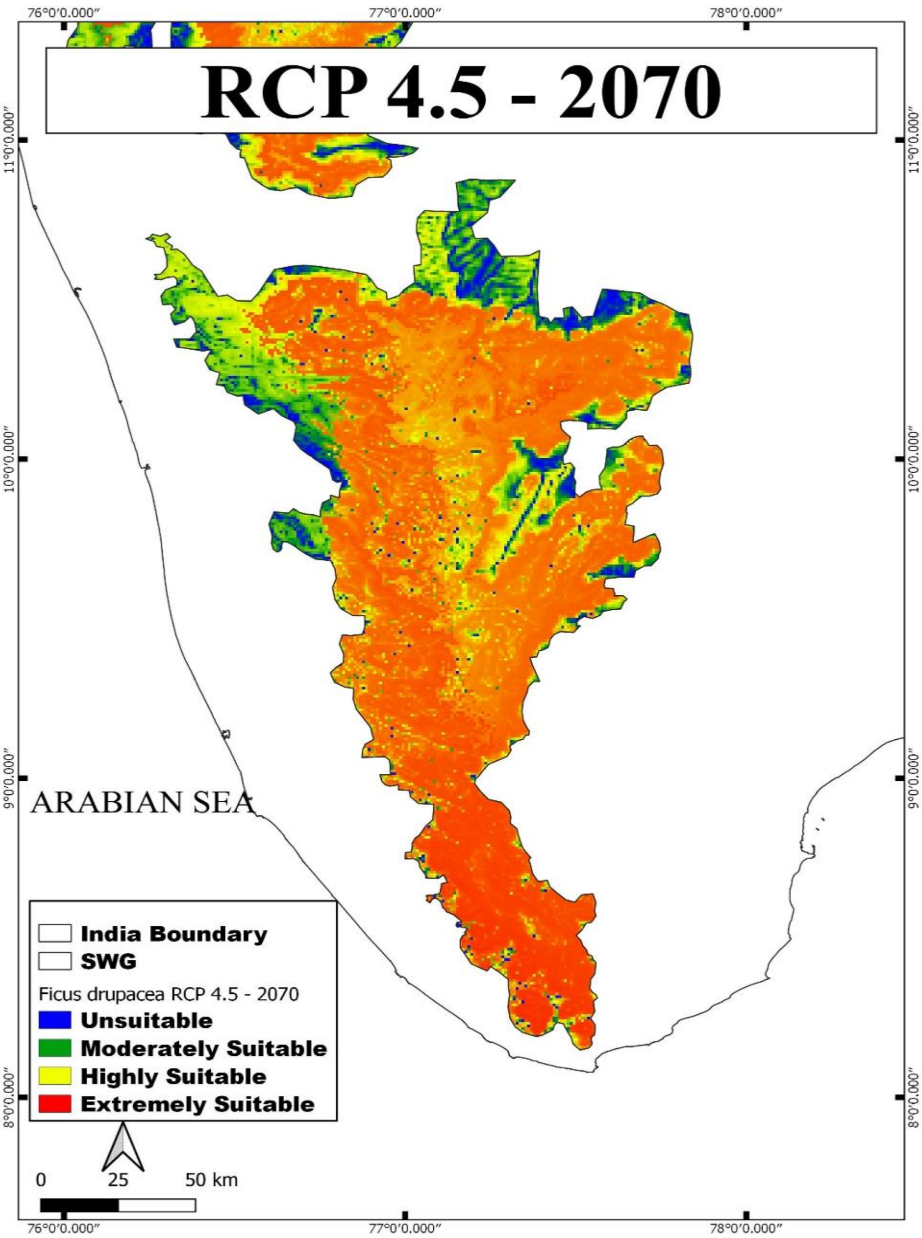
The extremely suitable area for Ficus drupacea is 14902.133 km$^2$. The places of extreme suitability are Agasthyamalai, Neyyar Wildlife Sanctuary, Singampatti Zamindar Forest, Mundanthurai Tiger Reserve, Ponmudi, Mahendragiri Reserved Forest, Papanasam Reserve Forest etc.

Fig 10: Map showing the distribution of suitability areas under RCP 4.5 for the year 2050



4.3.2.2 RCP 4.5 – 2070

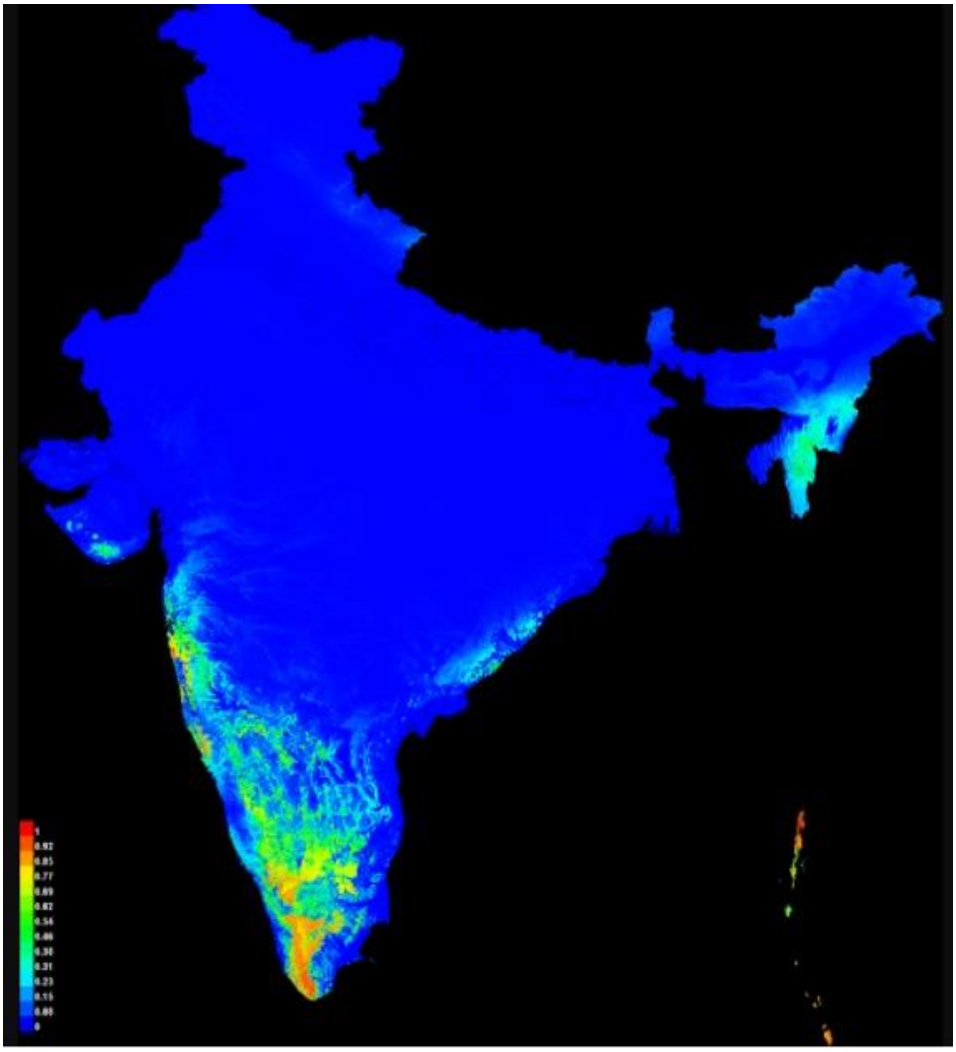
Fig 11: Distribution map showing the suitability areas under RCP 4.5 for the year 2070.




Under RCP 4.5, the highly suitable area for the potential distribution for 2070 is 3058.708 km$^2$. The highly relevant regions are Chimmini wildlife sanctuary, Kuthiran, Peechi – Vazhani Wildlife Sanctuary, Wadakkanchery and some parts of Kerala – Tamil Nadu border.

The extremely suitable area available for the year 2070 is 14739.93 km$^2$. The places are Nelliyampathy Forest Reserve, Idamalayar Reserve Forest, Valparai, Anamalai Tiger Reserve, Marayoor, Kanthalloor, Kookal, Kodaikanal, Anamudi, Munnar, Kuttambhuzha, Neriamangalam, Idukki Wildlife Sanctuary, Vagamon, Periyar National Park, Megamalai, Thenmala Reserve Forest, Konni Reserve Forest, Shendurney Wildlife Sanctuary, Ponmudi, Agasthyamalai, Neyyar Wildlife Sanctuary etc.

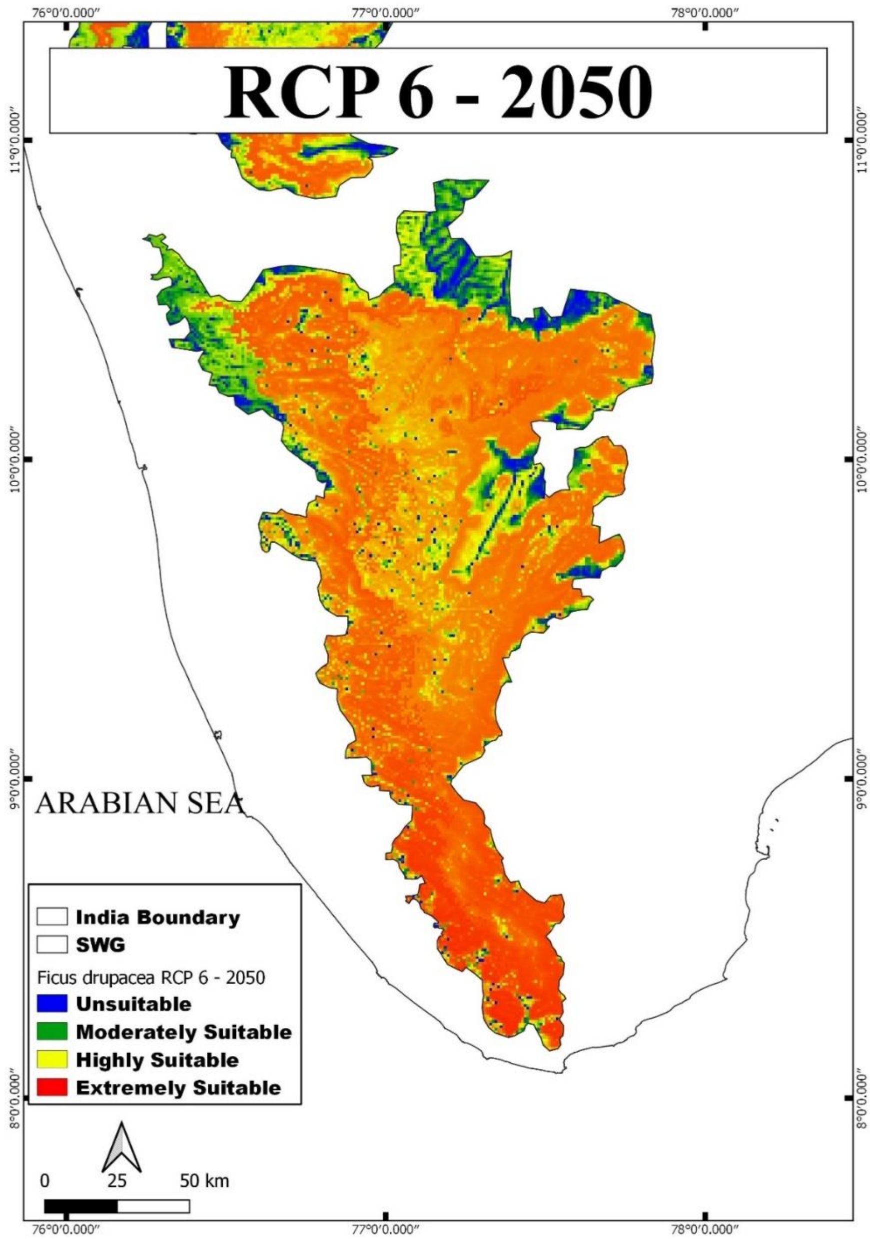
Fig 12: Map showing the distribution of suitability areas under RCP 4.5 for the year 2070.



4.3.3 Climate Space Suitability Under RCP 6

4.3.3.1 RCP 6 – 2050

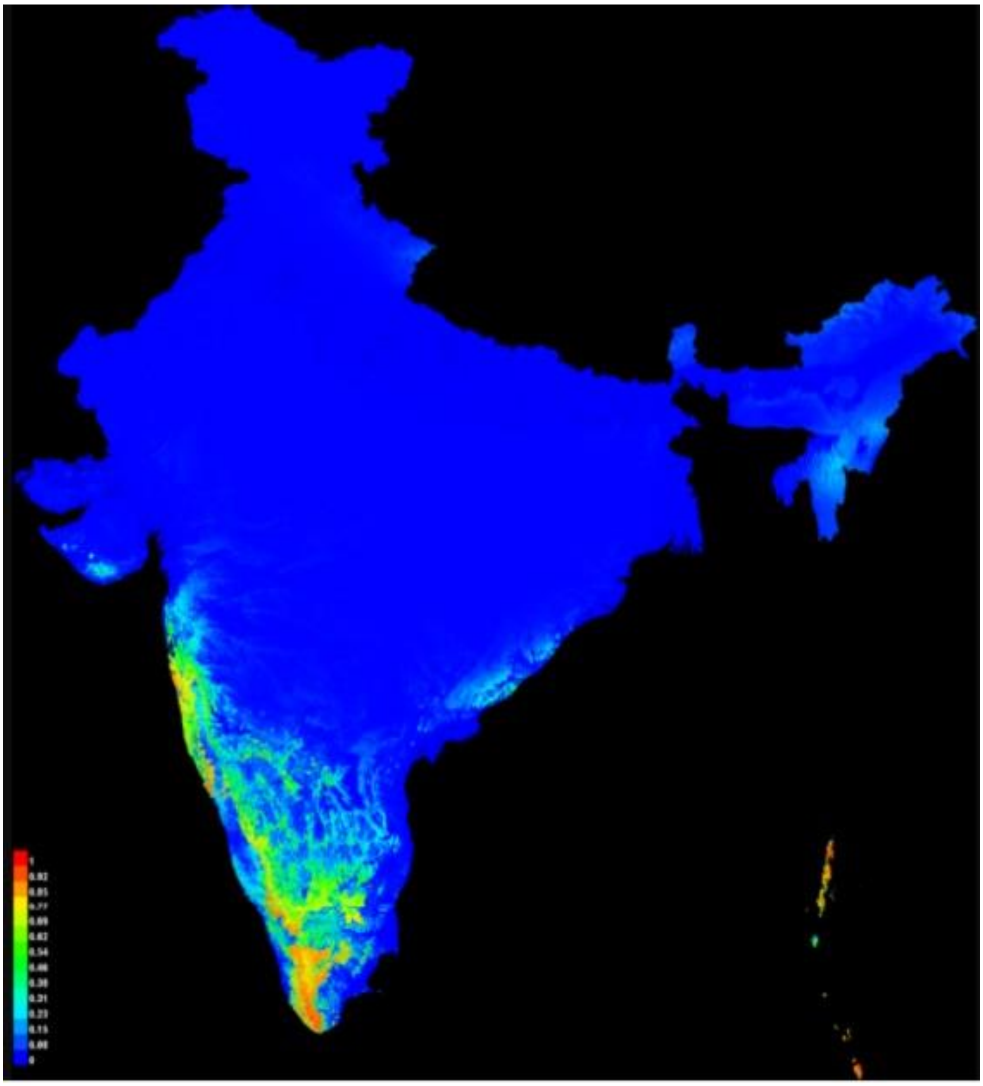
Fig 13: Distribution map showing the suitability areas under RCP 6 for the year 2050.



Under RCP 6, the highly suitable area available for the year 2050 is 2984.602 km$^2$. We can find highly suitable areas are some parts of Thrissur district, Udumalapettai, some parts of Cumbum etc.

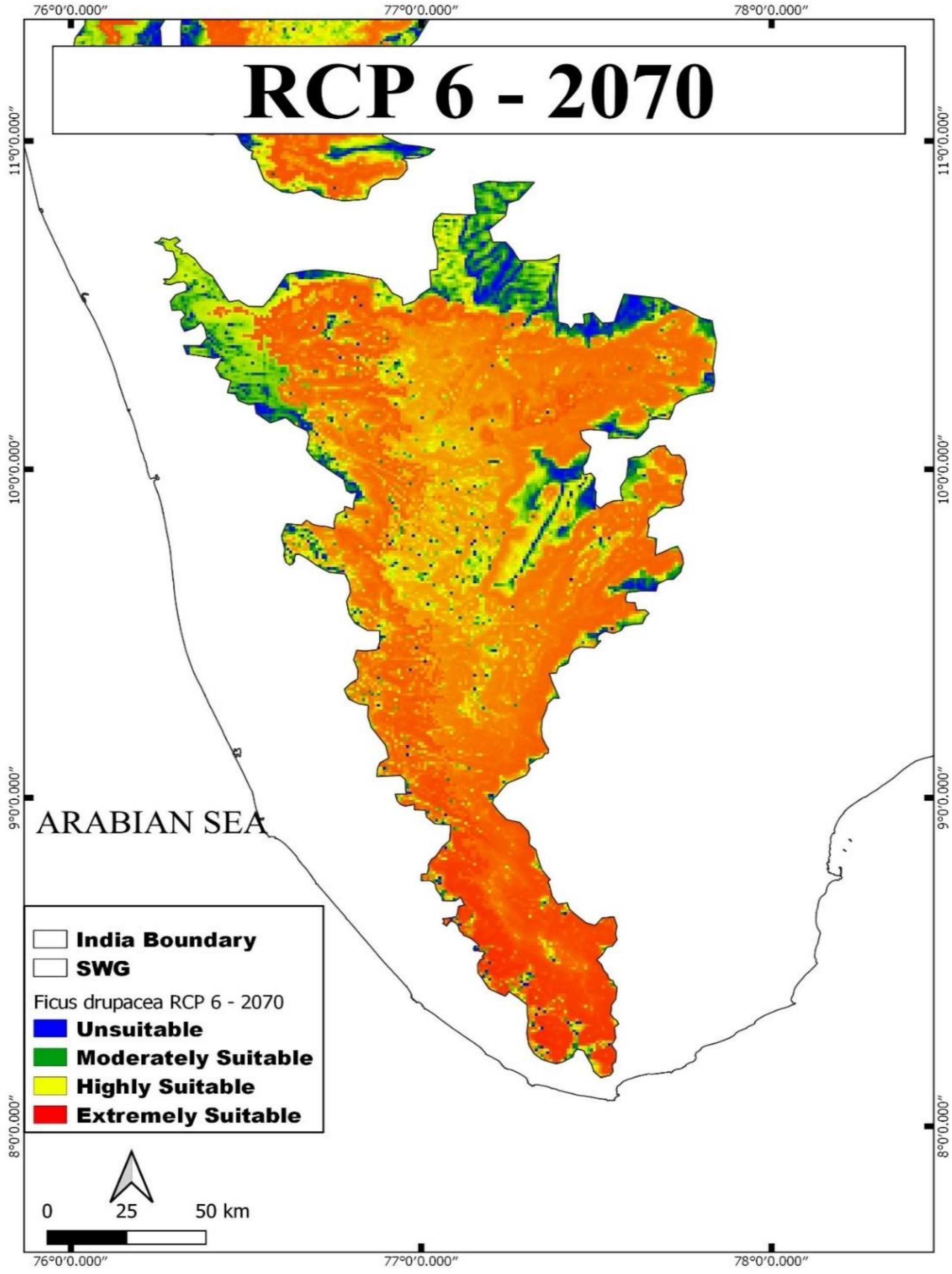
The extremely suitable area available for the potential distribution of *Ficus drupacea* in 2050 under the RCP 6 is 15020.788 km$^2$. The places are most of southern western Ghats starting from the Nelliyampathy Forest Reserve to Nagercoil.

Fig 14: Map showing the distribution of suitability areas under RCP 6 for the year 2050.



4.3.3.2 RCP 6 – 2070

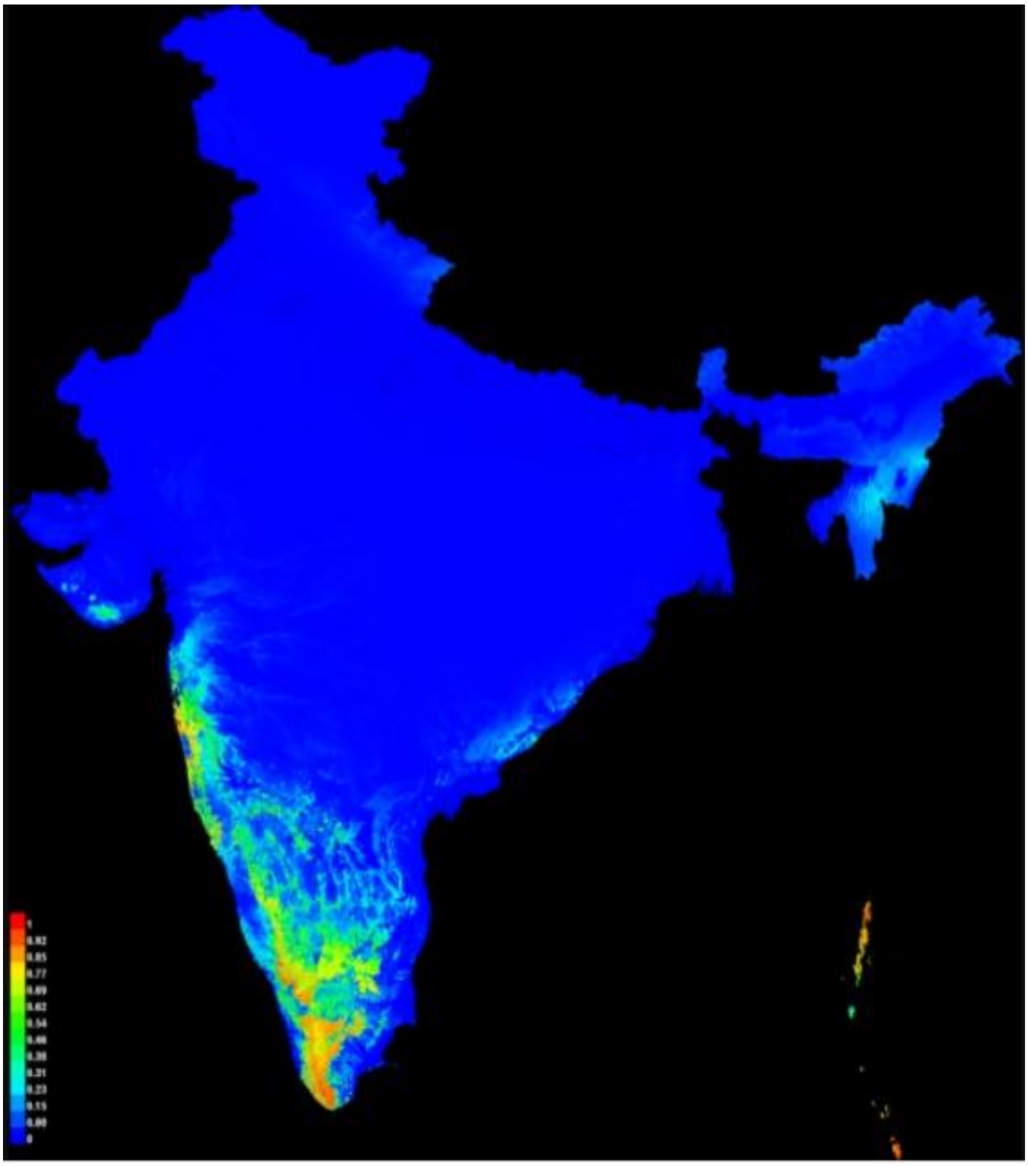
Fig 15: Distribution map showing the suitability areas under RCP 6 for the year 2070.



Under RCP 6, the highly suitable area for the potential distribution of *Ficus drupacea* in 2070 is 3381.857 km$^2$. The places are some parts of Thrissur districts, Pollachi area, some traces in Cumbum area, Vagamon area etc.

The extremely suitable area available in the year 2070 under the RCP 6 is 14796.67 km$^2$. The places are almost the whole southern Western Ghats.

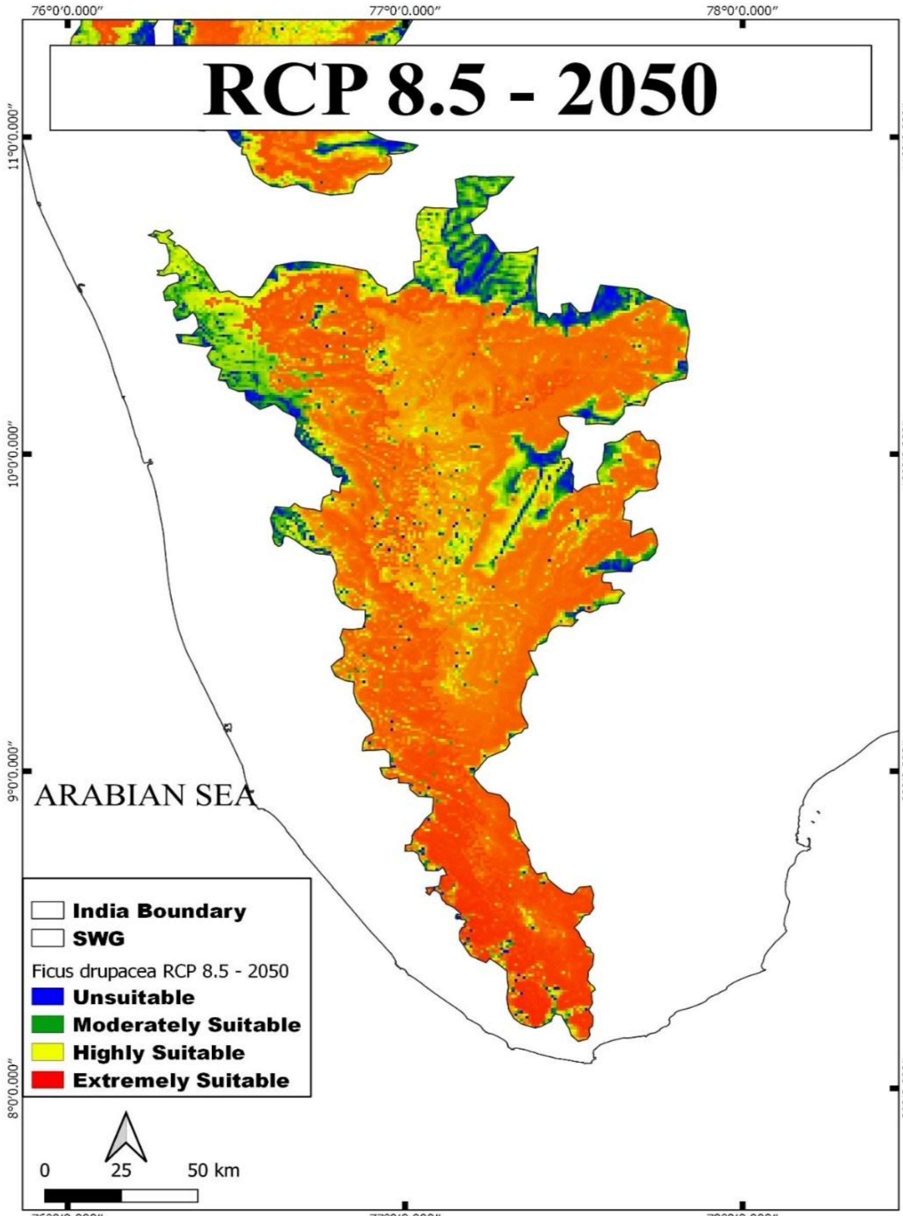
Fig 16: Map showing the distribution of suitability areas under RCP 6 for the year 2070.



4.3.4 Climate Space Suitability Under RCP 8.5

4.3.4.1 RCP 8.5 – 2050

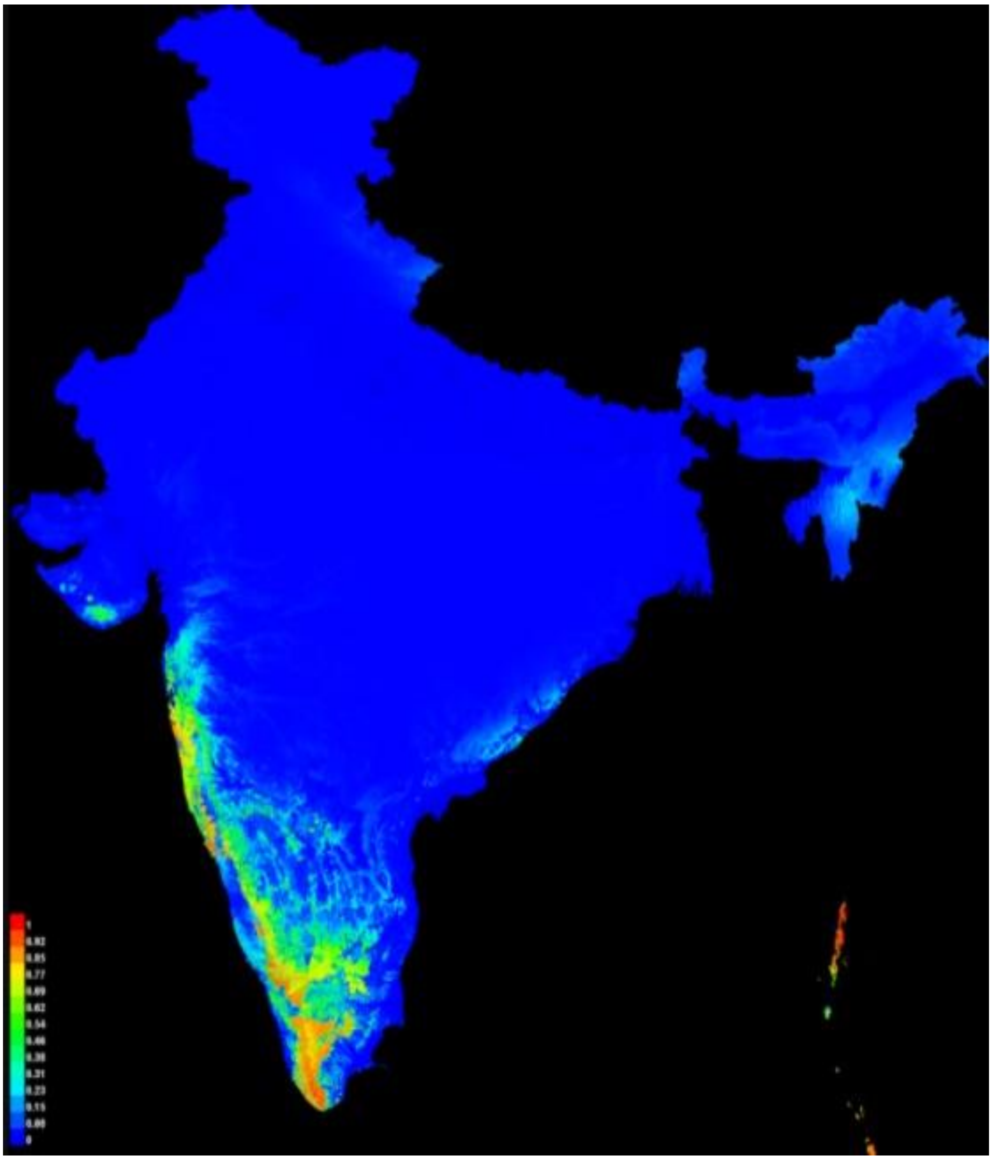
Fig 17: Distribution map showing the suitability areas under RCP 8.5 for the year 2050.



Under the RCP 8.5, the highly suitable area available for the potential distribution of *Ficus drupacea* in 2050 is 3030.364 km$^2$. The places are some parts of Thrissur districts, Pollachi, Palani, Cumbum etc.

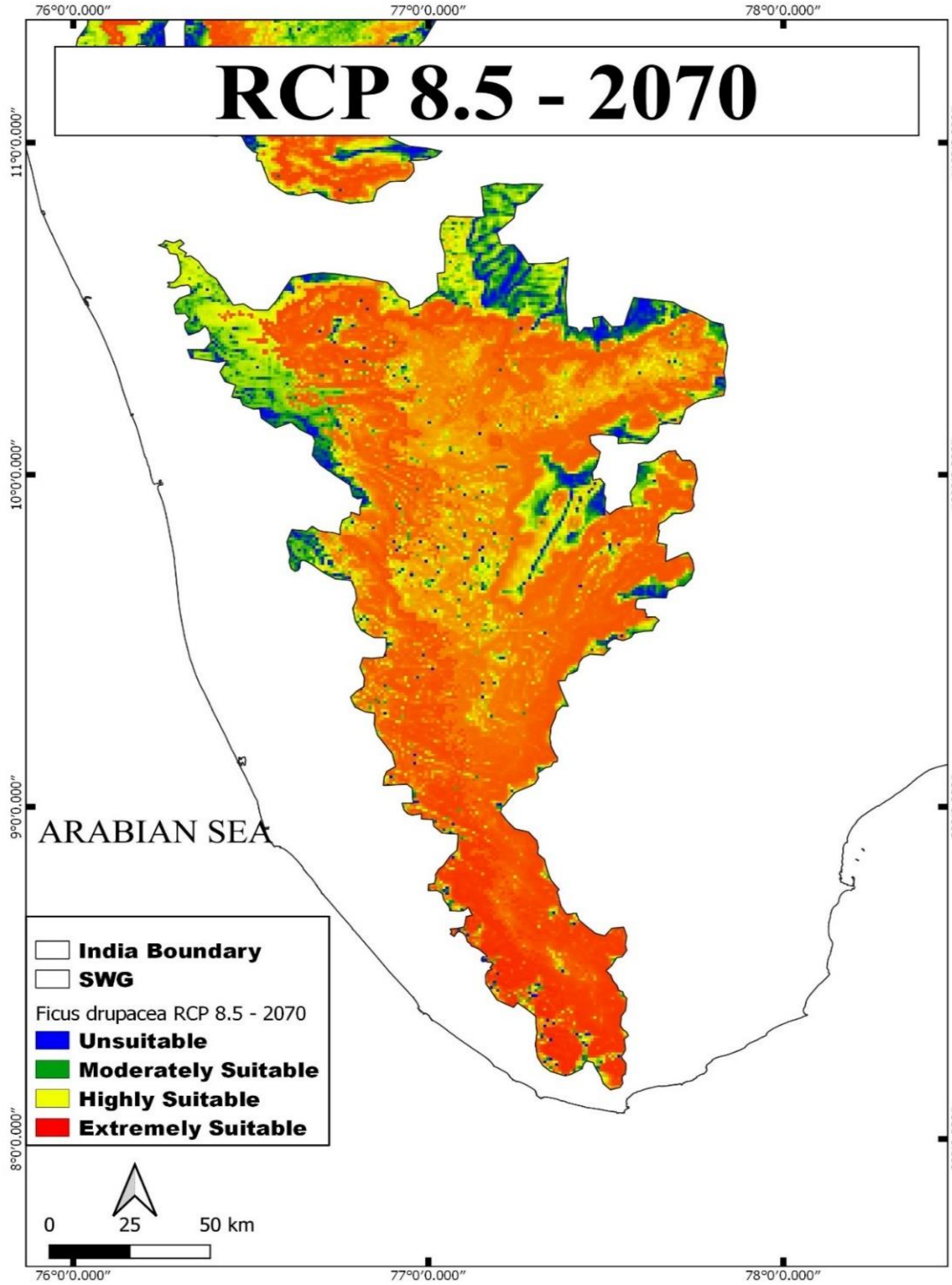
The extremely suitable area available for the potential distribution of *Ficus drupacea* in 2050 is 15153.146 km$^2$. It is spread to almost the whole southern Western Ghats.

Fig 18: Map showing the distribution of suitability areas under RCP 8.5 for the year 2050.



4.3.4.2 RCP 8.5 – 2070

Fig 19: Distribution map showing the suitability areas under RCP 8.5 for the year 2070.




Under the RCP 8.5, the highly suitable area available for the potential distribution of *Ficus drupacea* in 2070 is 3293.409 km$^2$. The places are some parts of Thrissur districts, Chimmini Wildlife Sanctuary, Pollachi, Kodaikanal, Ramakalmedu etc.

The extremely suitable area available for the potential distribution of *Ficus drupacea* in the year 2070 is 15028.831km$^2$. The places with extreme suitability are found to be spread almost the whole southern Western Ghats.

Fig 20: Map showing the distribution of suitability areas under RCP 8.5 for the year 2070.

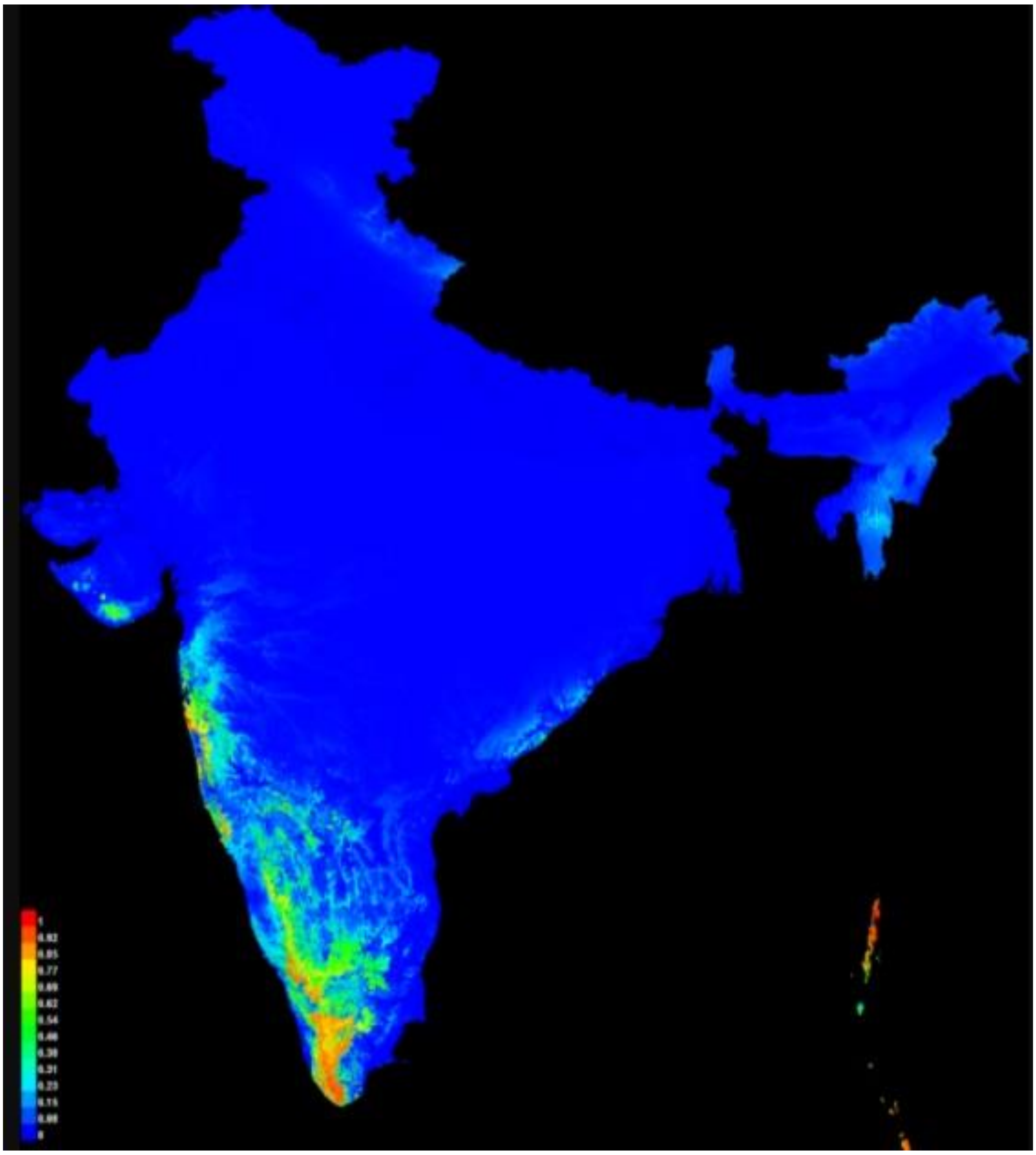
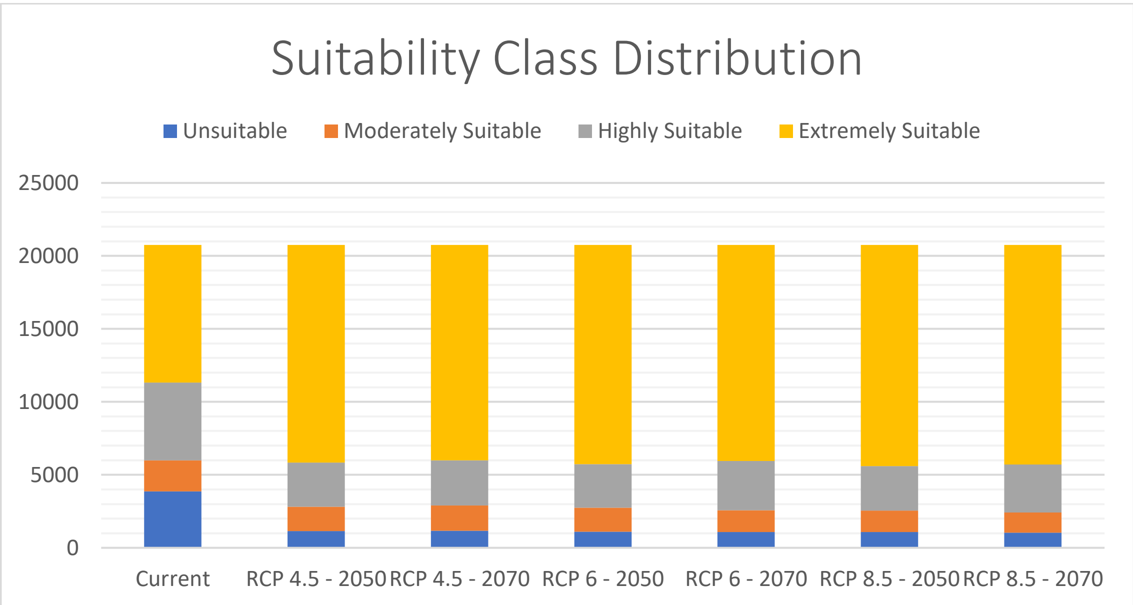


Table 3: Suitability class distribution of *Ficus drupacea* under various RCP scenarios with their area of extent (km$^2$).

| | Current | RCP 4.5 - 2050 | RCP 4.5 - 2070 | RCP 6 - 2050 | RCP 6 - 2070 | RCP 8.5 - 2050 | RCP 8.5 - 2070 |
|---|---|---|---|---|---|---|---|
| Unsuitable | 3868.378 | 1140.403 | 1170.78 | 1105.836 | 1077.26 | 1072.254 | 1036.113 |
| Moderately Suitable | 2135.125 | 1667.006 | 1721.921 | 1631.523 | 1486.962 | 1486.987 | 1384.394 |
| Highly Suitable | 5312.845 | 3033.212 | 3110.111 | 2984.602 | 3381.857 | 3030.364 | 3293.409 |
| Extremely Suitable | 9426.397 | 14902.133 | 14739.928 | 15020.788 | 14796.67 | 15153.146 | 15028.831 |

Fig 21: Chart illustrating the habitat suitability class distribution for *Ficus drupacea* under each RCP scenario.



# DISCUSSION

# CHAPTER 5

# DISCUSSION

The Western Ghats mountain range, which is older than the Himalayas, contains geomorphic features of tremendous importance and, distinct biophysical and biological processes. The high montane forest ecosystems at the site have an impact on the Indian monsoon weather pattern. The site, which helps to moderate the region's tropical temperature, is one of the best examples of the monsoon system on the planet. It also possesses a high level of biological diversity and endemism and is considered one of the world's eight "hotspots" of biological diversity.

There are various studies related to the distribution of many species in the area. Most of the studies demonstrate that the species distribution is declining as the year passes and RCPs increase. Climate change is predicted to negatively influence the marshy Myristica species of the myristicacea family in the Western Ghats (Priti *et al*., 2016). In the Western Ghats, a similar study on Myristica dactyloides revealed a decreasing trend in habitat appropriateness (Remya *et al*., 2015). These findings are consistent with one of the valid regional-scale studies on the impacts of climate change on India's forests, which found that forests in the northern and middle Western Ghats responded differently than tropical evergreen forests in the southern Western Ghats.

While changing climate, when the northern and central forests of the Western Ghats were negatively affected, the forest of southern Western Ghats remained more over stable. In the future they are also expected to remain silent (Chaturvedi *et al*., 2011). This difference in the north and south parts is due to the precipitation they receive. In the future, southern Western Ghats will receive 5-15% increased precipitation (Krishna Kumar *et al*., 2011). In the study also, precipitation played a significant role in understanding the distribution of *Ficus drupacea* in future scenarios. Among the bioclimatic variables, Precipitation of the coldest quarter (Bio 19), Precipitation of the driest month (Bio 14) and Precipitation of the warmest quarter (Bio 18) were the variables that contributed to the suitability of

*Ficus drupacea*. This answers why montane shola species *Ficus drupacea* show an increase in the distribution in the future from its current scenario.

Another factor in consideration is carbon dioxide concentration. As per the RCP scenarios given out by IPCC, the temperature will increase in the future. As the temperature increases, the carbon dioxide concentration is also going to increase in the future. The carbon dioxide concentration is expected to grow 650 parts per million in RCP as radiative forcing increases. It increases the carbon dioxide concentration in the atmosphere and thus increases the temperature. According to the percentage contribution table, Mean Diurnal Range (Bio 2), which is a derivative of temperature, is critical in the probability of *Ficus drupacea.* Unlike the current scenario, it is understood that the species will be adapted to plans even the temperature increases. Hence it is evident that all these factors promote the distribution of *Ficus drupacea.*

Among the five bioclimatic variables, 3 are derivatives of precipitation namely, Precipitation of coldest quarter (Bio 19), Precipitation of the driest month (Bio 14) and Precipitation of warmest quarter (Bio 18), which have influenced the distribution of *Ficus drupacea* suggests that increase in precipitation in the future may enhance the distribution of the species as predicted by the model.

# SUMMARY AND CONCLUSION

# CHAPTER 6

# SUMMARY AND CONCLUSION

The study explains the impact of climate change on the probable distribution of a montane shola species called *Ficus drupacea* present in the southern Western Ghats in the future. The study was done under all the RCPs and understood how the species would be reacting to the changing climate scenarios in the future. Due to the lack of occurrence points of the species, much study was not available. Only 13 occurrence points were available for the species *Ficus drupacea.* But this study can be considered a new opening for further research related to the species and the study area, montane shola forests.

This study explained how the species would react in different RCPs and their suitability in each RCPs. The extremely suitable and most suitable areas for the species *Ficus drupacea* were found from the results. The distribution of the species was increasing across all the RCPs from the current scenario. So, the changing climate is having a positive impact on the distribution of the species *Ficus drupacea.* The maximum probable distribution of *Ficus drupacea* was found in the RCP 8.5 in the year 2050.

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# CHAPTER 7

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**IMPACT OF CLIMATE CHANGE ON THE DISTRIBUTION OF MONTANE SHOLA SPECIES (*Ficus drupacea*) IN THE SOUTHERN WESTERN GHATS**

by

**Swathy Krishna G**

**(2015-20-005)**

**ABSTRACT**

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## CHAPTER 8

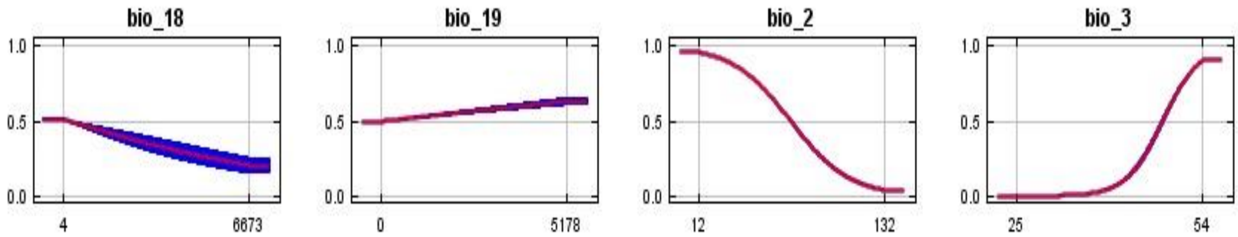
## ABSTRACT

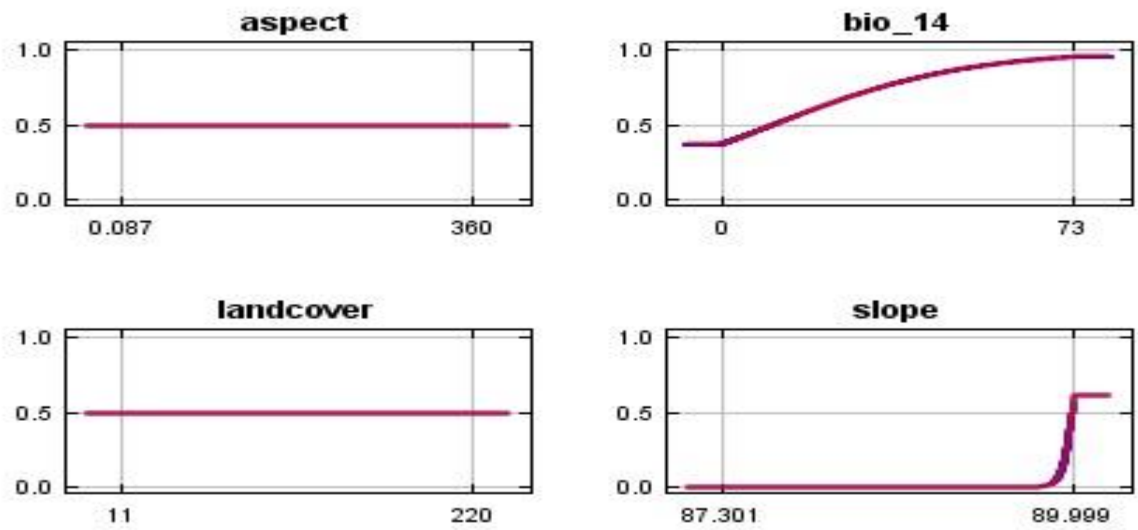
Climate change is severely affecting the ecosystem and its components. These changes affect the distribution of some species either beneficial or detrimental. The study was conducted to understand the impact of climate change on the distribution of montane shola species *Ficus drupacea* in the southern Western Ghats. Temperature rise and precipitation are the main factors that affect the climate system. To understand the influence of climate on the distribution of the species in the current and future scenarios, model called MaxEnt was run using the sample data and the selected bioclimatic variables. The result from the study showed that the distribution of the species *Ficus drupacea* in the current scenario is highly suitable in the southern Western Ghats. The model was run for the year 2050 and 2070 under different RCP scenarios – 4.5, 6 and 8.5. The model output explained that the distribution of *Ficus drupacea* was increasing under each RCP scenarios for the years 2050 and 2070. The maximum probable distribution of *Ficus drupacea* was found under RCP 8.5 in the year 2050. So from the study it is proved that the change in the climate scenario is having a positive impact on the distribution of a widespread species called *Ficus drupacea* which is keystone species found in the southern Western Ghats.

# APPENDIX – I

**APPENDIX – I**

Response curve showing the dependency of each selected variable to the potential distribution obtained from the MaxEnt model output

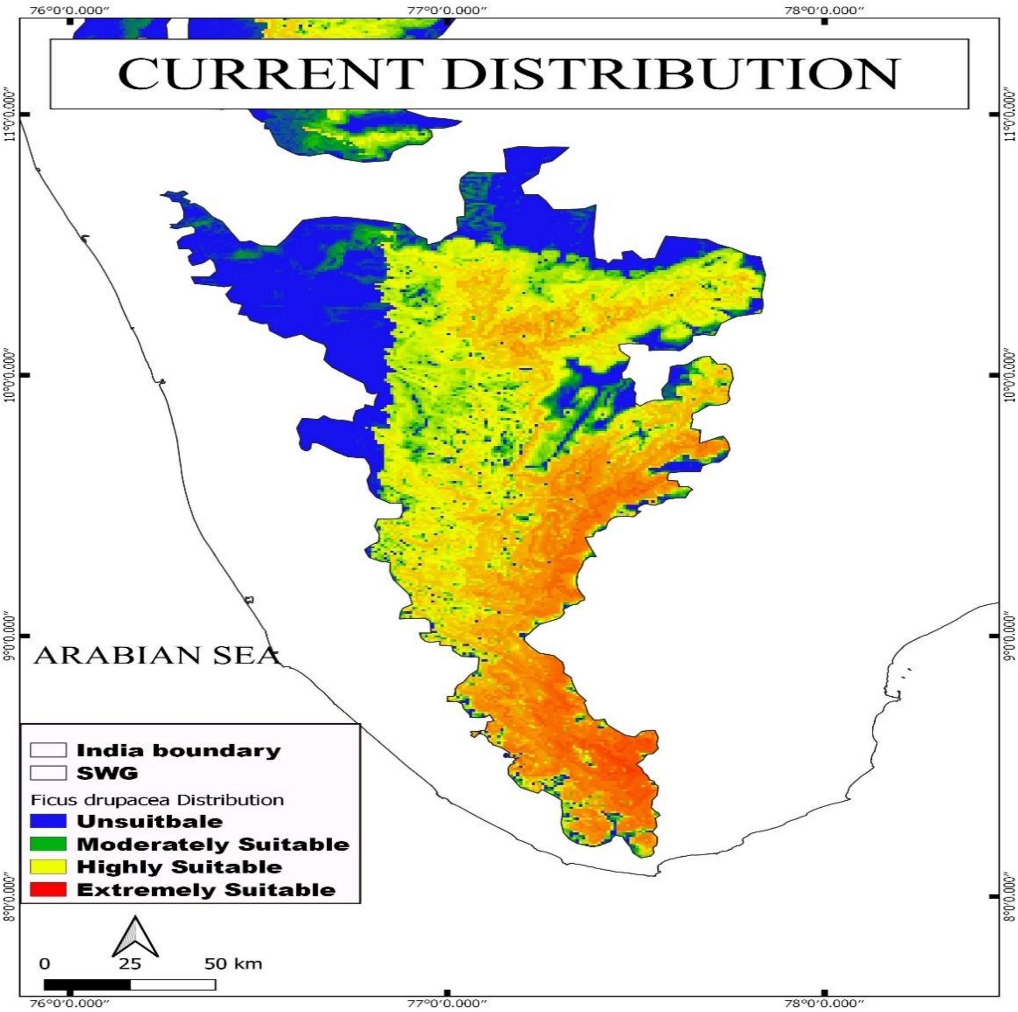


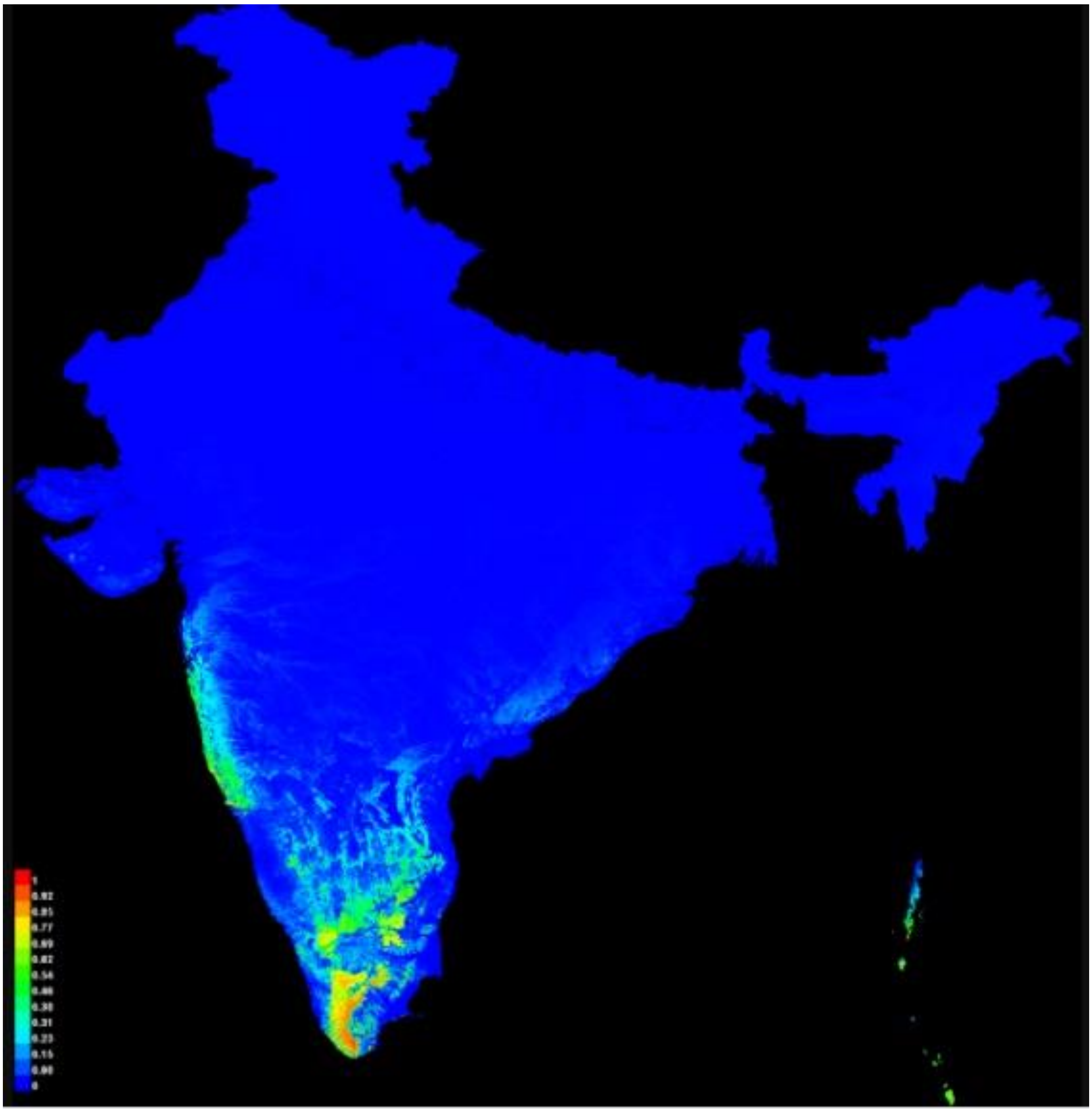
# APPENDIX – II

**APPENDIX – II**

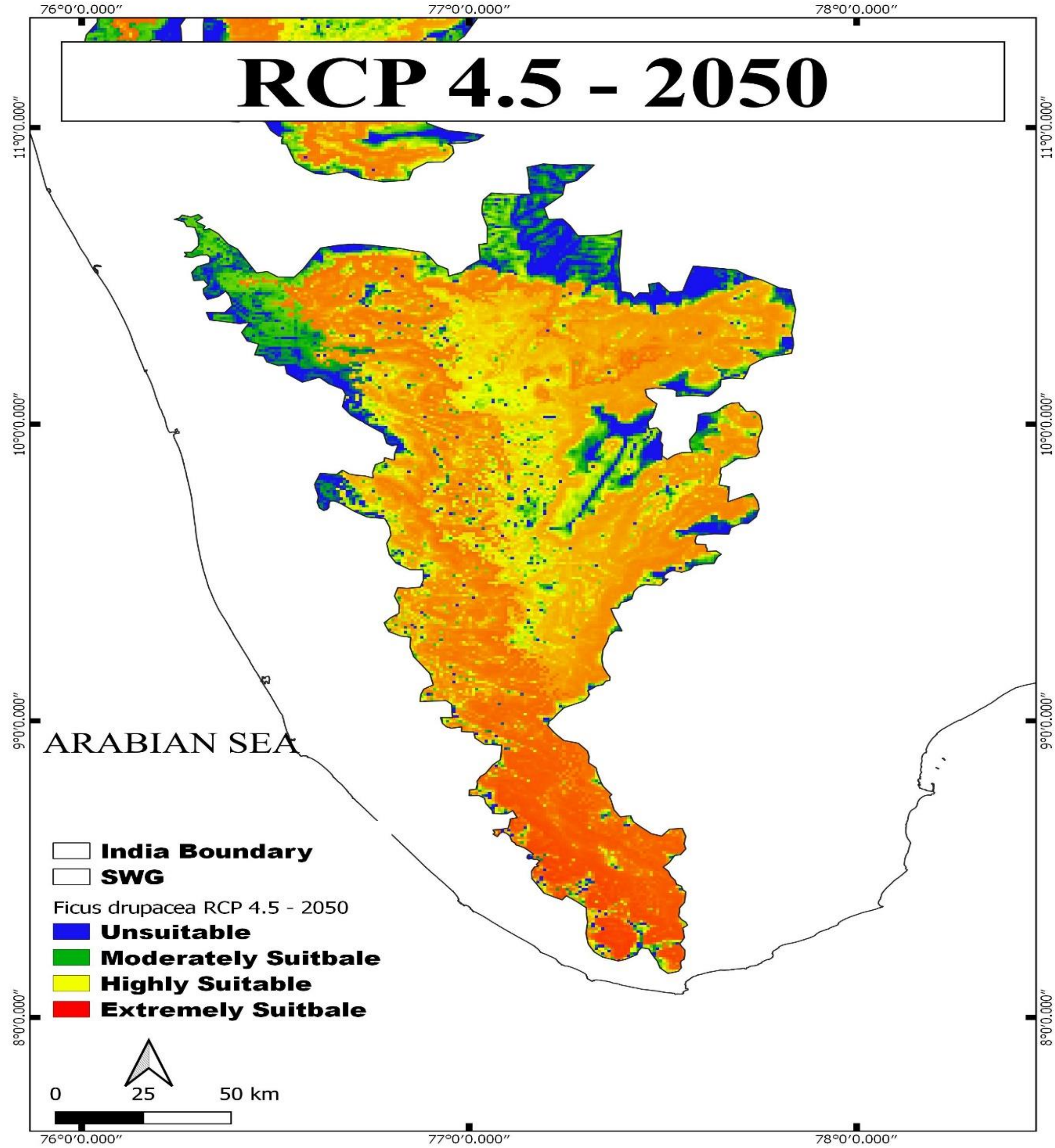
Distribution map showing the suitability areas under current scenario



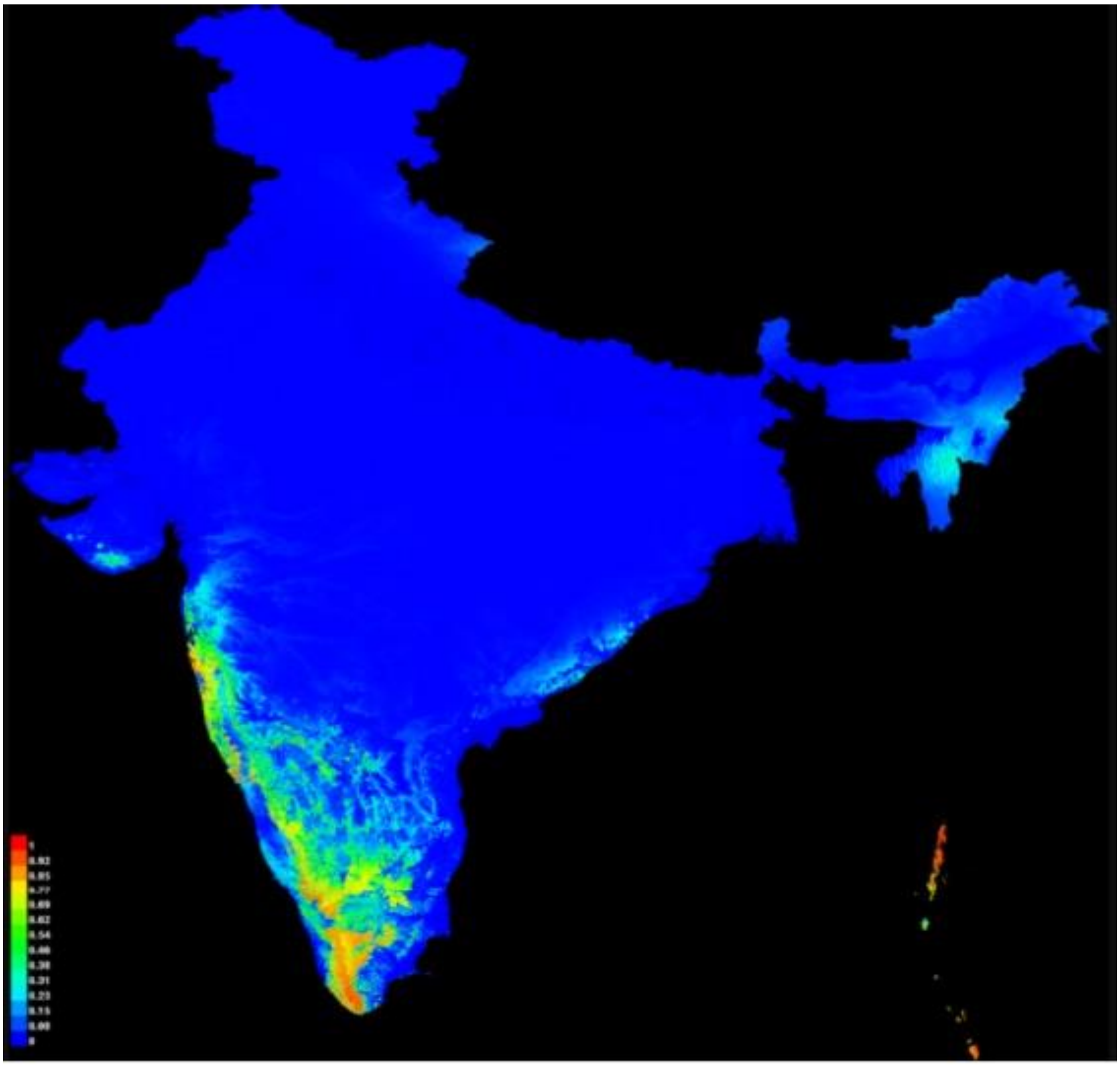
Map showing the distribution of suitability areas under the current scenario



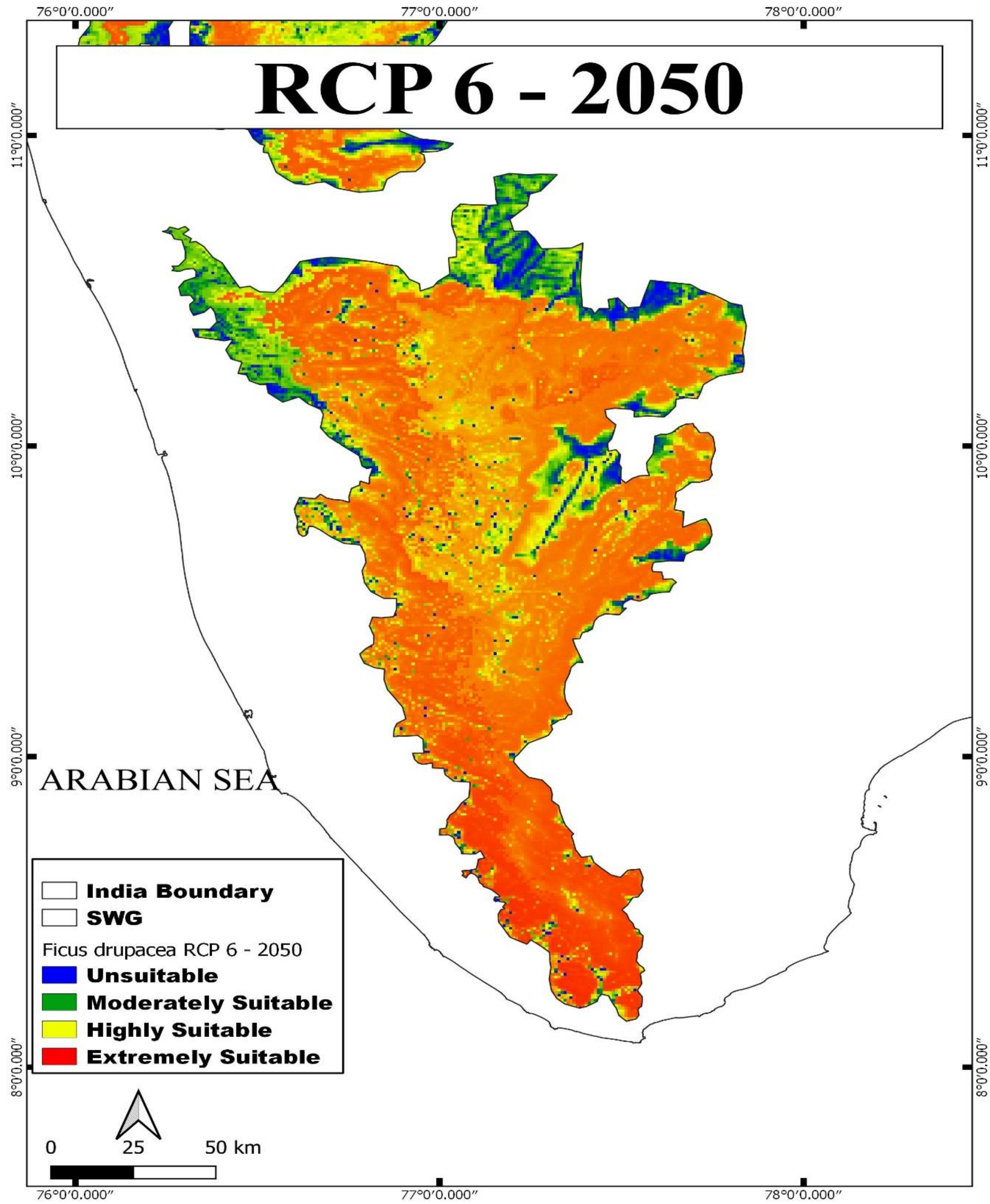
Distribution map showing the suitability area under the RCP 4.5 for the year 2050



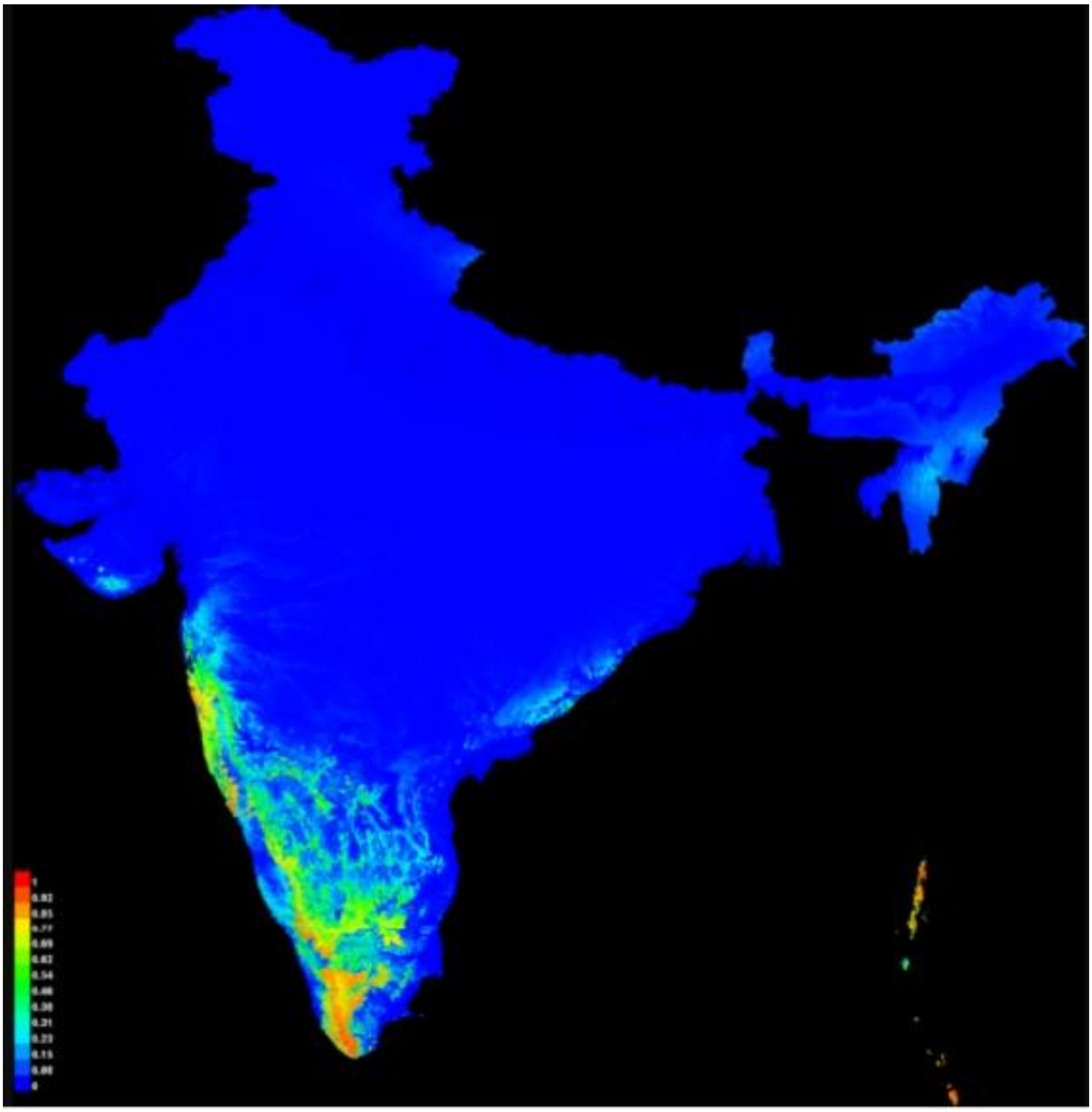
Map showing the distribution of suitability areas under RCP 4.5 for the year 2050



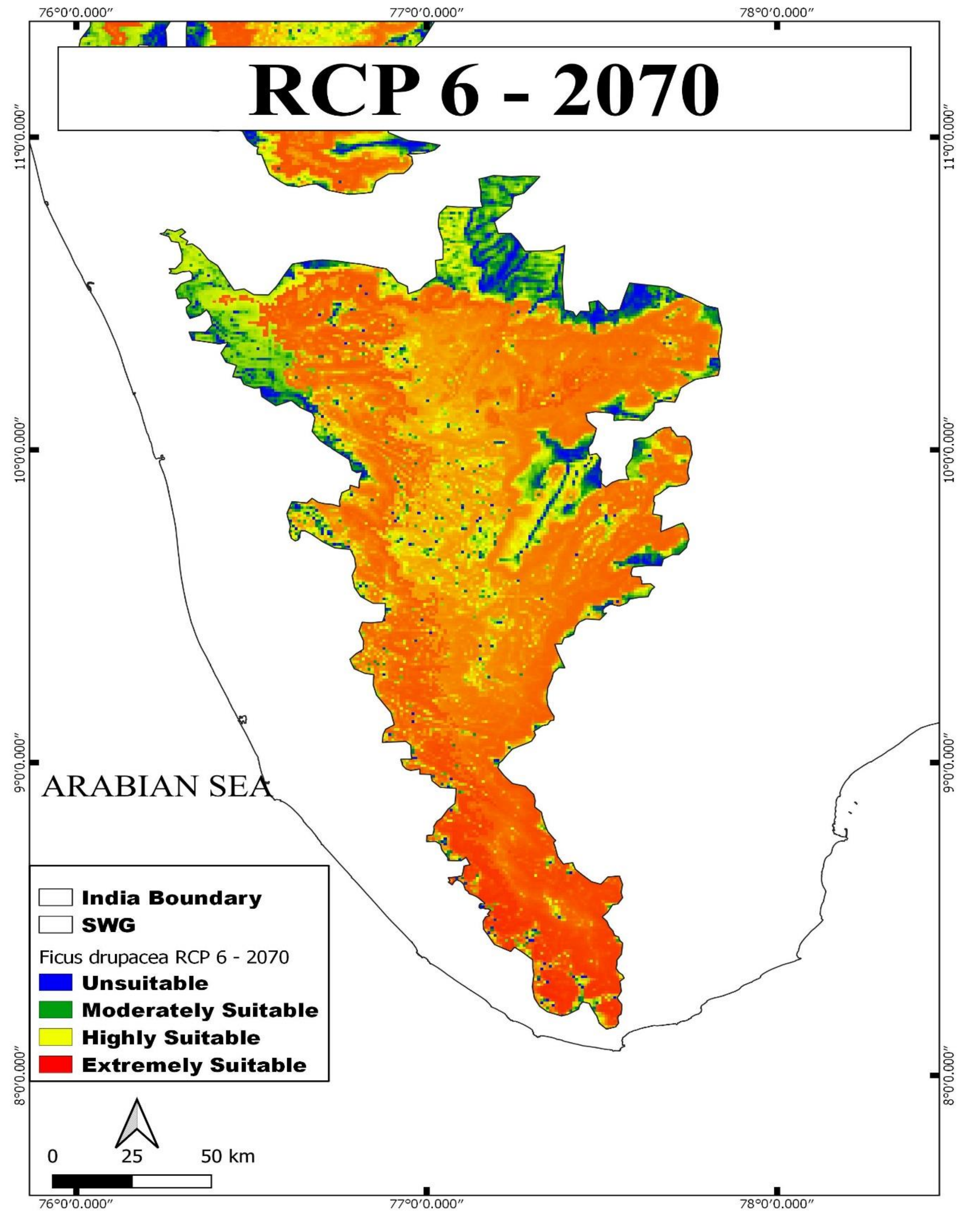
Distribution map showing the suitability areas under RCP 6 for the year 2050.



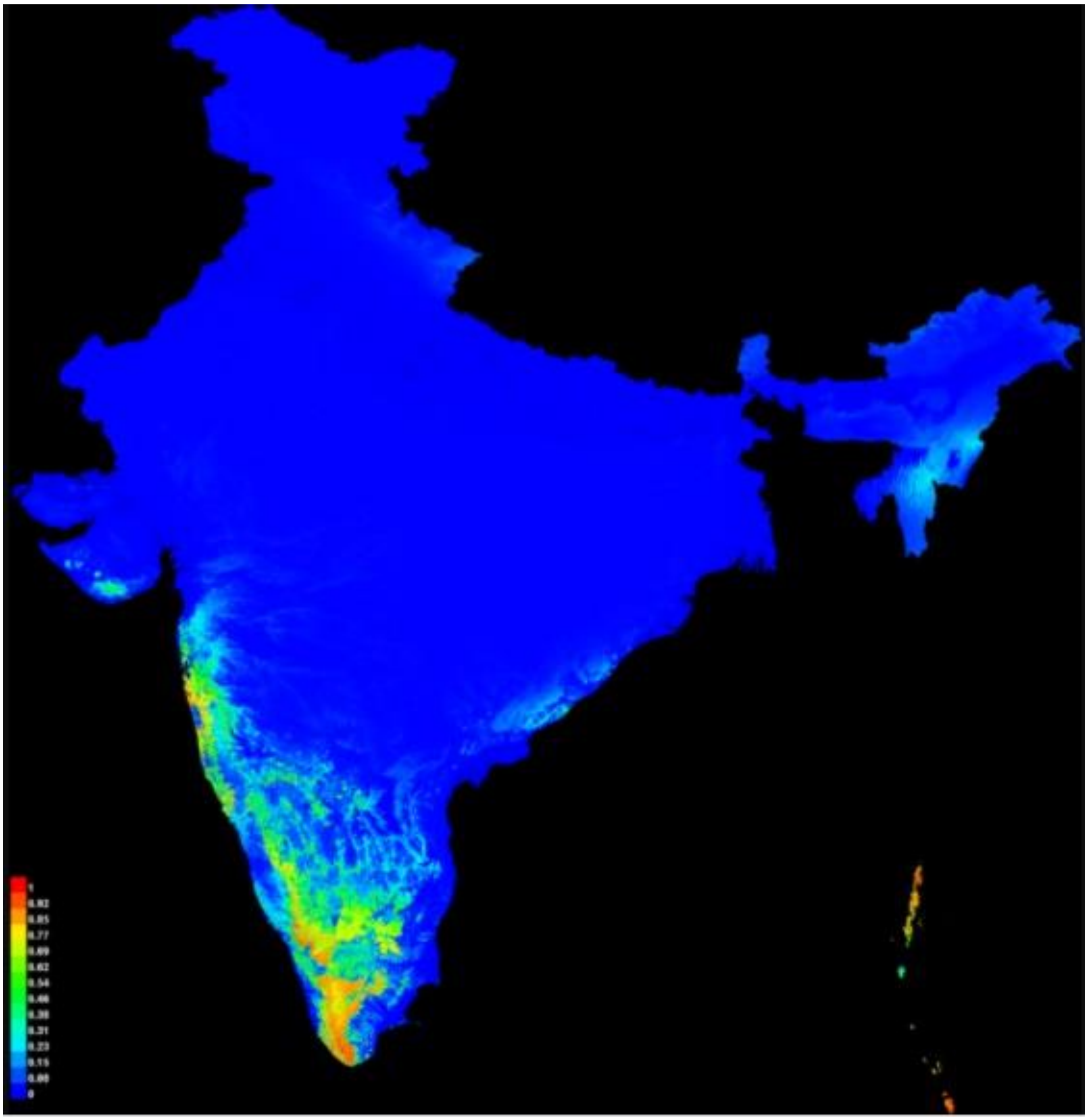
Map showing the distribution of suitability areas under RCP 6 for the year 2050.



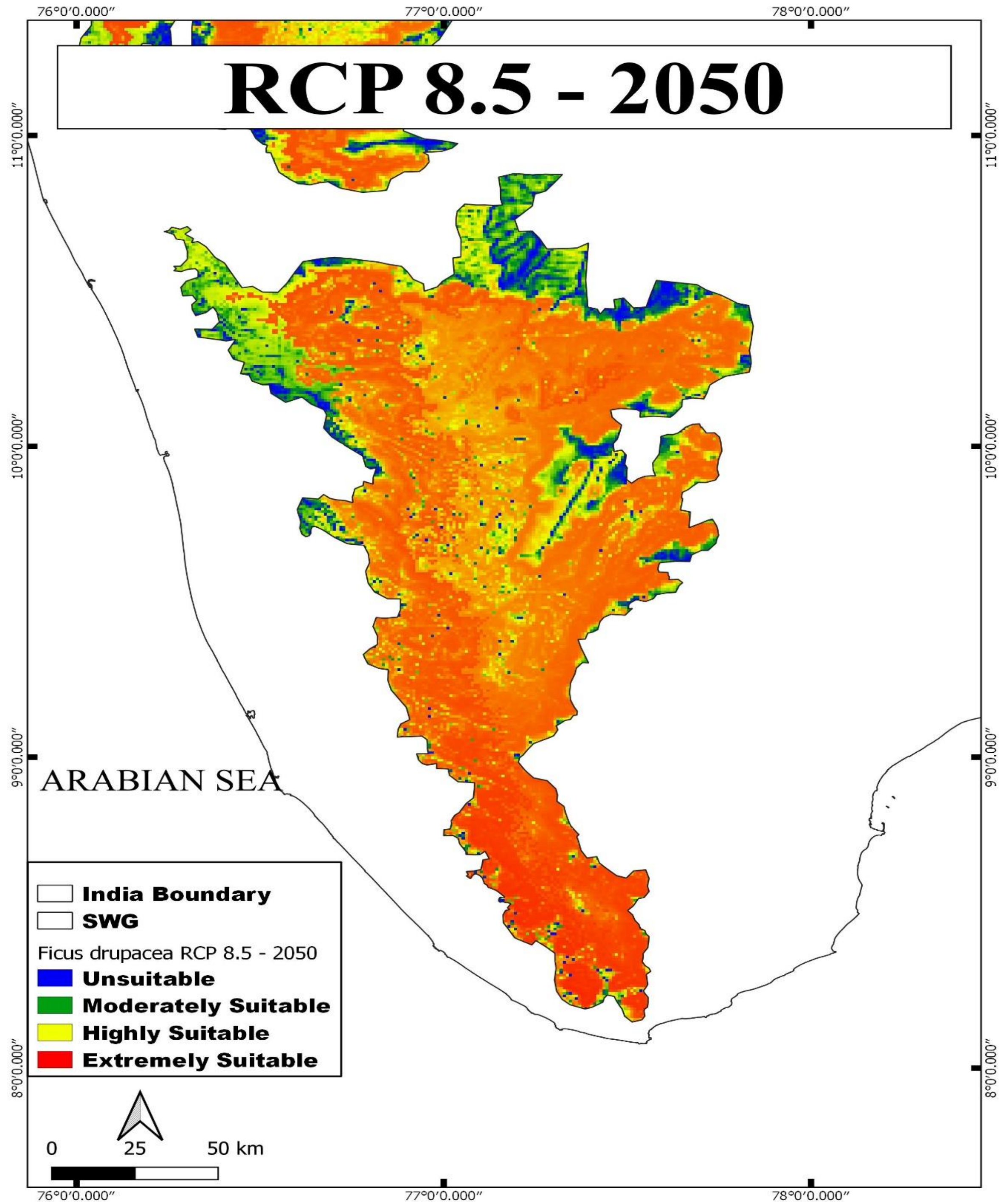
Distribution map showing the suitability areas under RCP 6 for the year 2070.



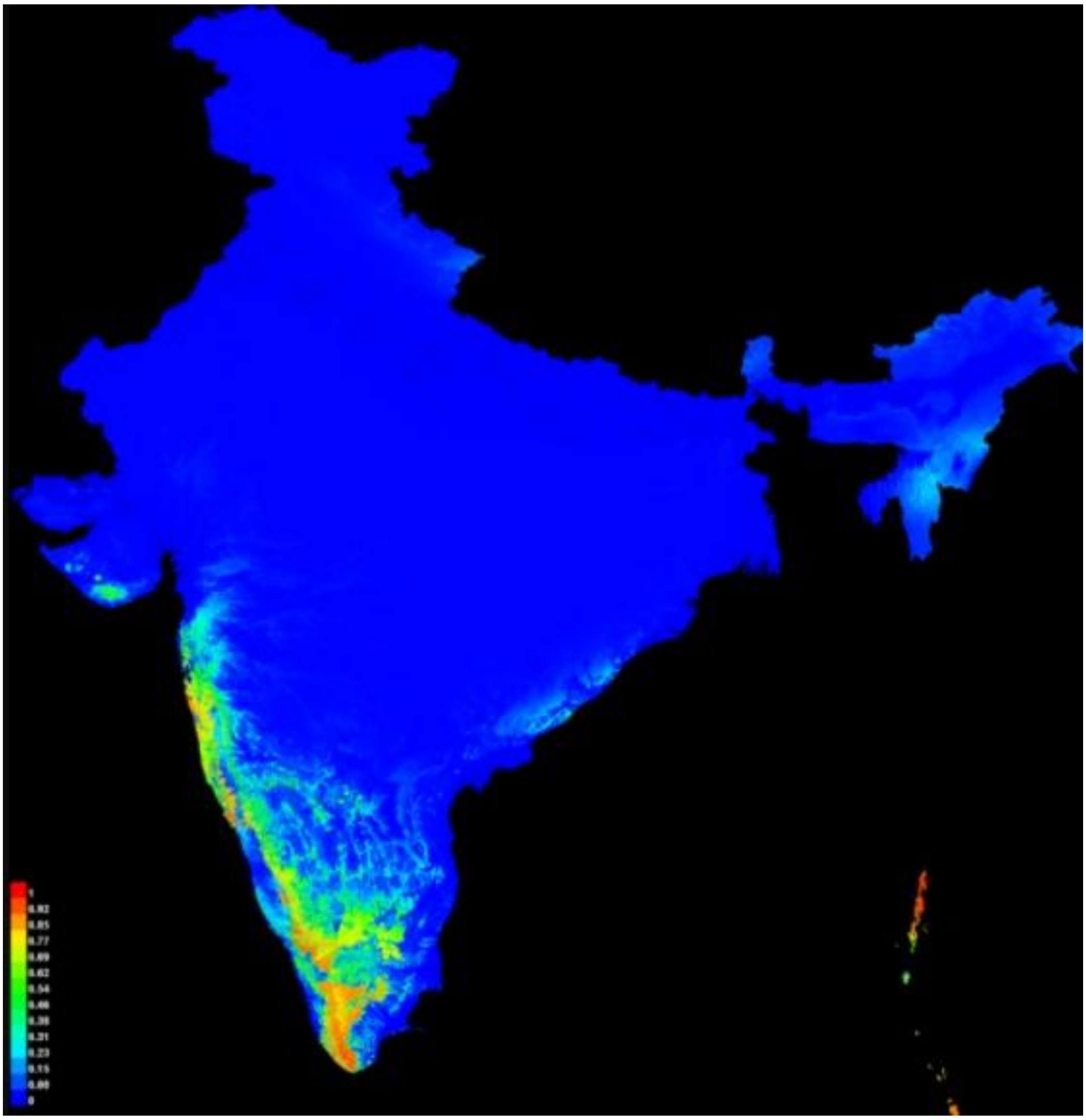
Map showing the distribution of suitability areas under RCP 6 for the year 2070.



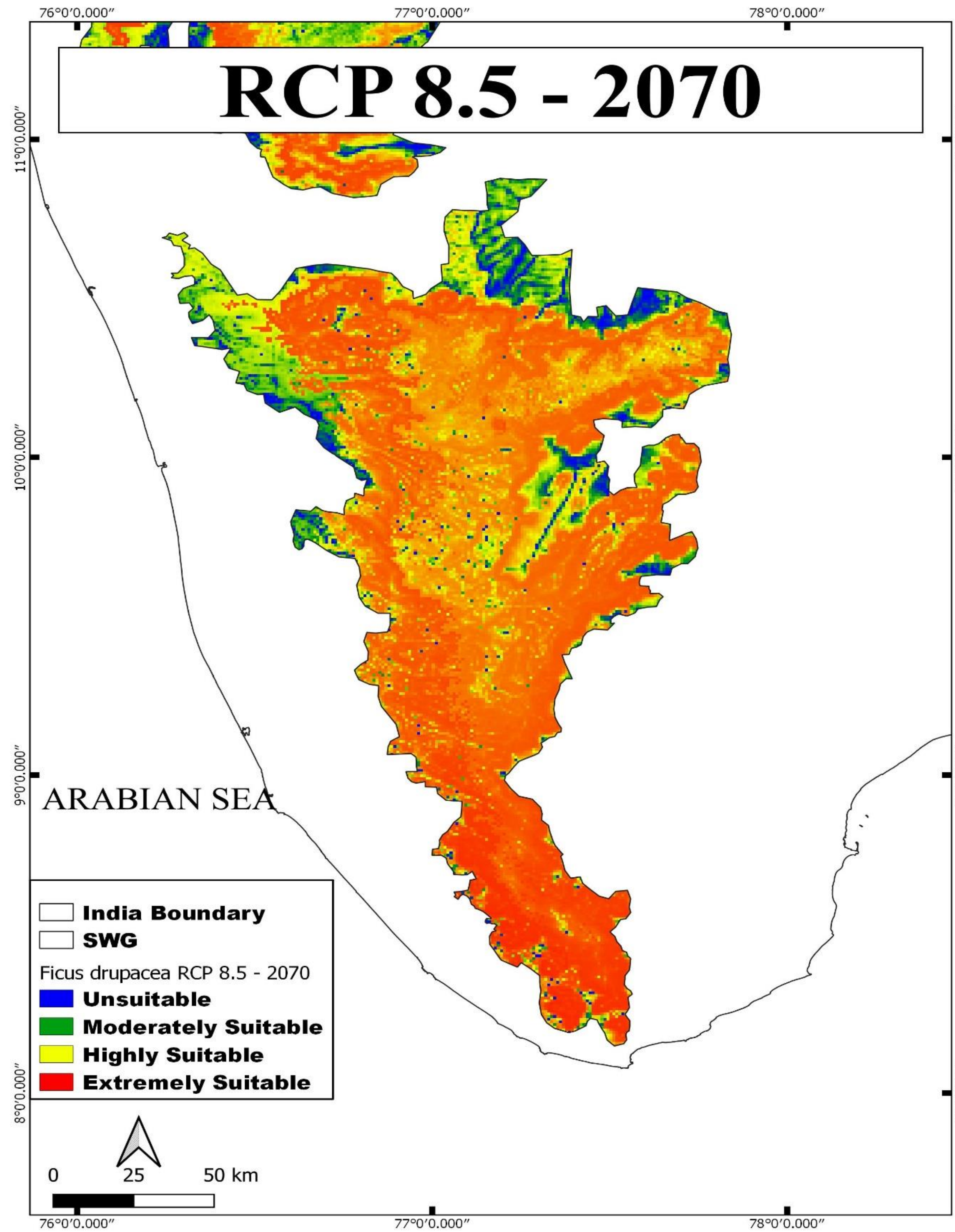
Distribution map showing the suitability areas under RCP 8.5 for the year 2050.



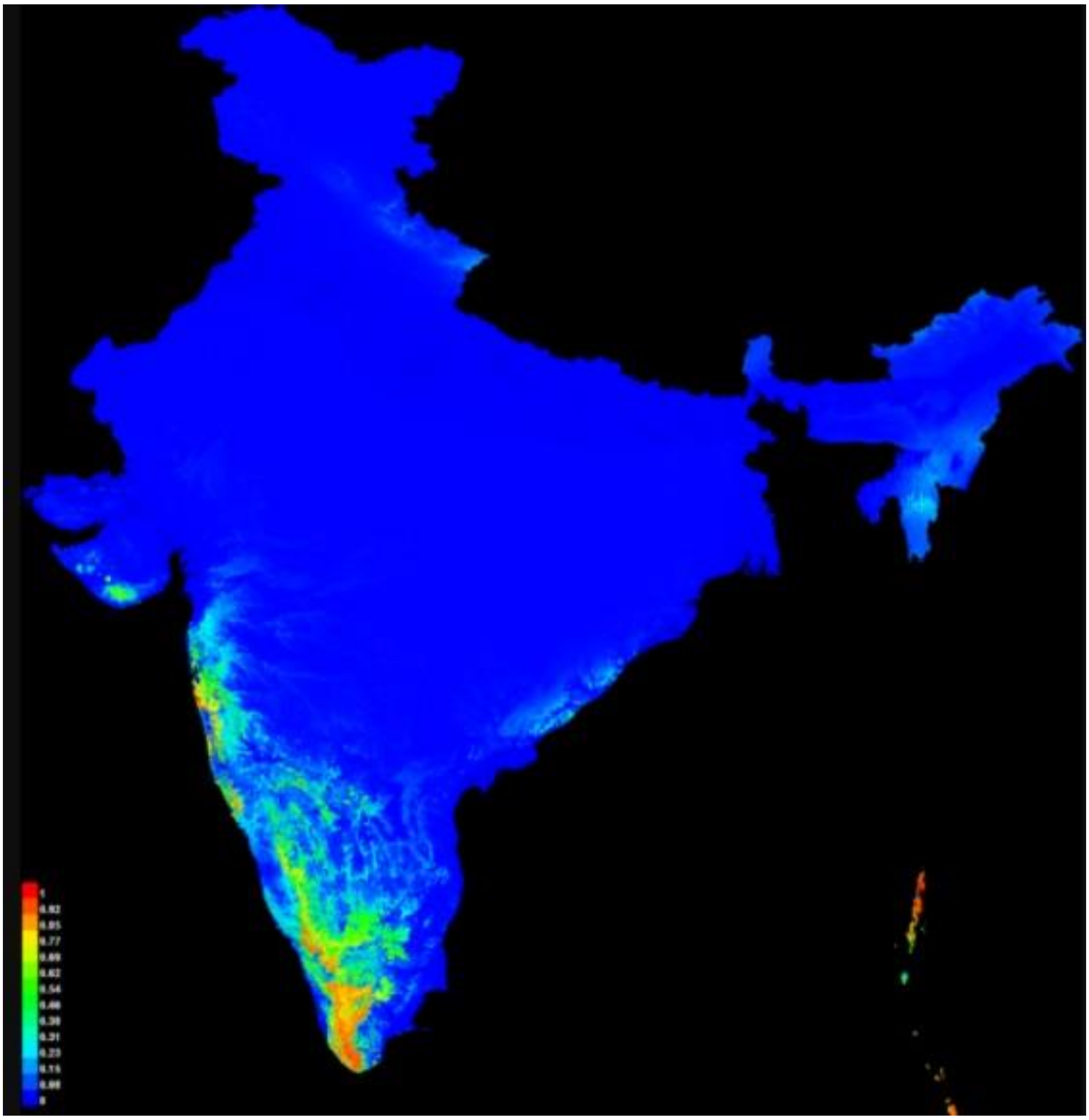
Map showing the distribution of suitability areas under RCP 8.5 for the year 2050.



Distribution map showing the suitability areas under RCP 8.5 for the year 2070.



Map showing the distribution of suitability areas under RCP 8.5 for the year 2070.



# APPENDIX – III

**APPENDIX – III**

Percentage contribution of the finalized bioclimatic variables and other factors in the distribution of *Ficus drupacea*.

| Variable | Name of the variable | Per cent contribution | Permutation importance |
|---|---|---|---|
| Bio 3 | Isothermality | 64.9 | 59 |
| Slope | Slope | 23.7 | 23.2 |
| Bio 2 | Mean Diurnal Range | 5.9 | 9.4 |
| Bio 19 | Precipitation of coldest quarter | 2.9 | 1.6 |
| Bio 14 | Precipitation of driest month | 2 | 0 |
| Bio 18 | Precipitation of warmest quarter | 0.6 | 6.9 |
| Aspect | Aspect | 0 | 0 |
| Land-cover | Land-cover | 0 | 0 |

Suitability class distribution of *Ficus drupacea* under various RCP scenarios with their area of extent ($km^2$).

| | Current | RCP 4.5 - 2050 | RCP 4.5 - 2070 | RCP 6 - 2050 | RCP 6 - 2070 | RCP 8.5 - 2050 | RCP 8.5 - 2070 |
|---|---|---|---|---|---|---|---|
| Unsuitable | 3868.378 | 1140.403 | 1170.78 | 1105.836 | 1077.26 | 1072.254 | 1036.113 |
| Moderately Suitable | 2135.125 | 1667.006 | 1721.921 | 1631.523 | 1486.962 | 1486.987 | 1384.394 |
| Highly Suitable | 5312.845 | 3033.212 | 3110.111 | 2984.602 | 3381.857 | 3030.364 | 3293.409 |
| Extremely Suitable | 9426.397 | 14902.133 | 14739.928 | 15020.788 | 14796.67 | 15153.146 | 15028.831 |