IMPACT OF PROJECTED CLIMATE CHANGE ON THE SPREAD AND DISTRIBUTION OF THE INVASIVE ALIEN SPECIES *Senna spectabilis* (DC.) H. S. Irwin & Barneby IN WAYANAD DISTRICT OF KERALA

by

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(2016 - 20 - 028)

THESIS

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DECLARATION

I, Prevena V. P. (2016 – 20 – 028) hereby declare that this thesis entitled **"Impact of projected climate change on the spread and distribution of the Invasive Alien Species *Senna spectabilis* (DC.) H. S. Irwin & Barneby in Wayanad district of Kerala"** is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title, of any other University or Society.

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SYMBOLS AND ABBREVIATIONS

|r|	Pearson correlation matrix
AIC	Akaike Index Criterion
AR5	Fifth assessment report
ASCII	American Standard Code for Information Interchange
AUC	area under curve
BIO1	Annual Mean Temperature
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
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO4	Temperature Seasonality (standard deviation ×100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter

CCAFS	Climate Change and Agricultural Food Security
CIAT	International Center for Tropical Agriculture
DAPA	Decision and Policy Analysis
DEM	Digital Elevation Model
ENM	Ecological or Environmental Niche Modelling
EROS	Earth Resources Observation and Science
FAO	Food and Agriculture Organization
GARP	Genetic Algorithm for Rule-Set Production
GCMs	General circulation models
GHCN	Global Historical Climatology Network
GPS	Global Positioning System
HadGEM2-ES	Hadley Global Environment Model 2-Earth system model
IAPS	Invasive Alien Plant Species
IAS	Invasive Alien Species
INCCA	Indian Network for Climate Change Assessment
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
KFRI	Kerala Forest Research Institute
LP DAAC	Land Processes Distributed Active Archive Center
MaxEnt	Maximum Entropy Modelling
MODIS	Moderate Resolution Imaging Spectroradiometer
RCPs	Representative Concentration Pathways
ROC	Receiver Operating Characteristic Curve
SAPCC	State Action Plan for climate change
SDM	Species distribution model

SEDAC	Socioeconomic Data and Applications Center
SRTM	Shuttle Radar Topography Mission
TSS	True Skill Statistics
UNESCO	United Nations Educational, Scientific and Cultural Organization
WMO	World Meteorological Organization

CHAPTER 1

INTRODUCTION

Acceleration of greenhouse gases witnessed a continued unabated global warming in the recent decades (Collins *et al*., 2013). Climate change, which was formerly thought to occur in the distant future, is now a certainty. According to IPCC AR5 report, the global average combined land and ocean surface temperature showed a warming of 0.85 ^{o} C (Allen *et al*., 2014) and the Earth's average temperature is projected to increase by 2.4^{o} C to 6.4^{o} C between 1900 and 2100 (Solomon *et al.,* 2009) along with various changes in rainfall patterns (Taylor *et al.,* 2012) and other weather patterns. The transformations in global climate patterns brought by climate change are expected to create imbalance of natural ecosystems and loss of biodiversity.

Globally, the two major drivers of biodiversity loss and ecosystem service change are biological invasions and climate change (Vila and Hulme, 2017). Biological invasions are considered the second most threat after habitat destruction and as per IPBES (2019), one-fifth of Earth's surface, including global biodiversity hotspots, is predicted to be under biologic invasion risk. Climate change has a profound effect on the introduction and establishment of invasive alien species (IAS) through competitiveness of invasive plants against the natives (Wan *et al*., 2016). Therefore, both climate change and bioinvasion have a synergistic impact. Climate change facilitates the performance of IAS by allowing range expansion and new invasions (Thiney *et al*., 2019). Climate change exacerbates the threat and loss of invasion into new areas through multiple mechanisms like removing climate barriers (Dullinger *et al*., 2017). When compared to native plant species, invading plant species have a greater capacity to shift their niche rapidly as they are highly adaptable to new environments (Shrestha and Shrestha, 2019). Invasive plant species benefit more than native plant species from atmospheric carbon dioxide (CO_2) enrichment and global warming (Liu *et al*., 2017). Under the changing global climate, studies have recently found changing trends in habitat suitability and invasive species range expansion and few studies have also reported range contraction of invasive species. According to many studies (Bellard *et al*., 2012), climate change in future may impact the distribution of many native and invasive species.

In the face of bioinvasion and climate change, prudent management and conservation require information about the expected potential distribution and relative abundance of invasive species under current and future climate change scenarios. To make an informed decision for biodiversity conservation, it is necessary to have a greater understanding of risks and the ability to predict accurately the implications of climate change on species distribution. Although the impact of climate change on the distribution of many invasive species is well established and studied in developed regions, not much is known about the consequences of climatic change on the dispersion of plant invasive species in developing regions.

Species distribution models (SDMs) have proved to be an essential tool to determine the relationship between species and their environment. It is an approach that predicts the distribution of a species across geographic space and time using the correlation between the geographic occurrence or abundance of a species and corresponding environmental conditions (Padalia and Bahuguna, 2017). This has been used in studies of various fields, for instance, biogeography, conservation biology, ecology and wildlife management and forecasts the range shifts of species under future climate change scenarios including invasive species (Bellard *et al*., 2013). Among the various species distribution models (SDMs), the Maximum entropy (MaxEnt) model is one of the most trusted machine-learning techniques that has a quite high and robust predictive performance even if using few occurrence records of presence data (Thapa *et al*., 2018; Shrestha and Shrestha, 2019).

Kerala having a longtime maritime history has paved way for the introduction of numerous invasive species (Kerala Biodiversity Board, 2012). Although there are numerous studies on invasive ecology, there are limited studies in species distribution and the impact of climate change on invasiveness, as this research gap creates a hindrance in the conservation and management actions to tackle the problems of plant invasion in Kerala. In recent years, climate change has been observed to result in species distributional changes in Kerala (Jose and Nameer, 2020). The failure in understanding this threat taking timely conservation and management measures can lead to great havoc as bioinvasions are considered to be one of the major drivers of species extinctions (Bellard *et al*., 2016).

In Kerala, 82% of invasive alien plant species are intentionally introduced in the forest of Kerala (Sajeev *et al*., 2012) of which most are chiefly natives of the American continent. Most of the intentional introduction of invasive plant species were for specific purposes especially ornamentals and it accounts for more than half of the introduced invasive species. The detrimental effects of invasive ornamentals on the biodiversity of natural areas have already raised serious concerns in recent years (Qin *et al*., 2015). One such introduced invasive tree species is *S. spectabilis* (DC.) H. S. Irwin & Barneby native to Central and South America (Satyanarayana and Gnanasekaran, 2013). It was earlier categorised as medium risk invasive species (Sajeev *et al*., 2012). It is now posing a major threat to the native species as there is a rampant spread in Wayanad especially in the wildlife sanctuary. Furthermore, *S. spectabilis* has a trait of suppressing the regeneration of native species which can increase the extinction risks among the natives.

Aiming to contribute to the future management of *S. spectabilis*, this project investigates the present habitat suitability and forecasts the future potential invasion range in the Wayanad district of Kerala. To our knowledge, the present study is the first attempt to model the potential distribution of *S. spectabilis*. We hypothesize that climate change will likely increase the occurrence probabilities. Thus, climate change will be a key factor in increased invasiveness and its profuse expansion. The objectives of the study are; Map the current distribution of *S. spectabilis* in Wayanad and map the future distribution of the species under RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5 climate change scenarios.

CHAPTER 2

REVIEW OF LITERATURE

2.1. Climate change, its impact and influence on species distribution

Since 1880, the Earth has warmed by 0.85 ºC globally (IPCC, 2014). Climate change is causing organisms in the marine, freshwater, and terrestrial settings to shift their distribution to remain in suitable habitats (Pearson and Dawson, 2003; Pecl *et al*., 2017; Root *et al*., 2003). There is a positive relationship between global warming and the distance moved by the species. According to Chen *et al*. (2011) and Thomas (2010), climate change could shift the species range expansion to higher latitudes and elevations. Chen *et al*. (2011) conducted a meta-analysis on terrestrial species and found that their range is shifting to higher latitudes at a median rate of 16.9 km per decade (or an average of 17.9 km per decade). Terrestrial creatures are migrating uphill to avoid the warming lowlands, while marine animals are migrating from hotter sea surfaces to deeper waters (Chen *et al.,* 2009; Dulvy *et al.,* 2008). The species mainly in temperate regions are changing their geographic distributions between glacial and interglacial cycles. All of these forced shifts will have a significant impact on their speciation, range extent, latitudinal patterns, activity timing, and microhabitat utilisation (Dynesius and Jansson, 2000; Williams *et al.,* 2008; Bates *et al.,* 2014). Nevertheless, Thuiller (2004) reported that ecological communities may deconstruct as individual species shift their ranges in different ways as different species respond uniquely to distinct ecological stresses. There will be a lag in distributional response to climate change in some species, which could be influenced by various other conditions. (Poloczanska *et al.,* 2013; Lenoir and Svenning, 2015; Williams *et al.,* 2008).

Species redistribution can have a variety of consequences. The impact of species redistribution can be seen in the quality of freshwater systems, terrestrial region productivity, functional features within a community, and so on (Weed *et al.,* 2013; Fossheim *et al.,* 2015; Paerl and Paul, 2012; Buisson *et al.,* 2013). It also affects the species diversity and species richness (Ochoa-Ochoa *et al.,* 2012). In extreme cases, it may potentially disrupt ecosystem productivity and cause chaos on carbon sequestration (Cavanaugh *et al.,* 2014). Based on climate change scenarios and niche-based simulations that project future suitable habitat from current distributions, numerous studies have suggested that species turnover may be very high in some regions, potentially resulting in community structure changes strong enough to trigger ecosystem destruction (Erasmus *et al*., 2002; Peterson *et al*., 2002).

2.2. Bioinvasion

For decades, ecologists have been fascinated by biological invasion. After habitat destruction, biological invasion is regarded as the second most serious danger to biodiversity (Miller *et al*.,2010; Ficetola *et al*., 2007). To this end, one-fifth of Earth's surface is predicted to be under biological invasion risk including the global biodiversity hotspots (IPBES, 2019). The biological invasion has been homogenizing the world's flora and fauna (Hobbs, 2000). Invaders and invasion were first described in an ecological context by Elton, the "father of invasion ecology," in his classic book on invasion (Elton, 1958). Invaders and invasion have been defined in a variety of ways since then. Alien invasive species, according to the IUCN (1999), are species that becomes established in a natural or semi-natural ecosystem or habitat, is a change agent, and poses harm to biological diversity. Invasive species, according to Kolar and Lodge (2001), are "non-indigenous species that spreads from the source of introduction and becomes abundant." Invasive species are so important in today's world that the Biodiversity Convention's article 8(h) recommends action ‘‘to prevent the introduction, control or even eradication of those alien species which threaten ecosystems, habitats or species’’.

2.2.1. Plant invasion

Plant, animal, or microbial species could be among the invaders. Invasive plants have arisen at various times throughout history and have always thrived and proliferated at the expense of native species. They have occupied vast land areas and driven many indigenous species into endangered status. Because of their aggressive nature, invasive plants can quickly expand their zone of occupancy, spread across wide areas, endangering natural flora and causing dramatic changes in floristic composition. Invasive species can go through intense reproductive periods without being hampered by seasonal fluctuations, which thwarts efforts to eliminate them. Invasive species can degrade an ecosystem's natural resources while also posing a hazard to human usage of those resources. Invasive species have the potential to cause extinctions of native plants and animals, reduce biodiversity, compete for limited resources with native creatures, and modify environments. These negative impacts might have significant environmental and economic consequences (Richardson *et al*. 2000; Hellmann *et al*. 2008; Kull *et al*. 2011; Shackleton *et al*. 2018). Regardless of this, invasive plants are useful since they are utilised for a variety of purposes ranging from therapeutic uses to religious sentiments to furniture and composting. Invasive species alter all main environmental processes in ways that benefit them. Changes in litter dynamics are the first and foremost noticeable impact on an invaded ecosystem. Other ecological processes that are influenced by litter dynamics, such as soil biota, nutrient dynamics, and biogeochemical cycles, are gradually altered. As the invasion progresses, the area's geomorphology and hydrology are also altered. These invasive plants also interfere with native species recruitment during their course of the establishment process, either by allelopathic suppression or by competing for resources with seedlings. Invasive species have also been related to changes in fire patterns (Sajeev *et al.,* 2012).

Introduction, colonisation, and naturalisation are the three stages of plant invasion (Richardson and Pyšek, 2000). Invasive species propagation takes advantage of the invasion window produced by the ecological disruption caused by natural or man-made sources. It outcompetes the invaded area's environmental, reproductive, and dispersion barriers, rapidly spreading its population. Because introduced propagule must compete with established native flora that is already well suited to the site, Environmental factors supporting alien propagule establishment, such as resource availability, are believed to be the most essential during the introduction period (Davis et al., 2000; Rejmánek *et al.*, 2005). The important factors responsible for the successful establishment and survival of the introduced species are unrestrained vegetative spread, escape from biotic limitations, profuse seed production, highly successful seed dispersal, germination, and colonization, and adaptive morphological and ecological characters, better propagule properties favouring increased movement, and ability to displace native flora either competing for resources or exhibiting allelopathic effects (Sajeev *et al.,* 2012).

2.2.2. Plant invasion and Environmental linkages

Environmental factors (both climatic and non-climatic) play a vital influence in determining a species' ecological niche. Climate change is the most significant factor influencing environmental processes. It hastens the invaders establishment and spread from the moment it is introduced (Walther *et al*., 2009). The Intergovernmental Panel on Climate Change (IPCC) has reported on the devastating effects of climate change on species. Topographic variables such as elevation, slope and aspect play an important role in determining the patterns of spread of several species and the shift in their range. Landscape heterogeneity on the other hand is considered as one of the major factors governing biodiversity and its functions; as it is known to enhance or retard the disturbance in the landscape. Many studies have analyzed the positive as well as the negative association between the landscape heterogeneity and species richness (Tews *et al*., 2004; Benton *et al*., 2003). In addition to climate change and landscape heterogeneity, human activities e.g., degradation of land, excessive agricultural practices, transcontinental transportation etc. is equally responsible for the spread of the non- native species in a region (Foley *et al*., 2005). Additionally, change from the forest into non-forest has a tremendous impact on the ecosystem through destruction of the existing habitats and change in the competitive regimes of the species (Mooney and Hofgard, 1999). Habitat fragmentation, changes in transportation corridors, and changes in native species habitats are caused due to change in the forested ecosystem (Bahuguna, 2015). Therefore, anthropogenic pressure and climate change have a cascade effect on ecological destruction. Various modelling techniques are available to predict the changes in the landscape patterns (Cheong *et al*., 2012). Changes within the forested ecosystems can promote the introduction and spread of invasive's. The introduction and establishment of invasive species in new places are mainly explained by two hypotheses. According to the niche conservatism concept, a species' climatic niche will be conserved over time and space, indicating that invading species will occupy a similar climatic envelope in both native and invaded habitats (Peterson *et al*., 1999; Prinzing *et al*., 2001). While there is much evidence that demonstrates spatial and temporal niche conservatism (Petitpierre *et al*., 2012), cases of a species' niche shift in its introduced range were also observed (Guisan *et al*., 2014). According to the biome conservatism hypothesis (Rejmanek *et al*., 2005), it states that an invading species tend to occupy similar biomes in its invaded range as it would be in its native range, related to the niche conservatism hypothesis (Crisp *et al*., 2009).

2.3. Climate change impact on plant invasion

Changes in temperature and precipitation conditions, as well as CO_2 and aerosol levels in the atmosphere, can be used to understand changes in climatic regimes. Climate change is expected to have a profound impact on biodiversity, through phenological, genetic, and other alterations and species ranges, as well as interactions between species (Root *et al*., 2003; Walther *et al*., 2002; Walther *et al.,* 2003). Broad climatic tolerances and large geographic ranges are seen for most of the invasive (Qian and Ricklefs, 2006), which may influence how they respond to climate change (Hellmann *et al*., 2008). Numerous studies imply that native biota is negatively affected, whereas alien biota is favoured by climate change (Vila *et al*., 2007; Hellmann *et al*., 2008; Thuiller *et al*., 2007). Climate change may influence human travel patterns, affecting the propagule pressure of invasive species (Hellmann *et al*., 2008). Droughts, floods, forest fires, and other stressful situations caused by climate change may provide novel opportunities for species to invade new areas by causing extreme perturbations. For conservation purposes, several ecologists and resource managers suggest actively shifting species to climatologically favourable areas outside of their historical geographic range (Hulme, 2005). If climate barriers prevent alien species from establishing in an area, they may have a higher survival rate, population growth and persistence in the wild if the climate facilitates (Chown *et al*., 2012; Loomans *et al*., 2013). Climate change has the potential to impact not only the introduction and distribution of foreign species but also the outcome of biological invasions. Climate change may have a significant impact on natural ecosystems, communities and habitats (Parmeason and Yohe, 2003) the most notable of which is a shift in their natural ranges (Bellard *et al*., 2013; Hulme, 2017; Kuczynski *et al*., 2018). Invasion is expected to be affected by climate change in three ways. Altering the nature of vectors and corridors, changing the abiotic nature of the recipient environment, and changing biotic interactions in recipient communities are the first three strategies (Robinson *et al.,* 2020). Invasive plants, in particular, benefit from increased atmospheric CO_2 and nitrogen deposition (Liu and Kleunen, 2017). More focus should be given to the environmental variables that are responsible for the current spread of invasive alien plant species and the loss of native species populations (Zhang *et al*., 2014). Buckley *et al*. (2010) noticed that range shifts from lower to higher climate change scenarios, with many invasive species undergoing significant range shifts. It was observed that as climate conditions change, invasive alien species' ranges expand more than contract due to physical barriers, limited dispersal, and the species' potential life history.

2.4. Climate change in Kerala

The presence of the Western Ghats (WG), one of the world's most biodiverse regions, has a major impact on Kerala's climate because it supplies a substantial amount of precipitation to Peninsular India (Paul *et al*., 2018). It has been reported that during the summer months, Kerala is prone to seasonal drought and heat stress (Wassmann *et al*., 2009; Sarun *et al*., 2018; SAPCC, 2019). According to the Indian Meteorological

Department, the mean maximum temperature has risen by about 0.8 ° C, the minimum by 0.2 ° C, and the average by 0.60 ° C over Kerala (27.3 - 27.9 ° C), indicating a clear upward trend in surface air temperature over the last 43 years (SAPCC, 2019). There was a significant (95%) trend on increasing annual mean maximum (+0.01° C/year) and minimum temperature (+0.01° C/year) over Kerala (IMD, 2013). Differences in maximum and minimum temperatures were also widening along Kerala's highlands. Kerala's climate has shifted from B4 to B2, going from wetness to dryness within the humid type of climate, as a result of changes in heat and moisture regimes throughout the year (Rao *et al*., 2009). Furthermore, there was a significant increase in annual mean diurnal temperature range(DTR) trends (+0.01° C/year). However, the annual average rainfall in Kerala had reduced by -1.43mm/year (IMD 2013). Numerous studies have suggested a decrease in yearly rainfall in Kerala's southern districts, but the northern regions do not appear to be experiencing comparable trends (Soman *et al*., 1988; Pal and Al-Tabbaa, 2009). Southwest monsoon rainfall and annual rainfall are diminishing, according to studies, but post-monsoon rainfall is rising (Krishnakumar *et al*., 2009). Annual rainfall in the Palakkad Gap in the Western Ghats region varied with altitude, and annual rainfall was significantly lower in these areas than in the rest of the state (Raj and Azeez, 2009; 2010). In comparison to 1980s temperatures, the Kerala region is expected to have a 1.5°C increase in mean surface temperature during the monsoon season throughout the decade 2040–2049 (Saseendran *et al*., 2000). According to Indian Network for Climate Change Assessment (INCCA), climate change scenarios for the Western Ghats and Kerala in the next 20 years include reduced rainfall, increased atmospheric temperature, and flooding due to sea-level rise (SAPCC, 2014).

By 2050, the temperature has been expected to rise by 2°C under the projected climate change scenario. In the Western Ghats, the minimum surface air temperature might increase by 2°C to 4.5°C. The average temperature in the Kerala border region is expected to rise by 1 to 3 ° C. In addition, if sea levels rise by one metre, 169 km^2 of the coastal region surrounding Kochi will be flooded according to Indian Network for Climate Change Assessment (SAPCC, 2014). The Southern and Central Districts of Kerala have had the greatest temperature rise. Most areas in southern Kerala have seen a rise in temperature from 1.66 to 1.77 degrees Celsius. The Northern Districts of Kerala have shown a negative change in rainfall variations. Kerala's rainfall has been steadily decreasing during the previous 100 years. This decline is most prominent in South Kerala, where annual rainfall has reduced by approximately 26% in the last 100 years especially in the Idukki district. Since the last 50-60 years, there has been a cyclic trend in annual rainfall with a declining trend in South West Monsoon rainfall and an increasing trend in post-monsoon rainfall in North Kerala (SAPCC, 2014). According to Rao *et al*. (2009), there exists a cyclic trend in annual rainfall with a declining trend in South West Monsoon rainfall and an increasing trend in post-monsoon rainfall.

2.5. Status of invasive alien plants

Studies carried out indicated that the threat of invasive alien plants has devastating effects to local biodiversity, ecosystem services, environmental quality and human welfare (Pejchar and Mooney, 2009; Kueffer, 2017; Jones and McDermott, 2017; Bartz and Kowarik, 2019; Pysek and Richardson, 2010; Stone *et al*., 2018; Jones, 2019). Furthermore, Seebens *et al*. (2018) also confirmed that the introduction of new invasive alien plants in novel ecosystems can impose threats to the environment and human health. Invasive trees and shrubs transmogrify the ecosystem, for example, by modifying soil-nutrient cycling, negatively impacting the composition of soil seed banks and changing fire regimes (Gioria *et al*., 2014; Shackleton *et al*., 2018) and changing microbial communities (Bowen *et al*., 2017). Notably, extinction risk is the ultimate threat to biodiversity. In brief, invasive species act as one of the major causes of biodiversity loss in a highly intricate fashion (Blackburn *et al*., 2019; IPBES, 2019). According to Sajeev *et al*. (2012), the impacts also include displacement of native plant species, rewarding pollinators better than the native species thereby reducing the reproductive success of local species, soil chemical profile change, changing hydrological regimes, making the new habitat fire-prone and limiting the photosynthetic efficiency of the local species by reducing light availability and as well as altering the phylogenetic and functional diversity of the novel invaded communities (Blackburn *et al*., 2019; Brooks *et al*., 2004; Suarez and Tsutsui, 2008; Ricciardi *et al*., 2013). There is still a lack of study on the quantitative assessments on how impacts differ based on the ecosystem and the invaders (Levine *et al*., 2003).

According to the study of Lowe *et al*. (2000), Lantana (*Lantana camara*), Luecaena (*Leucaena leucocephala*), Mimosa (*Mimosa pigra*), Wedelia (*Sphagneticola trilobata*), Miconia (*Miconia calvescens*) etc. are the world's worst invasive plant species in the world. About 545 invasive alien plants were reported in the three regions of Europe. It has been demonstrated that the tropics were less frequently invaded by the IAS than the temperate regions (Chytry *et al*., 2008). There is limited information base on IAS on how it is transferred to regions with other climates, and resulting in its rampant growth (Chytry et al., 2008). The developing countries are little represented in the scientific literature which doesn't indicate that developing countries are at a lower risk of being invaded by invasive alien species (Khuroo *et al*., 2012). Sankaran and Suresh (2013) recorded biological invasion in forests of the Pacific and Asia. Better implications in the conservation of biodiversity can only be possible in light of such studies. As per the studies, it is evident that over recent decades, developing countries are becoming a greater recipient of a potential invasion (Khuroo *et al*., 2012).

Over the last two decades, the expanding economy of India has led to the loss of natural habitats and opening of disturbance corridors providing favourable habitats to the establishment and spread of IAS (Sharma *et al*., 2010). According to Khuroo *et al*. (2012) about one thousand five hundred ninety-nine invasive alien species have been recorded which account for 8.5% of the vascular flora of India. Adhikari *et al*. (2015) reported that nineteen out of forty-seven existing ecoregions harbour invasion hotspots. Recently, IAS have become a major environmental concern in Kerala. However, there are few studies carried out in Kerala on the invasive species (Sajeev *et* *al*., 2012; Sankaran and Srinivasan, 2001; Chandrashekara, 2001). According to Sajeev *et al*. (2012), they identified 38 alien invasive species in the forests of Kerala. Furthermore, these were categorized into high risk, medium risk and low-risk invasive species according to the risk assessment. Trees, shrubs, subshrubs, herbs, climbers were among the invasive alien plant species. Kerala biodiversity Board accounted for 82 terrestrial and aquatic invasive alien species (Kerala Biodiversity Board, 2012). The land of origin of the alien invasives in Kerala is North, South and Central America, Asia, Africa, Australia, West and Central Africa and the West Indies. Most of the introductions of IAS were intentional in Kerala. A perusal of these literature (Sajeev *et al*., 2012; Sankaran and Srinivasan, 2001 and Chandrashekara, 2001) indicate that there is no in-depth study carried out regarding the inventory and distribution as well as ecology of the invasive species.

2.6. Ecological forecasting

Rapid climate change, combined with anthropogenic pressures, poses serious threats to ecosystems, including shifting natural habitats, the invasion of new species, and the introduction of new diseases. As a result, environmental dynamics modelling using characteristics such as species distribution and abundance, ecosystem variability, and community composition helps to better forecast ecosystem movements, facilitating better management decisions, conservation, and sustainability. Earlier, ecologists used a model based on the mean and variances of observable environmental parameters to make management decisions. However, faster ecological reformations as a result of climate variations cannot be exactly assessed by historical observations (Smith *et al.,* 2009; Milly, 2008; Craig, 2010). Based on current patterns and historical data, ecological forecasting attempts to predict how the environment will behave in the future. This includes agricultural yield forecast (Cane *et al*., 1994), species distributions (Guisan and Thuiller, 2005), species invasions (Levine and Antonio, 2003), pollinator performance (Corbet *et al*., 1995), extinction risk (Gotelli and Ellison, 2006), fishery dynamics (Hare *et al.*, 2010); disease dynamics (Ollerenshaw and Smith, 1969) and population size (Ward *et al*., 2014).

Population models and species distribution models are the widely used tools for monitoring structural and physical changes in the environment and for better forecasting.

2.6.1. Population Models

Models of population dynamics, often known as ecological population models, provide a clear picture of a population's dynamics. This model correlates population size and age distribution within a population with population decline or substantial growth, resulting in a more accurate prediction of a population's state. According to Uyenoyama *et al.* (2004), environmental factors, as well as interactions with other and similar species, may also be a deciding factor in the model. The overabundant species population is also managed with the help of the population dynamics. For eg., the population model's conclusions were used to cut the risk of elk (Bradford and Hobbs, 2008) and regulate the potency of white-tailed deer (Merrill *et al*., 2003). Although these models are often used for predicting population behaviour, the degree of ambiguity in the data causes prediction errors. Unless a substantial amount of data is provided, these models will not be able to accurately simulate complex biological interactions.

2.6.2. Species Distribution Models (SDMs)

Environmental (or ecological) niche modelling (ENM), habitat modelling, predictive habitat distribution modelling, and range mapping are examples of SDMs (Elith and Leathwick, 2009) commonly used in ecological and biodiversity conservation research to represent how species are distributed worldwide throughout a geographic area. These models accommodate the tools that incorporate known species occurrences with environmental data (Philips *et al*., 2006). Correlative and mechanistic are the types of SDMs. Correlative SDM's attempts to forecast the influence of climatic variations on the geographical distribution of data (Thomas *et al.* 2004). These SDMs analyses statistical records of environmental associations with species abundance and occurrence to identify the factors that hinder the spread of the species. According to Moilanen and Wintle (2007), the correlative SDMs are superior to other SDMs because of their simplicity and capacity to describe complicated environmental interactions with fewer data. On the other hand, mechanistic SDMs, also known as biophysical models or process-based models, attempts to map the link between a species' physiology and its surroundings, which influences its abundance and distribution (Kearney and Porter, 2009). Apart from the species' current radius, the model includes processes or physiological changes within the body of organisms due to thermal variations and vegetation, which helps in the prediction of future species range extension possibilities to a large extent of ecosystem levels (Porter *et al.,* 2002; Kearney and Porter, 2004; Kearney and Porter, 2009). The mechanistic SDMs will not be suitable for the complex analysis of interactions between the environment and climatic influences on large scales because it requires a large number of variables to be considered, making the model computationally and time-constrained to carry out both the train and validation phases.

2.7. Maximum entropy modelling (MaxEnt)

MaxEnt is a general-purpose machine learning method with accurate mathematical computations that was introduced by Philips *et al*. (2006) for modelling the spatial distribution of species. For modelling species habitat, it uses the maximum entropy method. MaxEnt uses a set of environmental variables as input, such as temperature, precipitation etc. along with the species occurrence data and obtains a range of given species i.e., it executes by finding out the maximum spread (maximum entropy) by estimating the probability distribution for the species in a geographic dataset to the ‘background’ environmental layers (Philips *et al*., 2006). MaxEnt is used for modelling the species distribution and the range making use of the presence-only data utilizing both continuous and categorical data. MaxEnt estimates the suitability of each grid cell as a function of the grid cell's environmental variable. The grid with a high value is likely to have been predicted with optimal conditions for the occurrence of the species. MaxEnt outperforms the other modelling approaches (Elith *et al*., 2006; Hernandez *et al*., 2006; Philips *et al*., 2006; Ortega-Huerta and Peterson, 2008).

MaxEnt, according to Phillips *et al*. (2006), adopts the maximum entropy distribution. For estimating the distribution of species, this data was subjected to the constraint that the expected value of each environment parameter (interactions) in the estimated distribution matched its empirical average. 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, the complexity of the fitted functions could be chosen in this model. According to Pearson *et al*. (2007) MaxEnt has a higher success rate than other algorithms, and it was able to identify differences even with limited sample sets. When sample sizes were artificially reduced, the model performance worsened. MaxEnt models projected a greater range of appropriate conditions, and the MaxEnt projection had the potential to anticipate excluded areas as well (Pearson *et al*., 2007). However, it has been found that species-specific model parameter tuning can improve the performance of MaxEnt models (Radosavljevic and Anderson, 2014.).

MaxEnt can generate highly complex, non-linear response curves with the use of different feature classes such as linear, quadratic, threshold, hinge, product, and categorical, which are all determined by the number of presences by default (Syfert *et al*., 2013). Besides the feature class, the Regularization Multiplier is another parameter that can be changed in the MaxEnt. It is a parameter that imposes new limits on the model, i.e., a penalty. By adjusting the intensity of the selected feature classes used to create the model, the major objective is to minimize overcomplexity and or overfitting (Morales *et al*., 2017). Several researchers have reported the variability in predictions that might result from different MaxEnt background samples, with a particular focus on the extend of the site from which they are chosen (Baasch *et al*., 2010; Giovanelli *et al*., 2010; Barve *et al*., 2011). The raw output, which is interpreted in terms of occurrence rate, the cumulative output, which is interpreted as omission rate, and the logistic output are the three types of outputs derived from MaxEnt models. However, the difference in scaling between these three types of outputs is critical in creating various prediction maps (Merow *et al*., 2013). MaxEnt has recently been shown to be mathematically associated with log-linear modelling, with the primary difference being in intercept terms (Renner and Warton, 2013). The ability of methods to correct the originally sampling bias varied widely depending on the bias, bias intensity, and species in an attempt to test the effect of bias kinds, bias intensity, and correction method on MaxEnt model performance (Fourcade *et al.,* 2014).

2.8. Modelling of species distribution

Species distribution models try to predict the distribution of species based on the presence or abundance of environmental variables. These models were commonly used to investigate various ecological, evolutionary, and conservation reasons (Elith *et al*., 2006). Several studies have shown that invaders have a significant impact on recipient ecosystems (Mack *et al*., 2000). Timely information from several sources about the present and future invasion areas can facilitate the development of efficient control and eradication strategies. Modelling the distribution of invasive species is one method of identifying potential areas of spread. Natural resource managers, agencies, and non-governmental groups that require accurate maps of species distributions and abundance for risk analysis are increasingly using spatial modelling and species-environment matching models (Stolhgren *et al*., 2010). Invasive species spatial distribution maps, area of spread, and factors affecting the magnitude and extent of invasion can all be generated using species prediction modelling. With the current availability of high-resolution bioclimatic data on different aspects of the environment, precise distribution modelling is achievable. The environmental conditions are defined using known species distributional information, resulting in the identification of geographical regions with similar environments and the modelling of species distribution (Pearson and Dawson, 2003). If the spread of a species is accurately mapped, environmental variables such as climate could be correlated to its presence or absence (Crick, 2004).

2.9. Species distribution modelling of invasive alien plant species

Numerous studies have been undertaken on invasive alien species. Invasive alien species introductions are unavoidable and predictable in new habitats (Walther *et al*., 2010). For an effective response, early detection and immediate action to incoming aliens are essential (Kaiser and Burnett, 2010). SDM's popularity has encouraged their application in invasive species management, as has their wide availability (Elith *et al*.,2009). SDM-assisted prevention efforts can be extremely beneficial, in areas where invasive species constitute a major contribution to global biodiversity change and are thought to be one of the leading causes of species extinction (Holmes *et al*., 2009). Species distribution models were used to analyse the spatial configuration and characteristics of habitats that permits the species continuity in landscapes (Araujo and Williams, 2000; Ferrier *et al*., 2002; Scotts and Drielsma, 2003), past species distribution (Hugall *et al*., 2002; Peterson *et al*., 2004), and species distribution in future climatic conditions (Bakkenes *et al*., 2002; Skov and Svenning, 2004). Padalia *et al*. (2014) investigated the prediction performance of two popular species distribution models (SDM); MaxEnt and GARP (Genetic Algorithm for Rule-Set Production) by modelling the potential invasion range of bushmint in India, according to whom MaxEnt outperformed GARP in terms of AUC (0.86). In terms of geographic regions predicted to be suitable or unsuited for bushmint in India, the outputs of MaxEnt and GARP were largely similar. Nevertheless, the greater predictive capability of GARP models has been reported in other studies relative to MaxEnt(Qin *et al*., 2015; Terribile and Diniz-Filho, 2010; Peterson *et al*., 2007).

According to species distribution modelling studies (Shreshta and Shreshta, 2019; Shrestha *et al*., 2018; Thapa *et al*., 2018), showed that changing climate will create additional climatically suitable areas for IAS in Nepal in the future. Furthermore, the study of Adhikari *et al*. (2019) also predicted an additional and continuous increase in the current and future potential habitats for invasive plant species in the different provinces of the Republic of Korea due to climate change. A significant niche expansion was observed in the study of Banerjee *et al*. (2019) which suggested that the species may be able to colonise new areas in India, that were also consistent with the results of the SDM study of invasion hotspots of Adhikari *et al*. (2015). Extrapolation beyond climatic constraints in the training data is an unreliable approach (Anderson *et al*., 2003) because alien species are rarely at equilibrium within their surroundings. Extrapolation limitations have been addressed in the past when projecting SDM into novel environments, with studies suggesting that SDM be associated with landscape, population, and physiological models modelling change processes to improve model extrapolations (Fernandez *et al*., 2015; Molin *et al*., 2018). A scientometric analysis was used to find the trends and patterns and also gaps in studies on the use of SDMs to predict species distribution of IAS (Barbosa *et al*.,2012). Peterson and Vieglais, (2001) used ecological niche modelling to address the difficulties in anticipating possible species invasions. Wan *et al*. (2018) have modelled 36 invasive alien plant species (IAPS) which are identified as the world's worst invasive species. Numerous studies have examined the risks of invasive plant species spreading across a region with a lot of plant diversity (Bradley *et al*., 2010; O'Donnell *et al*., 2012; Adhikari *et al*., 2015; Peknicova and Berchova-Bimova, 2016). Jimenez- Valverde *et al*. (2011) investigated the use of niche models in the risk assessment of invasive species. Phillips *et al*. (2004) investigated MaxEnt and compared it to GARP, a common distribution-modelling tool. Elith and Leathwick, (2009) investigated the performance of various species distribution modelling approaches in terms of prediction across space and time. Using predicted temperature scenarios, the impact of climate change on the possible spread of invasive species has been investigated at the global, continental, and country level.

2.10. Importance of SDMs for Invasive species

Regional biodiversity assessment, conservation biology, wildlife management, and conservation planning are some of the areas that predictive species distribution models are being used. The monitoring and restoration of declining native species populations, as well as the conservation of native species and habitat, require the prediction of potential habitat for alien species. The effectiveness of species distribution models can be summarised into two categories: first, these models can be used to detect the occurrence of rare species in remote regions where systematic surveys had not been conducted (Elith, 2002; Pearce *et al*., 2001); and second, habitat change mapping can be very crucial in assessing the direct impact of anthropogenic pressure on existing habitats in terms of land use, land cover, and climate change (Johnson *et al*., 2004). 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 colonised areas (Jimenez-Valverde *et al*., 2011; Jeschke and Strayer, 2008), and reserve planning (Thorn *et al*., 2009). Stolhgren *et al*. (2010) advocate that species distribution modelling can help with risk assessment and conservation. Guisan and Zimmermann (2000) also discussed a range of species distribution modelling approaches that can be used to predict a species' potential suitable habitat.

2.11. Methods used in species distribution modelling

Several steps were used to model species distribution: (1) Present species data in the form of occurrence points (Peterson *et al*., 1999; Peterson *et al*., 2002); (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 into the landscape of interest using general circulation models of climate change; (4) Distributional shifts are modelled using ecological niche models of particular species projected onto the altered landscapes. Models in the environmental space can estimate the suitable ecological niche by analysing 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).

2.12. Data used for modelling and performance of the model

The development of distribution modelling research had previously concentrated on the production of models based on presence/absence or abundance data, with systematic sampling methods utilised in the study areas (Austin and Cunningham, 1981; Hirzel and Guisan, 2002; Cawsey *et al*., 2002). In most presence/absence models, breeding habitats were assumed to be saturated (Capen *et al*., 1986). In several methods in the species distribution modelling, only presence data were evaluated (Nix, 1986; Carpenter *et al*., 1993). When considering presence/absence models, there occurred the possibility of two types of errors: false positives and false negatives (Fielding and Bell, 1997). Considering false-positive predictions would be regarded as failures when potentially suitable habitat was modelled, it was suggested not to consider absence data that would arise related to non-inclusion of data in the model (Anderson *et al*., 2003; Pearson and Dawson, 2003; Soberon and Peterson, 2005). Subsequently, there was an adaptation to model presence-only data from presence-absence techniques (which employed a binomial response for modelling) using background environment samples (data obtained by selecting random sites over the area of study) or ‘non-use' or ‘pseudo absence' area (Stockwell and Peters, 1999; Boyce *et al*., 2002; Ferrier *et al*., 2002; Zaniewski *et al*., 2002; Keating and Cherry, 2004; Pearce and Boyce, 2006). Since real 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 real absence data (Ferrier *et al*., 2002; Engler *et al*., 2004) or some methods used background data for the entire study area (Hirzel *et al*., 2002).

It was possible to test the model's performance by utilising artificial data and comparing fitted functions, or by using both presence and absence data and assessing anticipated responses (Austin *et al*., 1995). When independent data was not used to develop the model, which was referred to as "test" data, and only "training" data was used to build the model, it had an improved prediction performance level (Fielding and Bell, 1997). The model's predictive performance was more emphasized in the evaluation step, and some known occurrences were withheld (just presence data) from the model's development by splitting the data set, k-fold partitioning, or bootstrapping (Fielding and Bell, 1997; Hastie *et al*., 2001; Araujo *et al*., 2005). The accuracy of prediction based on withheld data was assessed (Boyce *et al*., 2002; Hirzel and Guisan, 2002). The indices that are used generally, such as Kappa and the area under the receiver operating characteristic curve (AUC), were not useful in assessing poorly sampled regions (Boyce *et al*., 2002; Phillips *et al*., 2006). Because the model was statistically equivalent to a random prediction, it would produce relevant predictionsif it predicted a higher number of test localities (low omission rate) and not a large proportion of the study area. When data portioning was done for testing, the Chi-square test or upper-tailed binomial probability was used to assess the statistical significance of the model (Anderson et al., 2002). The performance of the predicted model was dependent on the observed absence data available (Loiselle *et al*., 2003).

Despite widespread usage of distribution models and the increasing availability of data and modelling methods, large synthetic analyses of high predictive ability and accuracy of species distribution modelling methods for presence-only data were desperately required (Elith *et al*., 2006). Using an independent, well-structured presence-absence dataset for validation improved the evaluation of the model performance (Elith *et al*., 2006). The validation of the model was improved by using an independent, well-structured presence-absence dataset (Elith *et al*., 2006). As a result of advancements in machine learning and statistical sciences, many methods were developed and was able to capture complicated responses, even when the data was very noisy. However, it received no publicity in distribution modelling even though the study appeared promising, (Phillips *et al*., 2006; Leathwick *et al*., 2006).

Resampling designs also showed biases in the geographic and environmental space as well (Elith *et al*., 2006). When there were just a few observed occurrences records available, a jack-knife approach may be utilised to assess predicting ability. The Jack-knife (leave-one-out) approach worked well for evaluating models with a limited number of occurrence points. The model was built using the remaining *n-1* localities after excluding each observed locality (*n*) once. The predictability of the model was measured by the model's ability to predict a single locality from the training data (Pearson *et al*., 2007). Because absence data were seldom available and difficult to detect in surveys, the modelling methods and validation depended on presence data only (Pearson *et al*., 2007). Algar *et al*. (2009) found that temporal prediction was quite accurate, but to reduce the biases spatial autocorrelation could be done by using regression models.

2.13. Advancements over ensemble modelling

The ensemble approach is expected to reduce model uncertainty and improve its robustness in accurately modelling species distributions (Marmion *et al*., 2009; Thuiller, 2003). However, Kaky, (2020) demonstrated that MaxEnt could perform and predict comparatively well over an ensemble method that combined several well-known, highly regarded algorithms to highlight important habitats for Egyptian medicinal plant conservation in his study. These findings do not necessarily mean that MaxEnt is a better technique than other approaches, and there are still instances in which it is ineffective (Guillera-Arroita *et al*., 2014). However, when modelling species distributions from insufficient data, MaxEnt might be considered one of the most efficient and accessible methods (Abdelaala *et al*., 2019; Fois *et al*., 2018; Kaky and Gilbert, 2019; Kaki *et al*.,2020; Phillips *et al*. 2006; Koo *et al*. 2015; Dullinger *et al*. 2017; Deb *et al*., 2017; Lamsal *et al*. 2018; Thapa *et al*. 2018; Shrestha and Shrestha, 2019). It is thought to be easy to implement to help in the identification of important conservation sites, particularly in developing nations with limited conservation efforts (Kaky *et al*., 2020). Furthermore, MaxEnt has numerous advantages over other models such as the input species data can be presence points only, both categorical and continuous environmental layers can be applied and even when small sample sizes are used, prediction is consistent and reliable with a great accuracy it can predict the distribution of threatened species, create a spatially explicit map for habitat suitability with easy interpretation, and allow replicated runs to test model robustness. Regardless of the threshold rule, the jackknife test can be used to determine the importance of each environmental variable, and the MaxEnt model (bioclimatic envelope model) can be used to project into the future under climate change to predict habitat losses and gains within species ranges, assisting in the planning of appropriate conservation measures (Elith *et al*., 2011; Fois *et al*., 2018; Pearson *et al*., 2007; Phillips *et al*., 2006, Padalia and Bahuguna, 2017; Abdelaala *et al*., 2019).

2.14. Invasive species ecology of *Senna spectabilis*

Senna spectabilis (f. *Caesalpiniaceae*) is a shrub/tree native to Central and South America. It is also called ‘Spectacular Cassia’, ‘whitebark senna’. According to Irwin and Barneby (1982), it is one of the "most handsome ornamental sennas recommended for rapid growth". *S. spectabilis* is a nitrogen-fixing tree widely planted for ornamental purposes or as a shade or boundary tree. It can withstand a wide range of environmental conditions. *S. spectabilis* competes aggressively in disturbed forests, forest gaps, open vacant spaces, parks, riverbanks, plantations but not in closed canopies (Irwin and Barneby, 1982), which is typical of most invasive plant species (Kornas, 1990; Duggin and Gentle, 1998). For instance, Mugasha *et al*. (2000) concluded that the spread of *Maesopsis eminii* on the Tanzanian Mountains declined following the reduced forest disturbance by humans. It grows and spreads rampantly and prosper on acidic and even on infertile soils. It flowers and sets seedprecociously, and the viability of the seed remains for up to three years. It also has a great coppicing ability (Kerala Biodiversity Board, 2012). It resprouts quickly, profusely, and persistently when cut. The species is non-nodulating, but accumulates nitrogen efficiently, at times even exhausting soil nitrogen reserves and is regarded as a nitrogen-fixing tree (Kerala Biodiversity Board, 2012). It is allelopathic, although it is not allelopathic to maize or rice. In addition, the regeneration and growth of native tree species are also suppressed by *S. spectabilis* (Wakibara, 1998; Wakibara and Mnaya, 2002). *S. spectabilis* grows best in areas with a mean annual temperature of 19-22^{o} C; mean maximum temperature of hottest month ranges from 23 - 32^{o} C and mean minimum temperature of coldest month ranges from 14 - 17^{o} C. The annual precipitation of the species ranges from 800 – 2000 mm (CABI, 2021) and requires full sunlight (PIER, 2014).

Initially, it was introduced as ornamentals in the botanical gardens in India and further accidental introduction from the cultivation in the forest areas of Sikkim and Mysore in India (Singh, 2001). Satynarayana and Gnanasekaran (2013) reported this species in the forest areas of Sathyamangalam, suburban areas of Coimbatore and Wayanad Wildlife Sanctuary and confirmed that it has a high potential for flourishing rapidly and produce numerous viable seeds. It was first introduced to the Wayanad Wildlife Sanctuary in the early 1980s and has since grown to span approximately 23% of the sanctuary's total area in 40 years (Anoop et al., 2021). Even though it has also escaped from Trinidad and Tobago and invaded the northern parts of Orinoco in Venezuela (Irwin and Barneby, 1982), *S. spectabilis* is not recorded in the Global Invasive Species Database (2021).

CHAPTER 3

MATERIALS AND METHODS

3.1. Study area

The study area is Wayanad district (11°44 N–11°97 N and 75°77 E–76°43 E), is located on the crest of the Western Ghats in Kerala's north-eastern region (Fig 1.a). The altitude of the study area varies from 700 to 2100 metres above mean sea level, covering an area of 344.44 km^2. The district is contiguous to Nilgiri Biosphere Reserve (NBR). Wayanad district is Kerala's only district that shares a border with the Indian states of Karnataka (north and north-east) and Tamil Nadu (south-east). The district's annual mean rainfall is 2322 mm, while the average temperature over the last five years has ranged from 18 to 29°C (John *et al*., 2020). A diverse range of flora and wildlife and rich biodiversity is harboured by the district, which is a UNESCO world heritage site and a global biodiversity hotspot (Johna *et al*., 2020). Forest-protected zones cover over 40% of the district's total land area (Sand, 2016). Southern moist deciduous and dry deciduous forests are the principal vegetations along with monoculture plantations of teak and eucalyptus (Anoop *et al*., 2021).

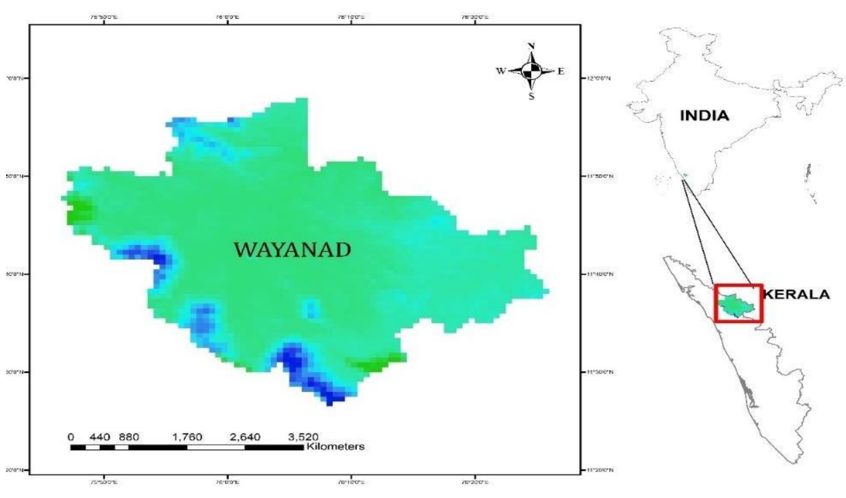
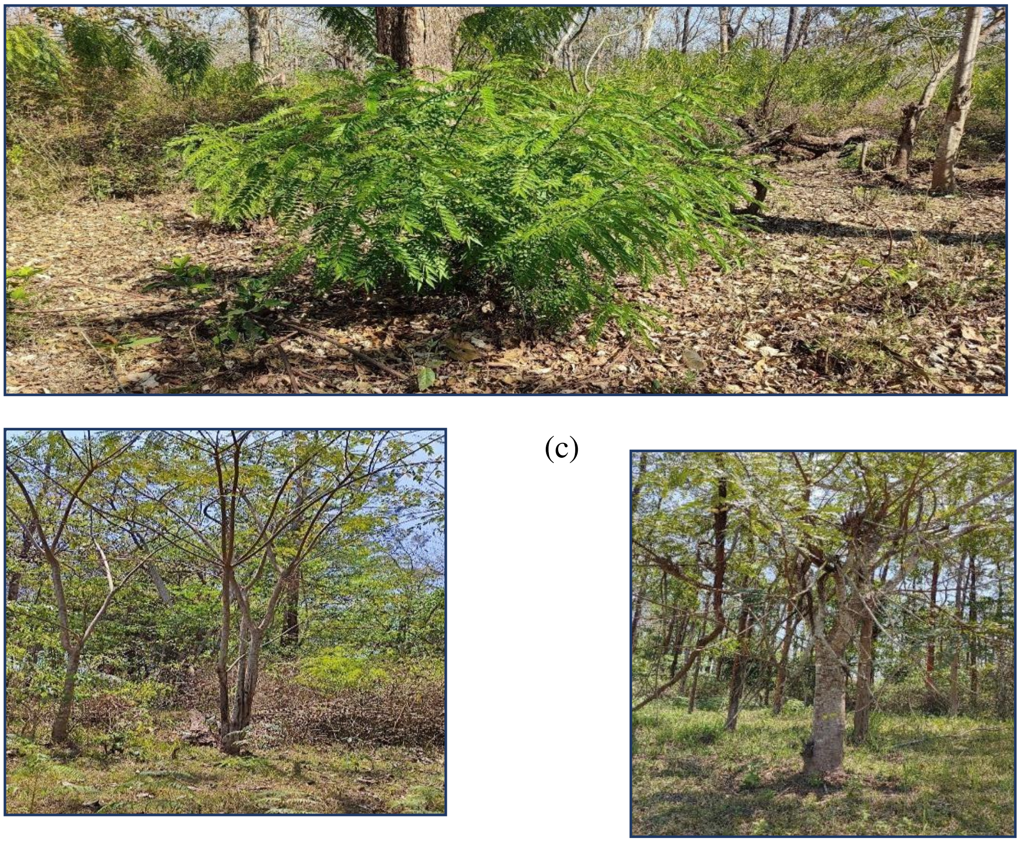


Figure 1. Location map of Wayanad, the study area

(a)



(b) (c)

Figure 2. (a), (b), (c) *Senna spectabilis* invasive species in Wayanad district (Photo taken on 11/03/2021)

3.3. Occurrence data

For occurrence data, both primary and secondary data were used. The primary data was obtained through a field survey. The field visit was done in Wayanad district of Kerala and was carried out during March 2021. A grid-based sampling design was adopted to systematize data collection on the presence of selected invasive species. The size of the individual grid was 1km x 1km. Systematic sampling was done in the area. Garmin *etrex* 20x GPS device was used to archive location coordinates and only one record was collected within each grid. The primary data records were mainly the roadside and open areas presence points. The secondary data was obtained from Kerala

Forest Research Institute which covers the presence records inside the wildlife sanctuary. A total of 374 presence records were compiled from the field survey and the secondary source data obtained from KFRI. Data refining was carried out for the occurrence record in Microsoft Excel for removing duplicates. The spatial autocorrelation between the occurrence of *S. spectabilis* was rectified using the package "spThin" (Aiello-Lammens *et al*., 2015) in the R platform. The incidence records were reduced to 94 from 394 after elimination spatial autocorrelation and multiple records (Figure.3).

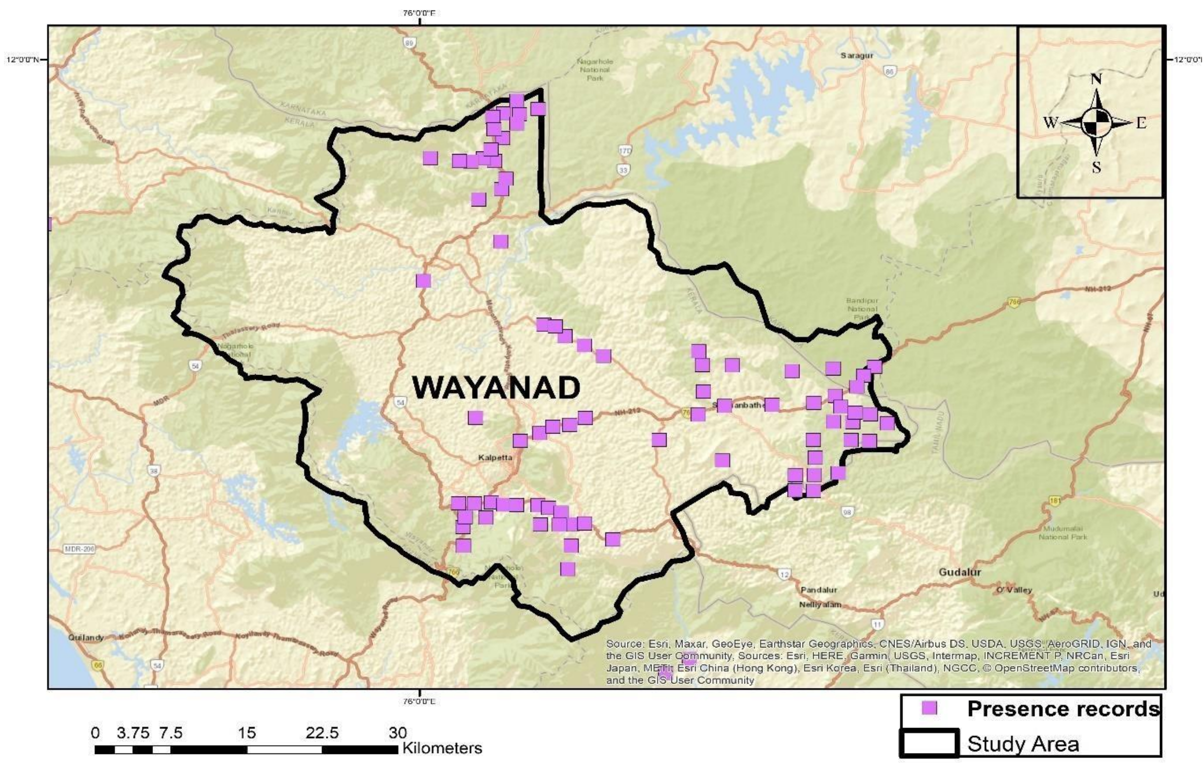


Figure 3. Spatial distribution of species occurrence of *Senna spectabilis* in Wayanad district of Kerala

3.4. Preparation of environmental variables

The bioclimatic predictor variables were obtained from the WorldClim database WorldClim version 2.1 (https://www.worldclim.org) at 30 arc-second scales (accessed the data on 23/11/2020). These bioclimatic variables are the derivatives of monthly rainfall and temperature values for the period 1970–2000 (Fick and Hijmans, 2017). Annual trends, seasonality and extreme or limiting environmental factors are represented by these variables. The 19 variables are as follows.

- BIO1 = Annual Mean Temperature (degree celsius)
- BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp)) (degree celsius)
- BIO3 = Isothermality (BIO2/BIO7) (×100) (dimensionless)
- BIO4 = Temperature Seasonality (standard deviation ×100) (degree celsius)
- BIO5 = Max Temperature of Warmest Month (degree celsius)
- BIO6 = Min Temperature of Coldest Month (degree celsius)
- BIO7 = Temperature Annual Range (BIO5-BIO6) (degree celsius)
- BIO8 = Mean Temperature of Wettest Quarter (degree celsius)
- BIO9 = Mean Temperature of Driest Quarter (degree celsius)
- BIO10 = Mean Temperature of Warmest Quarter (degree celsius)
- BIO11 = Mean Temperature of Coldest Quarter (degree celsius)
- BIO12 = Annual Precipitation (mm)

- BIO13 = Precipitation of Wettest Month (mm)
- BIO14 = Precipitation of Driest Month (mm)
- BIO15 = Precipitation Seasonality (Coefficient of Variation) (Fraction)
- BIO16 = Precipitation of Wettest Quarter (mm)
- BIO17 = Precipitation of Driest Quarter (mm)
- BIO18 = Precipitation of Warmest Quarter (mm)
- BIO19 = Precipitation of Coldest Quarter (mm)

The unit of temperature is '^{o} C' and precipitation is 'mm'. 30 arc-seconds (approximately 1 km^2 at the equator) resolution data were used for both current and future conditions. In addition, these were in the latitude/longitude coordinate reference system under the datum WGS84.

According to Fick and Hijmans, (2017); Hutchinson and Xu, (2013), the WorldClim database was created by interpolating average monthly data from weather stations all over the world excluding Antarctica. Besides, these climate data or the weather station data were compiled from a large number of sources and databases that comprises long term average values for creating 'climate surfaces'.

For future climate projections, the future bioclimatic data at a spatial resolution of 30 arc-seconds (~1 km) was downloaded (on 22/11/2020) from CCAFS on the Climate Change and Agricultural Food Security (CCAFS) climate data archive (http://ccafs-climate.org/). These datasets are a part of the Decision and Policy Analysis (DAPA) program's climate change downscaled data from the International Centre for Tropical Agriculture (CIAT) according to which, these future bioclimatic raster data were downscaled from IPCC general circulation models (GCM) from the IPCC's fifth report (IPCC 2013, future climate projections) and reprocessed using thin-plate spline interpolation algorithm anomalies and the current distribution of climates from the WorldClim version 1.4 database developed by Hijman *et al*. (2005). The unit of temperature is '^{o} Cx10'and precipitation is 'mm'. The temperature variables were further converted to ^{o} C using the raster calculator in ArcGIS version 10.7.1 ESRI. All the four representative concentration pathways viz., RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 were chosen (Table.1) and followed the Hadley Global Environment Model 2-Earth system model (HadGEM2-ES) with a spatial resolution of 30 arc-seconds (~1 km) as stated in the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2014).

Table 1. Different RCP scenarios used for the future projection of *Senna spectabilis* in Wayanad district of Kerala

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

In addition to climatic variables, land use land cover, topographic variables (slope, aspect and elevation), soil, population density, normalised vegetation index, distance from water bodies, distance from the road were also considered for modelling. The non - climatic variables were selected after the literature survey by understanding the importance of these variables to the invasive species. Digital elevation model was directly procured from Global 30 arc second elevation (GTOPO30) from the U.S. Geological Survey (https://lta.cr.usgs.gov/GTOPO30) on 16/05/2021. The slope and aspect maps were derived from DEM using ArcMap ver.10.7.1 ESRI. The Landcover dataset was accessed from the Global 1-km Consensus Land Cover Earthenv database archive (http://www.earthenv.org//landcover on 16/05/2021. These datasets provide one km resolution consensus data on the prevalence of 12 different land-cover classes by combining multiple global remote sensing-derived land-cover products. Normalized difference vegetation index layers were retrieved from the Land Processes Distributed Active Archive Center (LP DAAC, https://lpdaac.usgs.gov) maintained by NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC) at the USGS Earth Resources Observation and Science (EROS) Center on 16/05/2021. The datasets obtained were resultant of the temporal monthly average of the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13A3) Version 6 data at one km spatial resolution. Vegetation indices are used for global monitoring of vegetation conditions and these are continuous raster datasets. The soil type information was obtained from the Department of Soil Survey and Soil Conservation (http://www.keralasoils.gov.in/). The vector map was georeferenced and rasterised to one km spatial resolution. The layers distance from water bodies and distance from the road were derived using ArcMap ver.10.7.1 ESRI, the datasets for water bodies were obtained from Near-global freshwater-specific environmental variables for biodiversity analyses in one km resolution Earthenv database archive (Domisch *et al*., 2015, https://www.earthenv.org/) and datasets for road network was obtained from the NASA Socioeconomic Data and Applications Center (SEDAC) Global Roads Open Access Data Set, (gROADSv1, https://sedac.ciesin.columbia.edu/ data/ set/ groads -global- roads- open- access- v1). Anthropogenic pressure is an important driver of bioinvasion (Liu *et al*. 2005, Bhattarai *et al*. 2014; Shrestha *et al*. 2015) and therefore, the inclusion of population density layer is important. Population density layer was obtained from Gridded Population of the World (GPW, v4.11) from the NASA Socioeconomic Data and Applications Center (SEDAC, https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11) at 1 km spatial resolution. These datasets consist of estimates of human population density (number of persons per km^2). The geographic dimensions of all environmental layers for the study area and pixel size were made uniform using resample tool in ArcGIS ver.10.7.1 ESRI and the environmental layer tiles were available at ~ one km^2 spatial resolution.

3.5. Model Design

3.5.1. Selection of Optimal environmental variables

The accuracy of the model is influenced even when there remains a mild correlation between the explanatory variables (Veloz *et al*., 2009). Therefore, to reduce the masking effect of a large number of collinear variables and to obtain an optimum predictive model result, the variables were tested for multicollinearity using Pearson correlation coefficient (r). One among the two strongly cross-correlated variables (Pearson correlation coefficient $r>0.70$) was chosen for inclusion in the model considering its biological significance to the species and ease of interpretation. For example, precipitation of driest quarter was kept if precipitation seasonality (BIO14) and precipitation of driest quarter (BIO17) were correlated with each other, since it has more significance to species than precipitation seasonality. Additionally, the variability of the bioclimatic variables with the different RCP scenarios and current were also critically analysed.

3.6. Model development

3.6.1. Model Selection

Maximum entropy modelling (MaxEnt), the most accepted species distribution model was used for modelling presence-only data (Bosso *et al*., 2018; Soucy *et al*., 2018; Zhang *et al*., 2018). MaxEnt version 3.4.4 was downloaded from https://biodiversityinformatics.amnh.org/open_source/maxent/ on 24/11/2020. The model was used to predict the potential habitat suitability for invasion of *S. spectabilis* and generate a distribution map. It was also used to model the future suitability and distribution map under HadGEM2-ES climate change scenarios for 2050 and 2070. MaxEnt uses a machine-learning algorithm to estimate the relationship of site species occurrence presence data and the spatial/environmental characteristics of those sites (Franklin, 2009). MaxEnt computes for each grid cell predicted suitability of conditions for the species. The species distribution output is obtained when the georeferenced species occurrence records and environmental variables are fed into it. Species data was made into '.csv' (comma separated value) format and the bioclimatic layers as '. asc' (American Standard Code for Information Interchange) format when inputting into the MaxEnt model. All the selected fourteen variables except soil type were continuous. The default settings options in the software were programmed for the model training (Philips *et al*., 2004; 2006).

3.6.2. Model Training and optimization

Model optimization was determined using the "ENMeval" package (Muscarella *et al*., 2014) in R platform. The least delta AIC (Akaike Index Criterion) was selected for choosing the best fit model for the current species distribution modelling. Forty-eight models with different regularization multiplier values and different levels of complexity were developed. Regularization multiplier features were employed to prevent model overfitting (Philips and Dudik, 2008). The best replication run type was then determined from the literature review. Subsampling replication run type was determined finally where random replicate sample sets were chosen for evaluation by removing random test percentage without replacement. All variables were analysed to determine the contribution of each variable to the modelling of distribution for the species. This was done for the current distribution (no projections for the future).

3.6.3. Variable contribution to the model

The contribution of each selected variable (static and dynamic variables) to the modelling of the distribution of *S. spectabilis* was identified by analysis. This was carried out for modelling of current distribution (no future projection). The model was run for *S. spectabilis* with 5000 iterations, and 10 replicates with a subsampling procedure, among which 75 percent was used for testing and the remaining 25 percent of iterations were used for training. The output was made in logistic format to get the probability of occurrence in the range of 0-1. The increased regularised gain was added to the contribution of the corresponding variable in determining the percentage contribution, or subtracted from it if the change in the absolute value of lambda was negative in each run of the training algorithm. The values of each environmental variable on training presence and background data were randomly permuted to determine permutation importance.

3.7. Model Evaluation

3.7.1. Accuracy assessment

3.7.1.1. Threshold independent ROC AUC

AUC is a threshold-independent metric that quantifies the model's ability to distinguish between random and background points (Raman *et al.*, 2020). AUC values above 0.90 indicate excellent model accuracy, suggesting that the model can distinguish between presence and absence records; values between 0.7 and 0.9 indicate good accuracy; values between 0.5 and 0.7 indicate low accuracy, and values below 0.5 are no better than a random chance. It equally weighs omission and commission errors (reliable when using the presence/absence model). AUC values are correlated by the prevalence of the occurrence points and size of the study area and distribution of species and ignore the predicted probability and the goodness of fit of the model (Philips *et al.*, 2006).

3.7.1.2. True Skill Statistics

A highly suggested measurement/index, which is a threshold- dependant measure and it also accounts for omission and commission errors. TSS is defined as “sensitivity + specificity – 1”. The range of the index ranges from -1 (a random fit) to +1 (perfect fit). Unlike AUC, TSS values are not affected by the size of the study region and the prevalence of the occurrence records (Allouche et al., 2006).

3.7.2. Sensitivity analysis

Jackknife technique was used to test the sensitivity of the model. The relative importance of the predictor variable was determined by jackknifing and it calculates the training gain of each variable if the model is being run in isolation, and compares it to the training gain with all the variables.

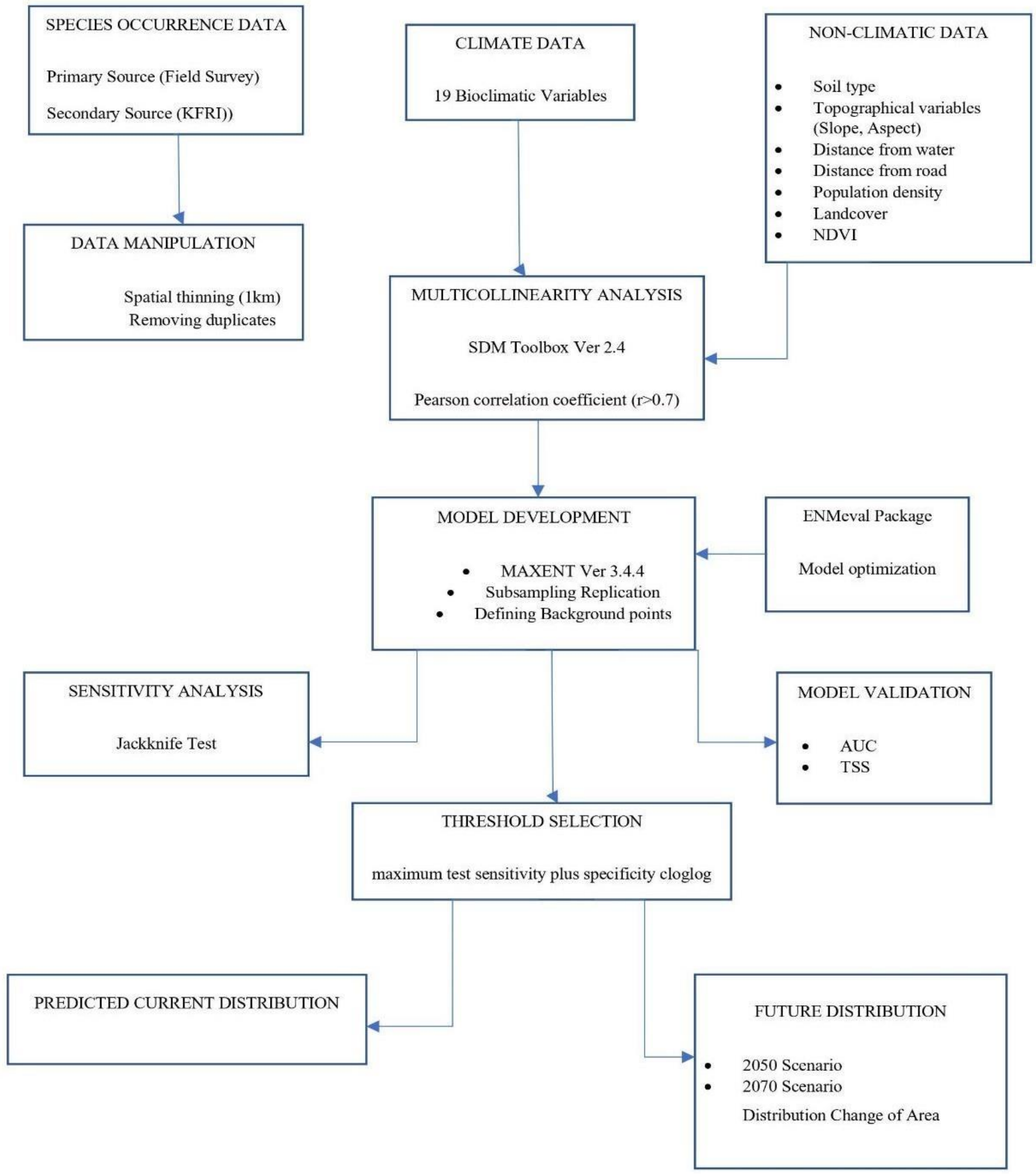
3.8. Thresholding of model outputs

The output was formatted in logistic format (binary maps) to obtain the probability of occurrence in the range of 0-1 (Phillips *et al*., 2004) based on the selected logistic threshold value ‘maximum test sensitivity plus specificity (*max sss*), regarded a recommended threshold selection method for presence/absence data (Liu *et al*., 2005). Across models, Sensitivity and Specificity were not affected by prevalence because they are independent of each other (Allouche *et al*., 2006). Furthermore, sensitivity is defined as the proportion of correctly predicted presences among all the presences and specificity is the proportion of correctly predicted absences among all the absences, therefore, it has been proved valid to use with presence-only data and instead of true absences, random records are used (Liu *et al*., 2013). The ‘max SSS' selects a point in the receiver operating characteristic (ROC) curve that plots sensitivity and 1-specificity to maximise the TSS where the tangent slope is equal to 1 (Smeraldo *et al*., 2017; Bosso *et al*., 2018). Using SDMtoolbox 2.4 in ArcMap ver.10.7.1, binary rasters were utilized to analyse the predicted contraction, expansion, areas of no change and no occupancy.

3.9. Potential Distribution under Future Scenarios

For the projected HadGEM2-ES climate change scenarios for 2050 and 2070 with 30 arc-second (~ 1 km) spatial resolution, as presented in the fifth assessment report (AR5) of the Intergovernmental Panel for Climate Change (IPCC, 2014), the impact of climate change on the potential distribution of the selected invasive species was done using MaxEnT modelling. Environmental variables and species occurrence records were used to train the model by projecting a future environmental variable onto a set of current environmental variables. Only the static non-climatic variables, for example, soil type, aspect, slope were kept whereas dynamic non-climatic variables and also the variables with negligible permutation importance obtained from the training gain was removed. Also, the variables chosen after multicollinearity analysis is chosen. Models of different RCPs 2.6, 4.5, 6.0, 8.5 were done for the years 2050 (2040 – 2069) and 2070 (2060 – 2089) with 10 replicates and 25 test percentage. The projection was done using a subsampling type of replication. Importantly, the layers should have the same name as the training data, and also, map projection and geographic dimensions must be the same. Maxent outputs were mapped using ArcMap ver.10.7.1 and the area of distribution and the change in the area of distribution was measured from the current and future binary species distribution maps (logistic threshold output, 0-1). The methodology flow diagram is shown in figure 4.

Figure 4. Methodology Flow diagram



CHAPTER 4

RESULTS

The currently increasing spread and risk of invasive alien plant species *S. spectabilis* in Wayanad wildlife sanctuary initiated this study considering its profuse growth affecting the biological diversity losses and ecosystem balance. Accordingly, the study investigates the current distribution patterns of *S. spectabilis* based on climatic and non-climatic variables and further examining the distribution of *S. spectabilis* in the future projection of RCP scenarios for both the years 2050 and 2070. The widely used software MaxEnt was used for both current and future distribution modelling of *S. spectabilis* thereby, relating the presence occurrence points to the climatic conditions prevailing in the study region. The occurrence data points consisting of both primary and secondary data were collected using GPS device and climate data from 1950-2000 for current conditions and the years 2050 and 2070, the climate was predicted by using the coupled model HadGEM2-ES of one km resolution under four different Representative Concentration Pathways (RCPs). This chapter examines the results obtained from the model.

4.1. Variable optimization

The statistical analysis using multicollinearity test conducted using Pearson correlation coefficient in ArcGIS ver.10.7.1 ESRI using SDM toolbox maintained 15 variables for modelling the potential habitat suitability of *S. spectabilis* invasive alien species. The Pearson correlation coefficient between variables is given in Table 2 and the highlighted ones are the highly correlated variables ($r > 0.7$) and were excluded from the model to avoid the effect of multi-collinearity thereby, improving the accuracy of the model by reducing the masking effect and overprediction of the model. The selected environmental variables for the study were Annual mean temperature (BIO1), Isothermality (BIO3), Temperature Seasonality (BIO4), Precipitation Seasonality (BIO15), Precipitation of Driest Quarter (BIO17), Precipitation of Warmest Quarter

(BIO18), Aspect, Slope, Distance from water bodies, Distance from Road, Landcover, NDVI (Normalised Difference Vegetation Index), Soil type, Population Density were used as inputs in the study. Only bioclimatic variables correlated with each other compared to the non-climatic variables. The variable that had the greater number of correlations between other variables were BIO1 (Annual mean Temperature), BIO6 (Min Temperature of Coldest Month), BIO7 (Temperature Annual Range), BIO8 (Mean Temperature of Wettest Quarter), BIO9 (Mean Temperature of Driest Quarter), BIO11 (Mean Temperature of Coldest Quarter), BIO15 (Precipitation Seasonality) (six correlations under |r|). In |r|>0.7 criteria variables BIO3 (Isothermality) and BIO18 (Precipitation of Warmest Quarter), both the variables were chosen due to its important contribution on distribution of *Senna* spp. Precipitation of Driest Quarter (BIO17) has a correlation with Precipitation of Driest Month (BIO14), from which Precipitation of Driest Quarter was selected. Precipitation Seasonality (BIO15) was selected among the correlated variables of Annual precipitation (BIO12), Precipitation of Wettest Quarter (BIO16), Precipitation of Wettest Month (BIO13), and Precipitation of Coldest Quarter (BIO19). Max Temperature of Warmest Month (BIO5) was excluded and Temperature Seasonality (BIO4) was chosen among the collinear variables. Among the bioclimatic variables, BIO1 (Annual mean temperature), BIO3 (Isothermality), BIO4 (Temperature Seasonality), BIO15 (Precipitation Seasonality), BIO17 (Precipitation of Driest Quarter), BIO18 (Precipitation of Warmest Quarter) were selected and all the non-correlated non-climatic variables were used as inputs in the model for the distribution of *S. spectabilis*.

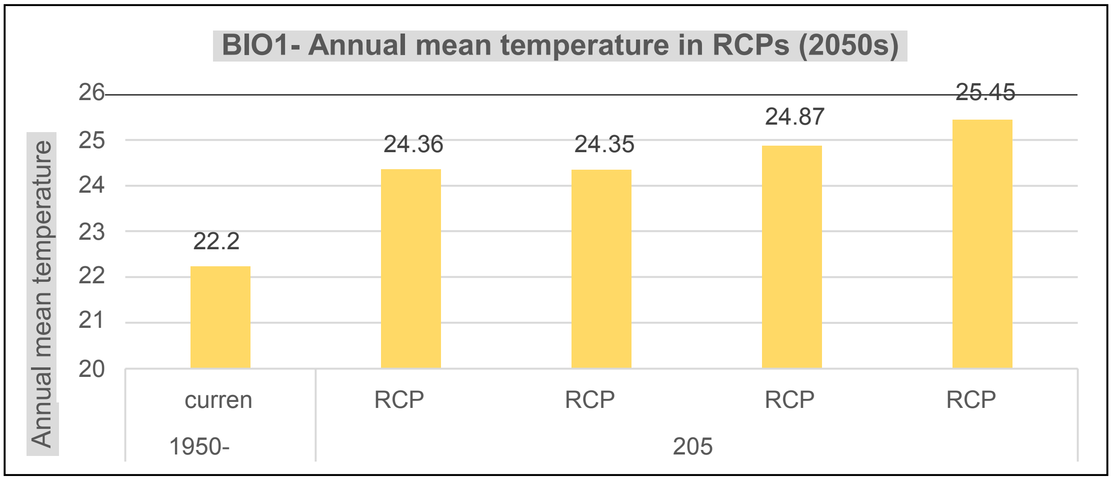
Table 2: Cross-correlations (Pearson correlation coefficient, r) among 28 bioclimatic and topographic variables. Correlations values depicted with bold highlighted text indicate high correlation

Layer	BIO 1	BIO 2	BIO 3	BIO 4	BIO 5	BIO 6	BIO 7	BIO 8	BIO 9	BIO 10	BIO 11	BIO 12	BIO 13	BIO 14	BIO 15	BIO 16	BIO 17	BIO 18	BIO 19	elev	aspect	slope	soil	NDVI	landcover	water	road	population
BIO1	1	-0.474	0.442	-0.01	-0.534	0.984	0.986	0.9616	0.993	0.994	0.99584	0.2203	0.1026	-0.3699	0.128	0.1642	-0.2207	0.55373	0.3779	-0.9896	0.0519	-0.089	0.1848	-0.296	-0.2045	0.4471	-0.376	-0.1941
BIO2	-0.474	1	-0.489	0.535	0.9105	-0.52	-0.428	-0.26023	-0.5504	-0.409	-0.5037	-0.027	0.17165	-0.1667	0.2453	0.1017	-0.2679	-0.6215	-0.0889	0.48629	-0.0223	0.1486	-0.323	0.1386	0.0564	-0.5457	0.0067	-0.0429
BIO3	0.4419	-0.489	1	-0.77	-0.804	0.548	0.353	0.23707	0.4921	0.351	0.49241	-0.261	-0.5052	0.44281	-0.63	-0.439	0.6066	0.74553	-0.2663	-0.4055	0.0362	-0.035	0.1053	-0.065	0.0902	0.22505	-0.128	0.0139
BIO4	-0.014	0.5353	-0.774	1	0.7204	-0.16	0.102	0.23982	-0.0662	0.095	-0.0877	0.2837	0.50159	-0.714	0.6991	0.458	-0.781	-0.5673	0.4899	0.007	0.0013	0.0308	-0.126	-0.102	-0.2429	-0.0983	-0.091	-0.1082
BIO5	-0.534	0.9105	-0.804	0.72	1	-0.61	-0.462	-0.29247	-0.61	-0.447	-0.576	0.0983	0.3499	-0.3214	0.4605	0.2699	-0.4663	-0.7712	0.0503	0.52373	-0.0344	0.1162	-0.266	0.1247	-0.004	-0.473	0.0588	-0.0345
BIO6	0.9837	-0.52	0.548	-0.16	-0.613	1	0.95	0.9117	0.9808	0.961	0.9889	0.112	-0.0238	-0.2228	-0.024	0.0378	-0.0746	0.59581	0.2545	-0.9685	0.0521	-0.089	0.1873	-0.272	-0.1545	0.43607	-0.352	-0.1944
BIO7	0.9864	-0.428	0.353	0.102	-0.462	0.95	1	0.97643	0.9788	0.993	0.97376	0.259	0.17218	-0.4703	0.2264	0.2268	-0.3309	0.47076	0.4521	-0.9782	0.0559	-0.087	0.1702	-0.31	-0.2454	0.46372	-0.382	-0.1861
BIO8	0.9616	-0.26	0.237	0.24	-0.292	0.912	0.976	1	0.9361	0.985	0.94179	0.2728	0.22346	-0.5411	0.2998	0.267	-0.4106	0.37283	0.459	-0.9519	0.0489	-0.067	0.1236	-0.306	-0.2502	0.36977	-0.397	-0.2214
BIO9	0.993	-0.55	0.492	-0.07	-0.61	0.981	0.979	0.93614	1	0.98	0.99217	0.1899	0.0565	-0.3302	0.079	0.122	-0.1688	0.59251	0.3618	-0.9813	0.0532	-0.098	0.2004	-0.3	-0.2059	0.4803	-0.351	-0.1708
BIO10	0.9937	-0.409	0.351	0.095	-0.447	0.961	0.993	0.98466	0.9803	1	0.98251	0.2589	0.1671	-0.4539	0.2145	0.2228	-0.3124	0.48771	0.4303	-0.9852	0.051	-0.085	0.1693	-0.304	-0.2291	0.43282	-0.387	-0.205
BIO11	0.9958	-0.504	0.492	-0.09	-0.576	0.989	0.974	0.94179	0.9922	0.983	1	0.2097	0.07872	-0.3322	0.0925	0.1413	-0.1738	0.59638	0.336	-0.9867	0.0493	-0.091	0.1935	-0.285	-0.1864	0.45035	-0.372	-0.1848
BIO12	0.2203	-0.027	-0.261	0.284	0.0983	0.112	0.259	0.27277	0.1899	0.259	0.20972	1	0.94149	-0.5916	0.8008	0.9722	-0.5836	0.22254	0.7714	-0.268	-0.0206	-0.002	0.0432	-0.006	-0.0725	0.11741	-0.121	0.0512
BIO13	0.1026	0.1717	-0.505	0.502	0.3499	-0.02	0.172	0.22346	0.0565	0.167	0.07872	0.9415	1	-0.6957	0.9223	0.9903	-0.7407	-0.0868	0.7674	-0.1538	-0.016	0.0277	-0.054	0.0412	-0.0618	0.03608	-0.093	0.0235
BIO14	-0.37	-0.167	0.443	-0.71	-0.321	-0.22	-0.47	-0.54108	-0.3302	-0.454	-0.3322	-0.592	-0.6957	1	-0.872	-0.694	0.9577	0.12557	-0.6678	0.40555	-0.0151	0.0326	-0.03	0.2094	0.3323	-0.2579	0.3168	0.0826
BIO15	0.128	0.2453	-0.63	0.699	0.4605	-0.02	0.226	0.29975	0.079	0.215	0.09245	0.8008	0.92233	-0.8719	1	0.9054	-0.9119	-0.2442	0.7241	-0.179	-0.0089	0.0072	-0.038	-0.047	-0.1907	0.08587	-0.166	-0.0189
BIO16	0.1642	0.1017	-0.439	0.458	0.2699	0.038	0.227	0.26697	0.122	0.223	0.14131	0.9722	0.99034	-0.6945	0.9054	1	-0.7224	0.00906	0.7932	-0.2146	-0.0143	0.0118	-0.013	0.002	-0.0945	0.07719	-0.117	0.0284
BIO17	-0.221	-0.268	0.607	-0.78	-0.466	-0.07	-0.331	-0.41058	-0.1688	-0.312	-0.1738	-0.584	-0.7407	0.95769	-0.912	-0.722	1	0.32825	-0.6651	0.25975	-0.0191	0.0201	0.0071	0.1572	0.31	-0.2039	0.2704	0.0734
BIO18	0.5537	-0.621	0.746	-0.57	-0.771	0.596	0.471	0.37283	0.5925	0.488	0.59638	0.2225	-0.0868	0.12557	-0.244	0.0091	0.3283	1	0.092	-0.5468	-0.0113	-0.096	0.2962	-0.162	-0.0411	0.34497	-0.194	0.0106
BIO19	0.3779	-0.089	-0.266	0.49	0.0503	0.255	0.452	0.45898	0.3618	0.43	0.33601	0.7714	0.76743	-0.6678	0.7241	0.7932	-0.6651	0.09203	1	-0.4022	0.021	-0.029	0.0599	-0.112	-0.193	0.23935	-0.139	-0.0059
elev	-0.99	0.4863	-0.406	0.007	0.5237	-0.97	-0.978	-0.95185	-0.9813	-0.985	-0.9867	-0.268	-0.1538	0.40555	-0.179	-0.215	0.2598	-0.5468	-0.4022	1	-0.0441	0.091	-0.189	0.281	0.1916	-0.4536	0.3726	0.1972
aspect	0.0519	-0.022	0.036	0.001	-0.034	0.052	0.056	0.0489	0.0532	0.051	0.04932	-0.021	-0.016	-0.0151	-0.009	-0.014	-0.0191	-0.0113	0.021	-0.0441	1	0.2107	-0.061	-0.005	0.0073	0.02017	0.0033	-0.0188
slope	-0.089	0.1486	-0.035	0.031	0.1162	-0.09	-0.087	-0.06685	-0.0981	-0.085	-0.091	-0.002	0.02771	0.03255	0.0072	0.0118	0.0201	-0.0963	-0.0285	0.09104	0.2107	1	-0.249	0.1222	0.1524	-0.1651	0.0585	-0.0157
soil	0.1848	-0.323	0.105	-0.13	-0.266	0.187	0.17	0.12364	0.2004	0.169	0.19351	0.0432	-0.0539	-0.0301	-0.038	-0.013	0.0071	0.29621	0.0599	-0.1891	-0.0606	-0.249	1	-0.243	-0.3103	0.30633	-0.085	-0.0241
NDVI	-0.296	0.1386	-0.065	-0.1	0.1247	-0.27	-0.31	-0.30623	-0.2996	-0.304	-0.2855	-0.006	0.04124	0.20942	-0.047	0.002	0.1572	-0.1615	-0.1125	0.28102	-0.0054	0.1222	-0.243	1	0.4988	-0.2896	0.2078	0.0974
LC	-0.205	0.0564	0.09	-0.24	-0.004	-0.15	-0.245	-0.25022	-0.2059	-0.229	-0.1864	-0.073	-0.0618	0.3323	-0.191	-0.095	0.31	-0.0411	-0.193	0.19157	0.0073	0.1524	-0.31	0.4988	1	-0.3532	0.2679	0.08
water	0.4471	-0.546	0.225	-0.1	-0.473	0.436	0.464	0.36977	0.4803	0.433	0.45035	0.1174	0.03608	-0.2579	0.0859	0.0772	-0.2039	0.34497	0.2394	-0.4536	0.0202	-0.165	0.3063	-0.29	-0.3532	1	-0.28	0.0416
road	-0.376	0.0067	-0.128	-0.09	0.0588	-0.35	-0.382	-0.39748	-0.351	-0.387	-0.3721	-0.121	-0.0926	0.31675	-0.166	-0.117	0.2704	-0.194	-0.1395	0.37257	0.0033	0.0585	-0.085	0.2078	0.2679	-0.2802	1	0.0353
population	-0.194	-0.043	0.014	-0.11	-0.034	-0.19	-0.186	-0.22142	-0.1708	-0.205	-0.1848	0.0512	0.02349	0.08257	-0.019	0.0284	0.0734	0.01056	-0.0059	0.19723	-0.0188	-0.016	-0.024	0.0974	0.08	0.04156	0.0353	1

Additionally, the variability of each chosen non-collinear bioclimatic variable with respect to different RCP scenarios also analysed using the mean value of bioclimatic variables in the study area, which were calculated in R.

All the selected bioclimatic variables showed variation in both the time periods. The annual mean temperature (BIO1) in Wayanad showed an increasing trend in both the time periods of 2050 and 2070 (Figures 5.a, b.). Isothermality (BIO3) also showed a great variation in both 2050s and 2070s with highest fraction value in RCP 4.5 scenario (Figures 6.a, b.). The highest temperature seasonality in Wayanad in 2050s time period was shown in RCP 4.5 scenario whereas, in RCP 2.6 scenario in 2070s (Figures 7.a, b.). There is a decrease in precipitation seasonality (BIO15) compared to current in both the time periods of 2050s and 2070s. Precipitation seasonality is highest in RCP 4.5 and lowest in RCP 8.5 (Figures 8.a, b.). Similarly, Precipitation of driest quarter (BIO17) is lower compared to current scenario. However, RCP 8.5 scenario has the lowest projected precipitation in driest quarter in 2050, in contrast highest precipitation in driest quarter is projected to be in RCP 8.5 in 2070 (Figures 9.a, b.). The variability analysis of precipitation of warmest quarter (BIO18) showed variability in all RCP scenarios, which is higher than the current scenario in Wayanad. The highest projected precipitation of warmest quarter is shown in the RCP 2.6 for both the time periods (Figures 10.a, b.).

(a)



(b)

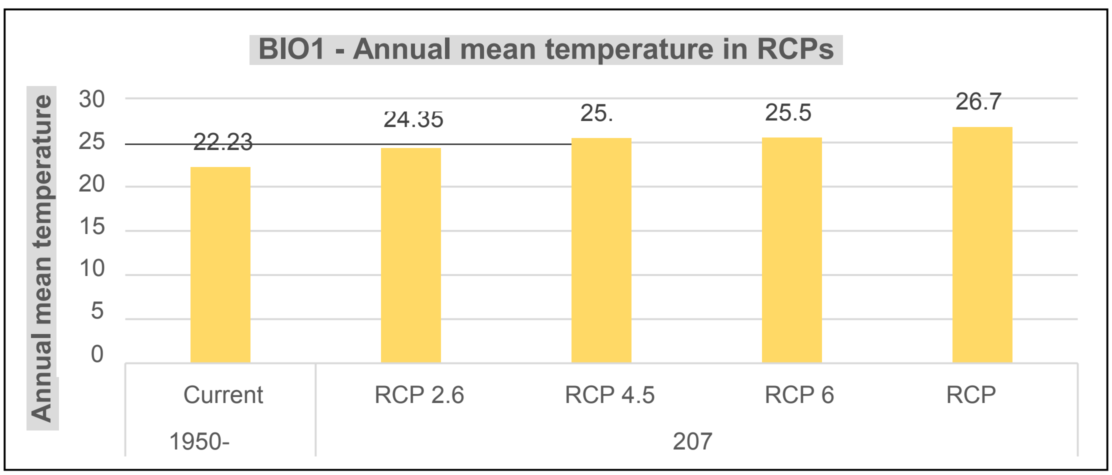
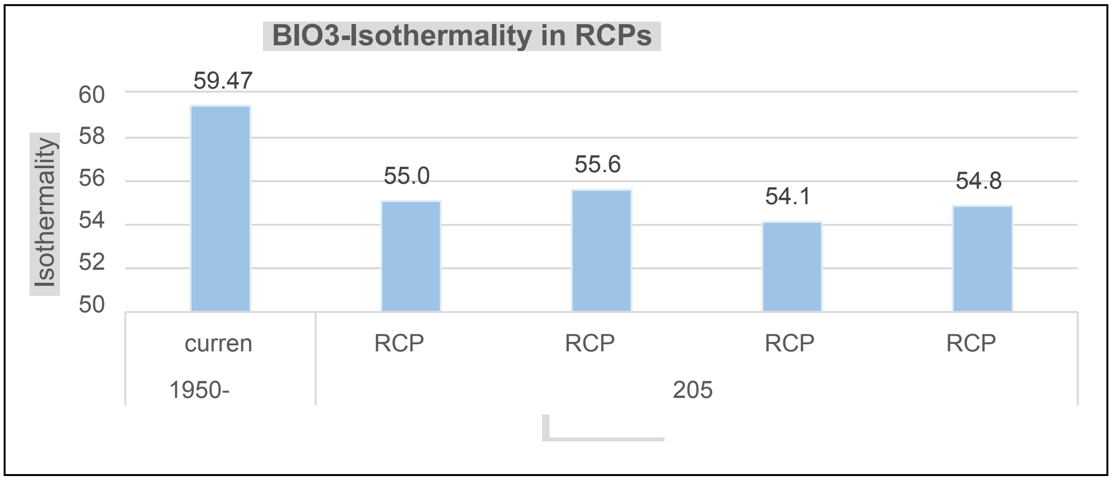


Figure 5. Variability of annual mean temperature (BIO1) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

(a)



(b)

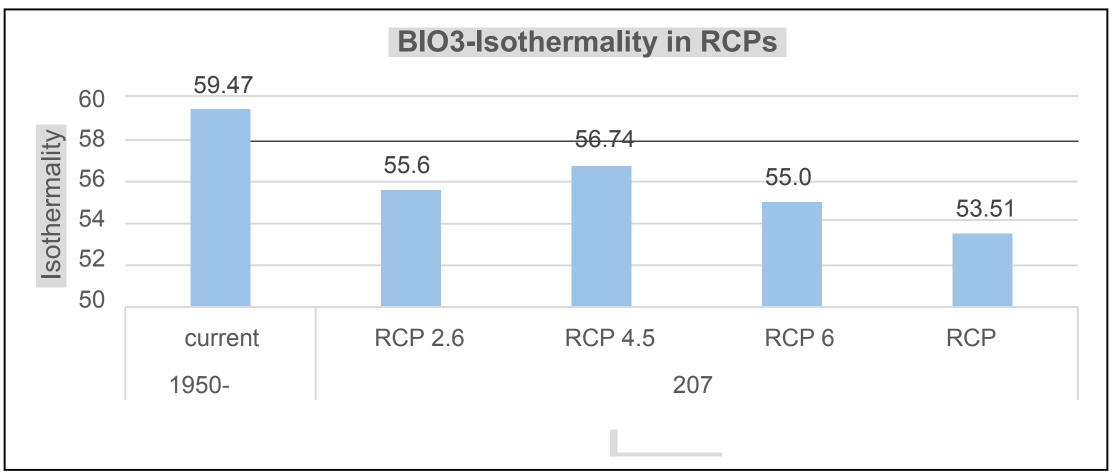
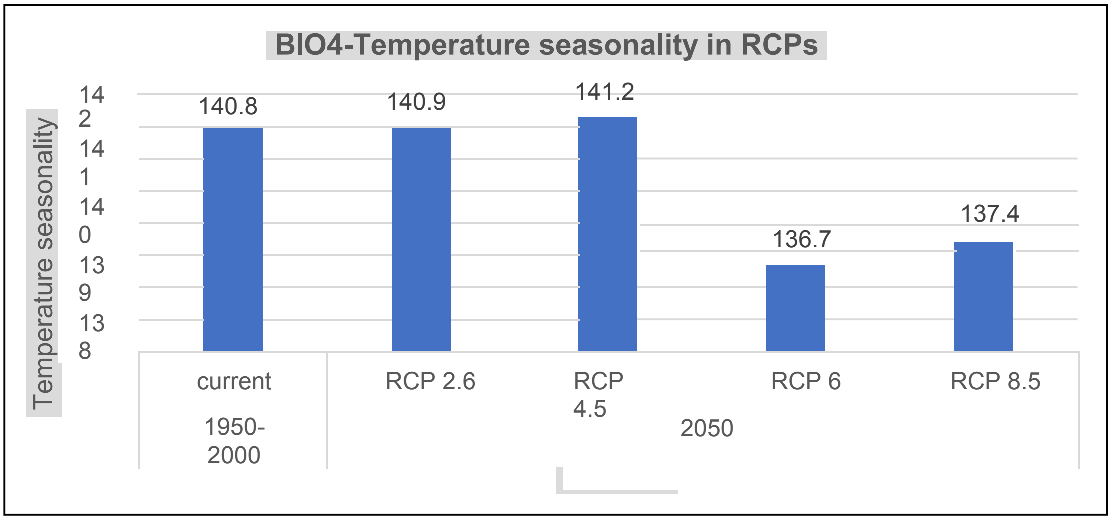


Figure 6. Variability of isothermality (BIO3) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

(a)



(b)

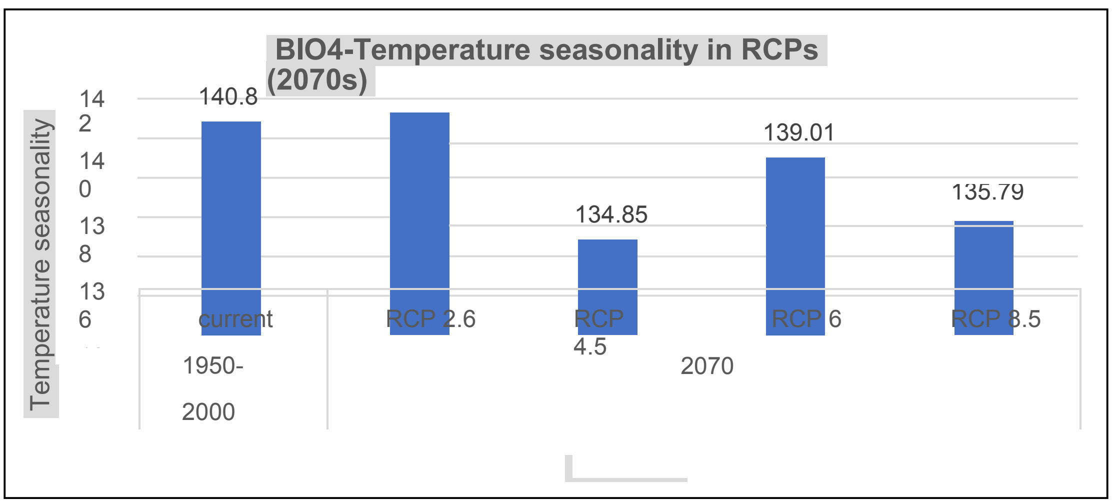
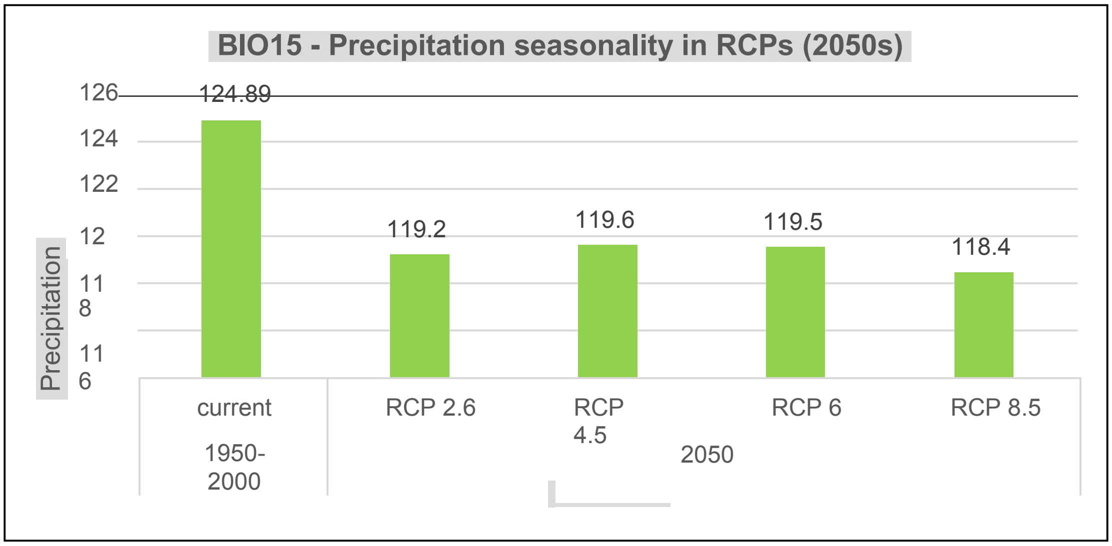


Figure 7. Variability of temperature seasonality (BIO4) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

(a)



(b)

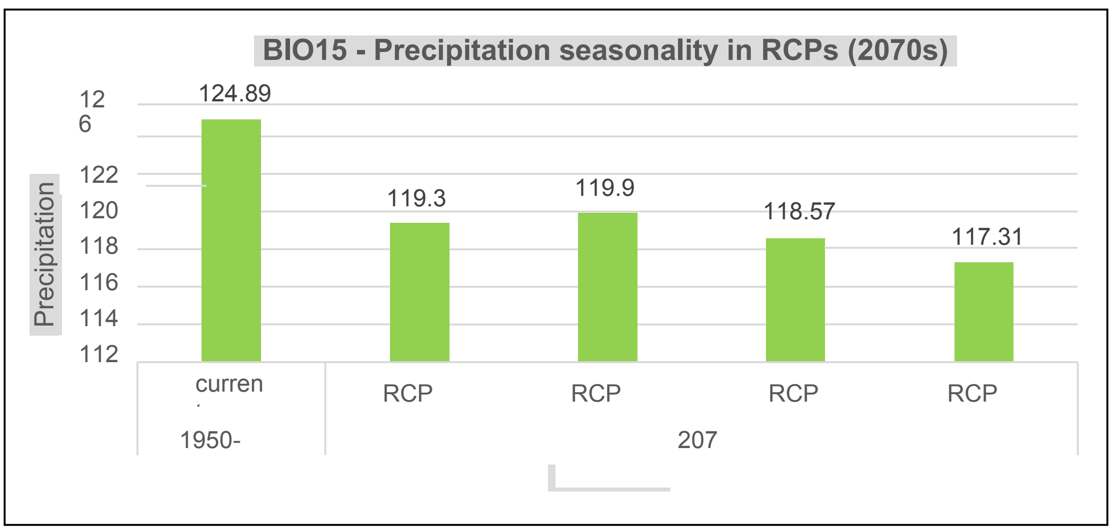
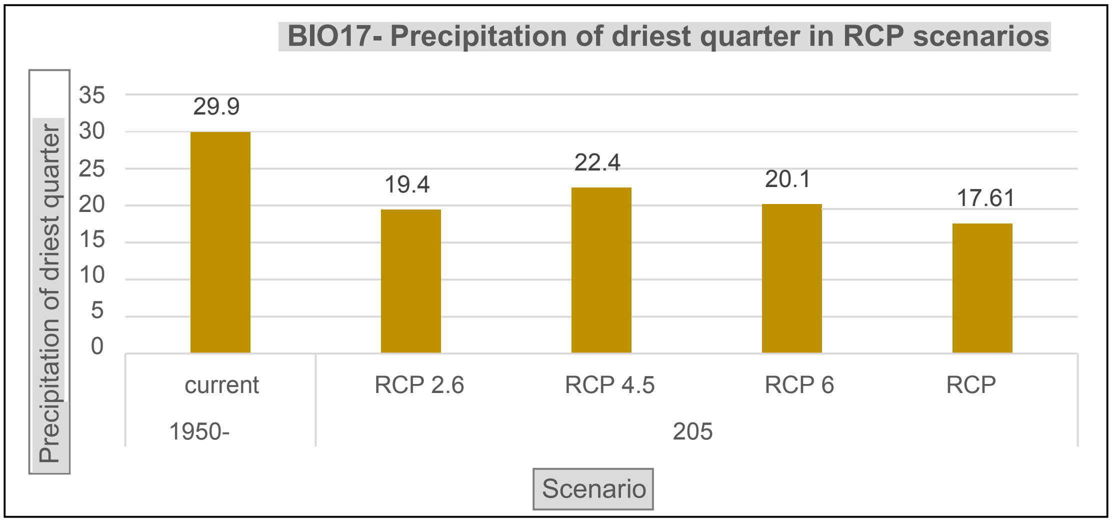


Figure 8. Variability of Precipitation seasonality (BIO15) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

(a)



(b)

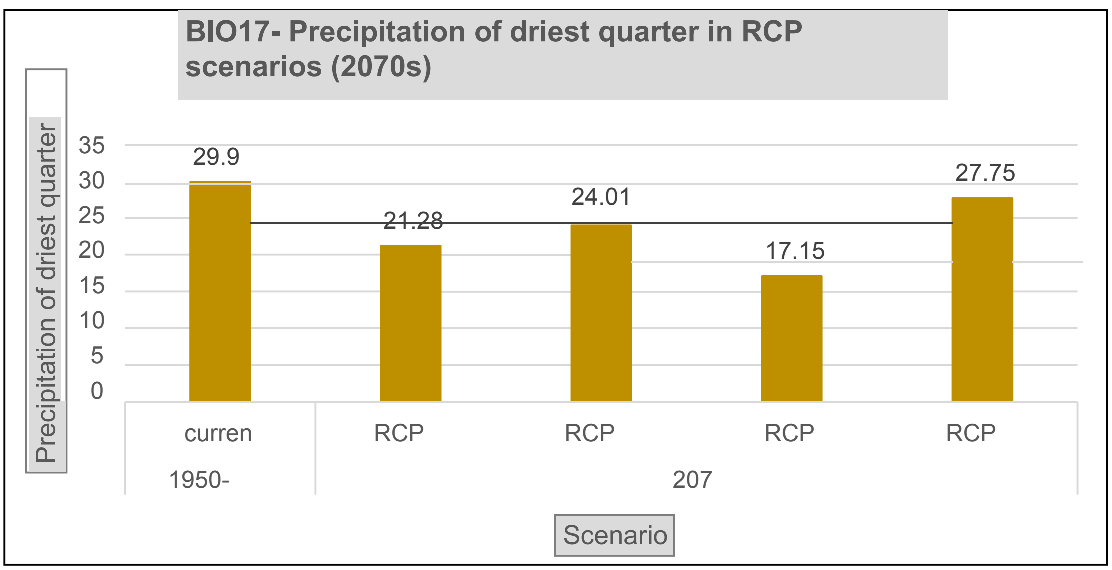
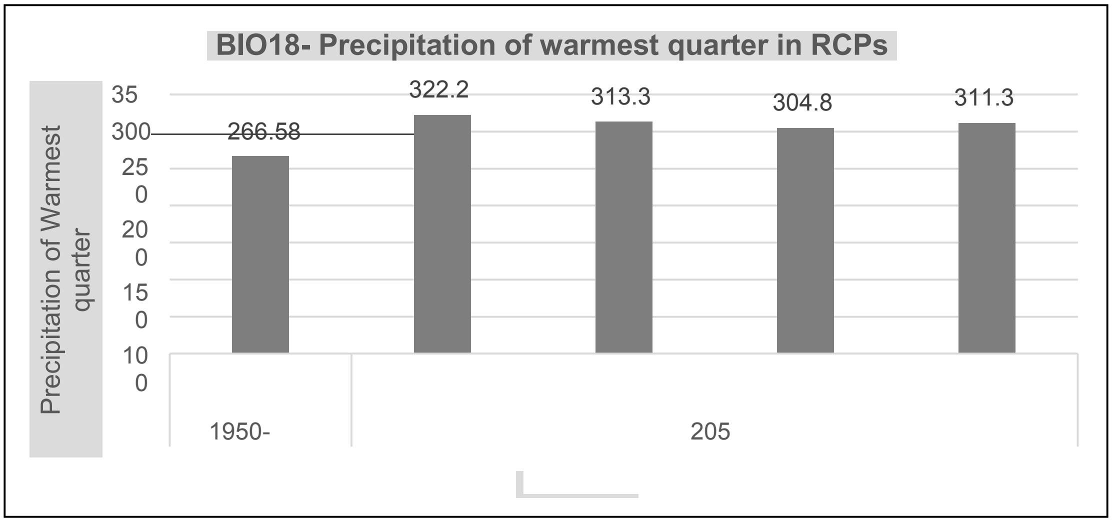


Figure 9. Variability of Precipitation of driest quarter (BIO17) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

(a)



(b)

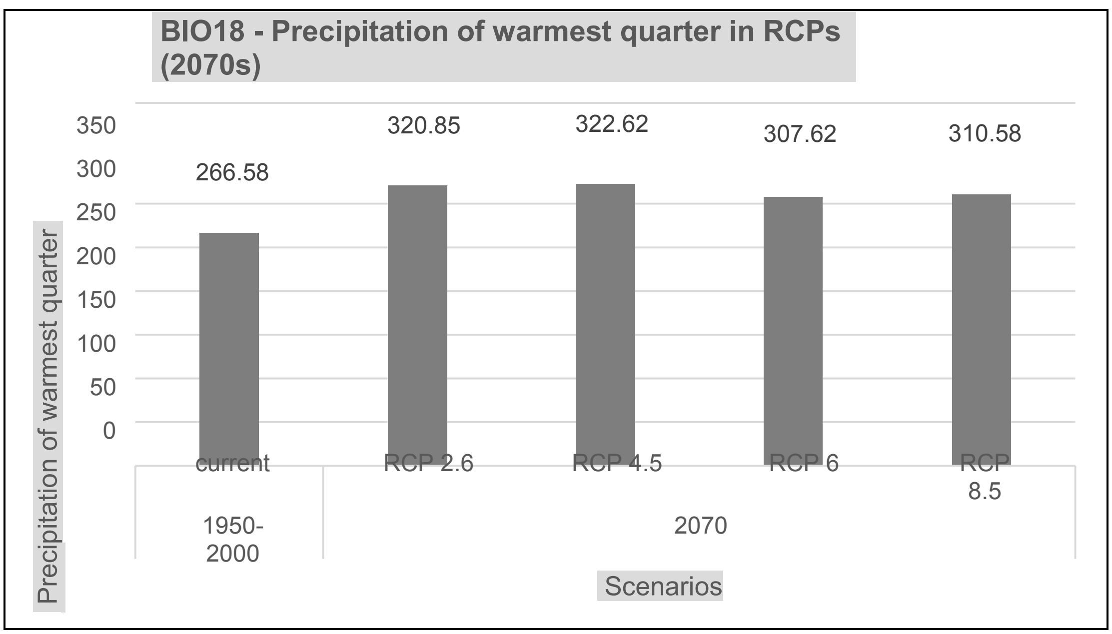


Figure 10. Variability of Precipitation of warmest quarter (BIO18) for the current scenario and all the four RCP scenarios in Wayanad, (a). for the near future of 2050s, (b). for the far future of 2070s

4.2. Model Optimization

The model settings were determined using the ENMeval script in R programming language. Accordingly, the MaxEnt model was run with the combination of model features Linear, Quadratic, Hinge and Product (L, Q, H, P) and a regularization multiplier value of four and with 10000 maximum background points obtained from the output of ENMeval algorithm using R software as given in Table 4. The selected random test percentage was 25 and replicated run type as subsampling and with 10 replicates were fed into the MaxEnt model 3.4.4.

Table 3. Optimization of Model tested using ENMeval algorithm and model settings chosen by the criteria of least delta AIC (Akaike Index Criterion)

Features	**Regularization Multiplier**	**Train AUC**	**Average Test.AUC**	**Delta AIC**
LQHP	3	0.92	0.89	2.71
LQHPT	3	0.92	0.89	5.48
L	3.5	0.89	0.87	14.50
LQ	3.5	0.89	0.87	15.55
H	3.5	0.91	0.89	107.63
LQH	3.5	0.90	0.88	7.09
LQHP	3.5	0.92	0.89	7.57
LQHPT	3.5	0.92	0.89	21.49
L	4	0.89	0.87	16.04

LQ	4	0.89	0.87	19.50
H	4	0.91	0.89	112.52
LQH	4	0.90	0.88	10.56
LQHP	4	0.91	0.89	0
LQHPT	4	0.92	0.89	1.80
L	0.5	0.89	0.87	16.41
LQ	0.5	0.90	0.88	28.99
H	0.5	0.95	0.90	NA
LQH	0.5	0.95	0.90	NA
LQHP	0.5	0.95	0.90	NA
LQHPT	0.5	0.98	0.90	NA
L	1	0.89	0.87	12.90
LQ	1	0.90	0.88	11.64
H	1	0.93	0.90	1401.26
LQH	1	0.93	0.89	787.92
LQHP	1	0.94	0.90	5569.17
LQHPT	1	0.95	0.90	2601.75
L	1.5	0.89	0.87	11.74

L- linear; H- hinge; Q- quadratic; P- product; and T- threshold.

4.3. Variable contribution to the current model distribution of *Senna spectabilis*

Assessing the cross-correlation analysis (Pearson correlation coefficient test) and the percentage contribution of each variable in the distribution of *S. spectabilis*, the most significant variables observed to influence the spatial distribution of *S. spectabilis* were Isothermality (BIO3), Elevation, Annual Mean Temperature (BIO1), Slope, landcover, Distance from the road, Temperature Seasonality (BIO4), Mean Diurnal Temperature (BIO2), Precipitation of warmest quarter (BIO18), Precipitation seasonality (BIO15), Temperature seasonality (BIO4), Precipitation of driest quarter (BIO17) and Distance from water bodies. The cumulative contribution of these variables were 98%. Soil type, NDVI, Aspect and population density contributed only 1.7%, which was negligible compared to other variables. Isothermality was the most influencing variable when taken in isolation whereas, Population density was the least influencing variable (Table. 4)

Table 4. Contribution and permutation importance of all the environmental variables to current distribution model of *S. spectabilis*

Variables	**Percent contribution**	**Permutation importance**
Isothermality (BIO3)	37.4	1
Elevation	20.8	15.7
Annual Mean Temperature (BIO1)	7.8	10.1
Slope	6.4	4.2
Landcover	6	0.8
Distance from road	4.3	17
Precipitation of warmest quarter (BIO18)	3.9	19.3

Precipitation seasonality (BIO15)	3.6	6.2
Temperature seasonality (BIO4)	3.3	0.1
Precipitation of driest quarter (BIO17)	2.7	3.9
Distance from water bodies	2.1	16.6
Aspect	0.6	1.7
Soil type	0.5	0.5
NDVI	0.5	2.8
Population density	0.1	0.1

From the Table 4. The temperature variables (BIO3, BIO1) contributed more than precipitation variables (BIO18, BIO15, BIO17) in the distribution of *S. spectabilis.* Distance from road has a contribution of 4.3% than distance of water bodies which is only 2.1% to the distribution of *S. spectabilis*. The highest permutation importance is observed for the bioclimatic variable precipitation of warmest quarter (19.3), followed by aspect and distance from road (17). Nevertheless, isothermality variable which has the showed the highest percent contribution to distribution of the invasive species, showed least permutation importance.

4.3.3. Model Sensitivity Analysis using Jack-knife test

The Jack-knife test gain describes how important each variable is based on the 'gain' in the model with its inclusion. The Jack-knife test gain identified Isothermality (BIO3), Precipitation of warmest quarter (BIO18), Annual Mean Temperature, Slope, Distance from the road as the most important environmental variables for predicting the potential habitat suitability of *S. spectabilis* in the Wayanad study area.

The Jack-knife results (Figure. 11) indicates that the environmental variable with the highest gain, when used in isolation, was BIO3 (Isothermality), which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is Distance from road, which therefore appears to have the most information that isn't present in the other variables. Test gain values given (Table. 5) are averages over replicate runs when taken in isolation. BIO3 (Isothermality), BIO18 (Precipitation of warmest quarter), BIO1 (Annual mean temperature), Elevation showed a gain greater than 1.0 whereas, Distance from water bodies showed a gain lesser than 0.1. Population density, Precipitation of Driest Quarter (BIO17), Precipitation seasonality (BIO15), Temperature seasonality (BIO4) showed a gain greater than 0.5.

Table 5. Test gain values of contributing variables when taken in isolation obtained from the results of Jackknife test of variables in MaxEnt modelling for the distribution of *S. spectabilis* in Wayanad

<table>
<tr><td rowspan="9">Test gain of variables in isolation</td><th>Variables</th><th>Test gain</th></tr>
<tr><td>Isothermality</td><td>1.79</td></tr>
<tr><td>Precipitation of warmest quarter</td><td>1.37</td></tr>
<tr><td>Annual mean temperature</td><td>1.25</td></tr>
<tr><td>Elevation</td><td>1.19</td></tr>
<tr><td>Population density</td><td>0.91</td></tr>
<tr><td>Precipitation of driest quarter</td><td>0.84</td></tr>
<tr><td>Precipitation seasonality</td><td>0.68</td></tr>
<tr><td>Temperature seasonality</td><td>0.65</td></tr>
</table>

	Landcover	0.37
	Soil type	0.33
	Slope	0.19
	NDVI	0.16
	Distance from road	0.16
	Aspect	0.13
	Distance from water bodies	0.01

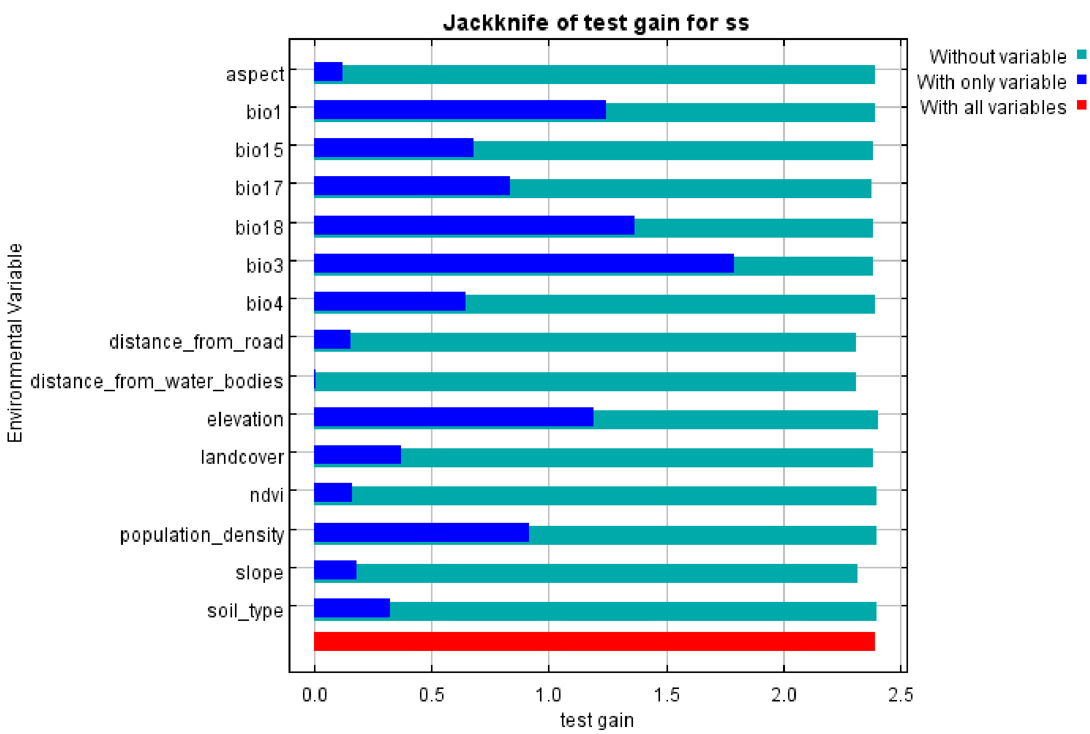


Figure 11. Results of Jackknife test showing the influence (test gain) of each environmental variable relative to all environment variables in the MaxEnt modelling of the current distribution of *S. spectabilis* in Wayanad using selected variables

Table 6. Test data AUC values of variables when taken in isolation obtained from the results of Jackknife test of variables in MaxEnt modelling for the distribution of *S. spectabilis* in Wayanad

Variables	**Test data AUC**
Isothermality	0.93
Precipitation of warmest quarter	0.91
Annual mean temperature	0.91
Elevation	0.90
Population density	0.90
Precipitation of driest quarter	0.85
Precipitation seasonality	0.80
Temperature seasonality	0.81
Landcover	0.72
Soil type	0.71
Slope	0.69
NDVI	0.67
Distance from road	0.68
Aspect	0.64
Distance from water bodies	0.57

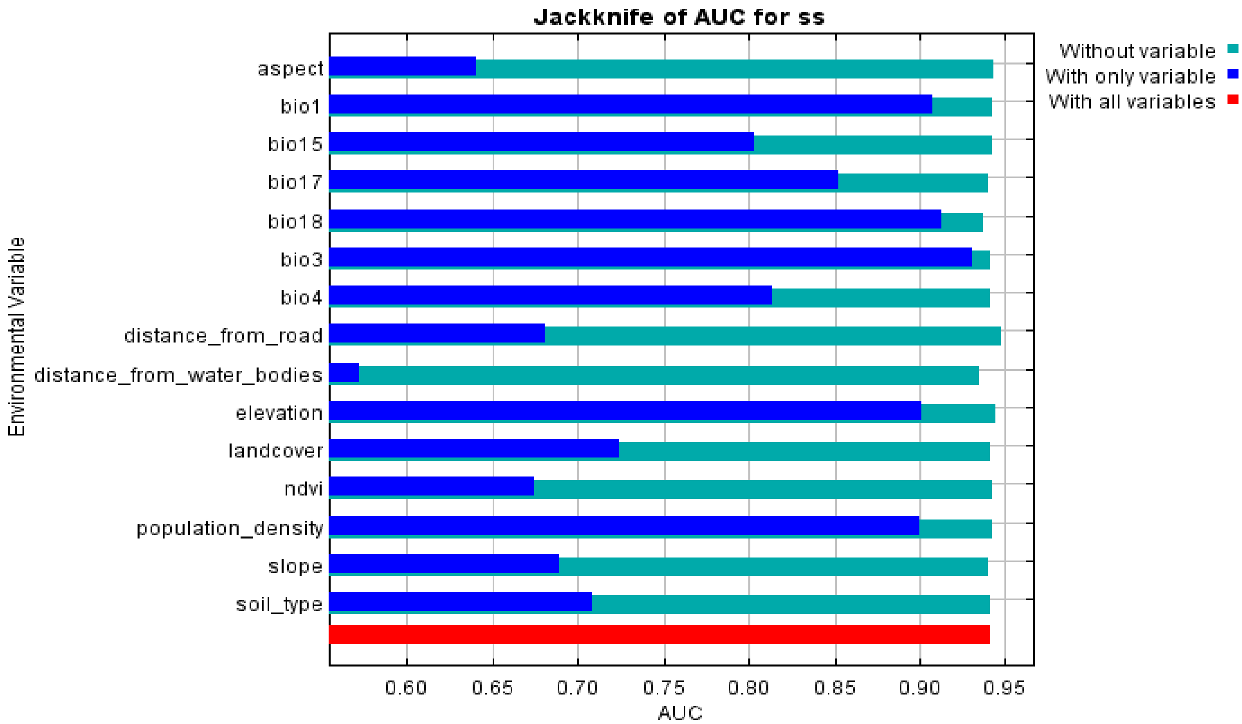


Figure 12. Results of Jackknife test showing the influence (AUC) of each environmental variable relative to all environment variables in the MaxEnt model current distribution of *S. spectabilis* in Wayanad

The results of jackknife test using test data AUC is given in Figure 11. and the AUC values are given in Table 7. Isothermality (BIO3) variable in isolation showed a model AUC value with 0.93. AUC of test data value is observed to be same when precipitation of warmest quarter (BIO18) and annual mean temperature (BIO1) is in isolation. Similarly, elevation and population density showed same AUC value of test data when these are in isolation. AUC of test data with only distance water bodies is negligible with 0.57.

The response curves (Figure 13.) obtained also indicated the influence of each environmental variable on the distribution of the invasive species graphically. Each of the following response curves represents a different model, namely, a MaxEnt model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables. The variables which showed a positive response in favour of the distribution at a particular location when the values were increased were BIO15 (Precipitation seasonality), BIO4 (Temperature seasonality), BIO1 (Annual Mean Temperature), BIO17 (Precipitation of driest quarter), elevation, NDVI and Landcover. Distance from the Water bodies, Distance from the road, BIO3 (Isothermality), Aspect, Population density, BIO18 (Precipitation of the warmest quarter) lowered the chance of potential distribution of *S. spectabilis* in the study area when the values were increased. Some variable like Soil Type showed no significant change to the survival of the species. The response curves created using only the corresponding variable are depicted in Figure 13.

The analysis of the response curves using only the corresponding variables is given below. These curves show how each environmental variable affects the MaxEnt prediction.

4.3.3. Annual mean temperature (BIO1)

When the annual mean temperature (BIO1) increased (>22.5^{o}C), the probability of the occurrence of the *S. spectabilis* decreases gradually to absence (Figure 13.b). The response of the species to annual mean temperature increased gradually when the temperature range was in between 14^{o} C – 22.5^{o} C. In addition, when the annual mean temperature (BIO1) was at 22.5^{o} C, the probability of the occurrence of the *S. spectabilis* was at the peak. The probability distribution showed no change when the annual mean temperature is below 14^{o} C. The similar pattern of two troughs and a peak is shown by response curves of precipitation of driest quarter (BIO17) (Figure 12.e), elevation (Figure 12.g), population density (Figure 13.j), NDVI (Figure 13.k), landcover (Figure 13.l), slope (Figure 13.i).

4.3.4. Isothermality (BIO3)

When the isothermality (BIO3) was in the range 55 to 57, the probability of presence for the *S. spectabilis* was greater than 90 percent, however, response of species to BIO3 remains constant. There was a gradual decrease in the probability of presence for the species when the isothermality increased from 58 to 67 and then no change. The response curve (Figure 13.a) showed a negative J-shaped curve which is similar to response curve of species to precipitation of warmest quarter (BIO18), shown in Figure 13.f) and also other non-climatic variables; distance from road (Figure 13.m), distance from water bodies (Figure 13.n).

4.3.5. Temperature seasonality (BIO4)

The probable presence of *S. spectabilis* increased with the increase in the temperature seasonality (BIO4). The probable presence of *S. spectabilis* was highest when temperature seasonality (BIO4) was at the range of 165° C. At less than 90 and greater than 165° C, the probability of presence for the *S. spectabilis* was constant. The response curve (Figure 13.c), is a J-shaped curve and the similar pattern in response curve is showed by precipitation seasonality (BIO15) (Figure 13.d).

4.3.6. Precipitation of the driest quarter (BIO17)

The precipitation of the Driest Quarter affects model prediction as the species distribution escalated when BIO14 rises above 15mm – 23mm, also the maximum probability of presence for the *S. spectabilis* (90%) when BIO17 is at 23mm. Followed by a sudden fall in distribution and a gradual decrease showed in Figure 13.e), from 50mm to 216mm where the distribution declined. The probability occurrence of *S. spectabilis* showed a narrow range between 15mm to 50mm precipitation in driest quarter (BIO17).

4.3.7. Precipitation of warmest quarter (BIO18)

The highest distribution of *S. spectabilis* is observed (100%) when the precipitation of warmest quarter (Figure 13.f) was in the range of 130mm – 200mm. On reaching 200mm, the probable distribution of the invasive species slowly decreased to no change when reaching 400mm. Precipitation of warmest quarter showed an inverted J-shaped curve similar to BIO3 (Isothermality), aspect, distance from road and distance from water bodies.

4.3.8. Precipitation seasonality (BIO15)

The probability occurrence of *S. spectabilis* was observed to be 95% when precipitation seasonality has value of 143 (Figure13.d). The response curve followed a J-shaped curve and when BIO15 is between the range of value 40 – 90, a lower presence of the species is observed (15%) that remains constant. The distribution is then gradually increased beyond the precipitation seasonality value of 90 upto 143. Subsequently, the response curve remained constant upto the value 152.

4.3.9. Slope

The probable presence for the *S. spectabilis* was found to gradually increase upto 89m, followed by a sudden acceleration in distribution upto 74% where the species distribution is at its peak (Figure 13.i). Subsequently, a sudden drop in distribution (20%) on reaching 90m followed by no change in distribution upto 100m.

4.3.10. Aspect

A negative response of aspect to *S. spectabilis* was observed, When the aspect was 400m, the chance of occupancy of *S. spectabilis* was comparatively less (50%). The response curve showed a higher species presence when the aspect is negative (Figure 13.h). A decline in occupancy was seen when the aspect range is between 0 – 200.

4.3.11. Landcover

When the landcover was deciduous forest or degraded/Scrub Forest, the presence of *S. spectabilis* was highest (>0.75) (Figure 13.l). The potential distribution of *S. spectabilis* in the agricultural land was 50%. The plantation landcover had a chance of distribution greater than agricultural land. The potential distribution of *S. spectabilis* decreased in Littoral Swamp, Shifting Cultivation, Barren area, Snow Cover, Waterbodies however, the chance of potential distribution is higher.

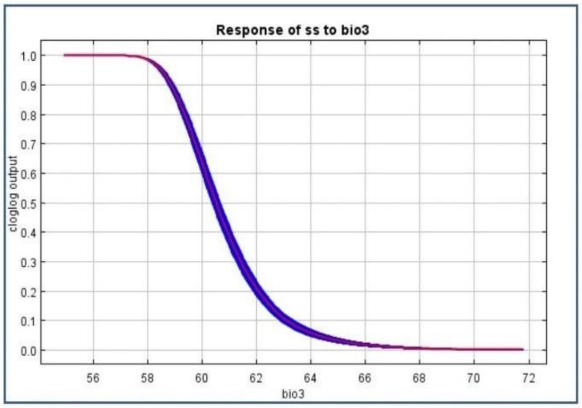
4.3.12. Soil type

S. spectabilis had a higher potential of occurrence in the forest soils, Black soils, Laterite plateau, Marayur soils, soils of Wayanad uplands, Upland soils of Palakkad central plain, lowland soils of Palakkad central plain and Poonthal padam soils of Palakkad eastern plain (>70%). The other soil types such as Gravelly laterite, Red soils, Brown hydromorphic soils, Riverine alluvium, Coastal alluvial oils, Coastal sandy soils, Onattukara sandy soils remained constant and had a probable positive response by *S. spectabilis* (40% chance of occupancy) which is given in Figure 13.O.

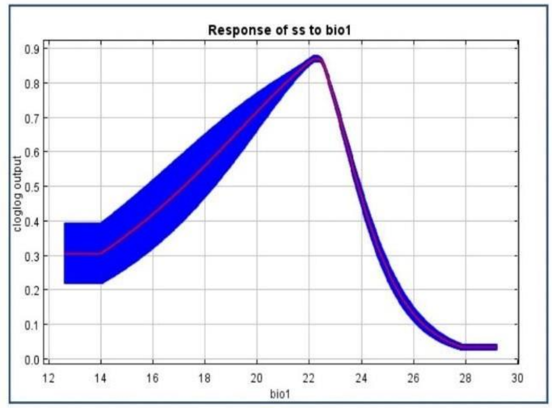
4.3.13. Other dynamic variables

Variables such as distance from water bodies (Figure 12.n), distance from the road (Figure 12.m), NDVI (Figure 12.k), population density (Figure 12.j) also had a role in the probability of distribution of the *S. spectabilis*. The potential distribution of *S. spectabilis* decreased significantly with the increase in distance from water bodies and distance from the road. Response of *S. spectabilis* remained constant when population density increased above 1000 persons per km^2. The probable presence of the species was at its peak (85%) when the population density is 500 persons per km^2. When normalized difference vegetation index (NDVI) increased ($> 1*10^6$), the potential distribution of the species decreased. There is a 40-75% chance of occupancy of the invasive species when the index value is below $1*10^6$.

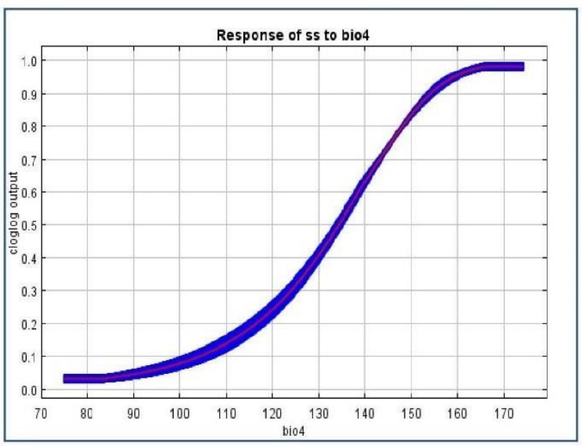
(a)


Response of ss to bio3
cloglog output
bio3

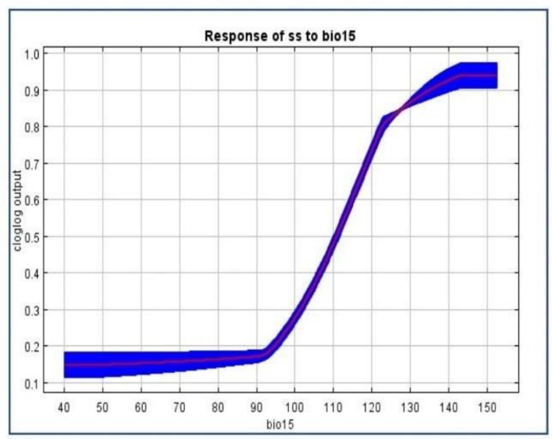
(b)


Response of ss to bio1
cloglog output
bio1

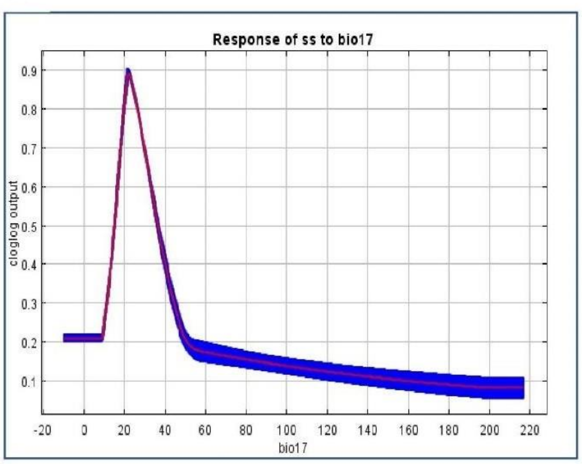
(c)


Response of ss to bio4
cloglog output
bio4

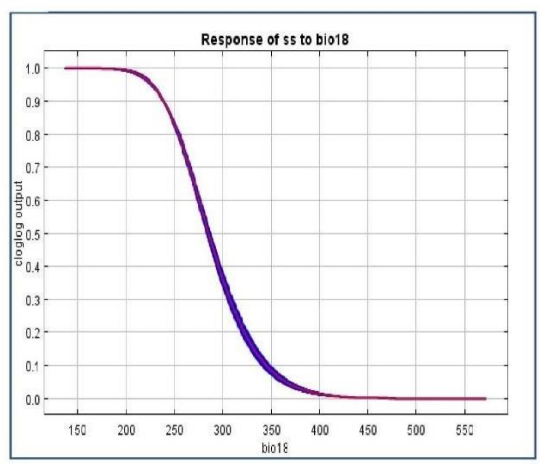
(d)


Response of ss to bio15
cloglog output
bio15

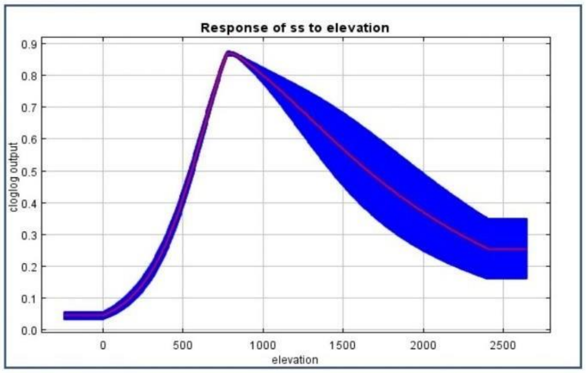
(e)


Response of ss to bio17
cloglog output
bio17

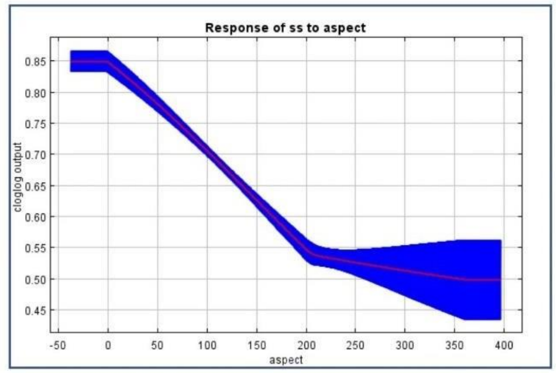
(f)


Response of ss to bio18
cloglog output
bio18

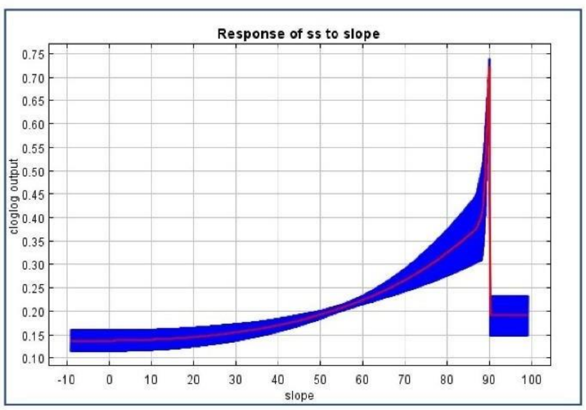
(g)


Response of ss to elevation
cloglog output
elevation

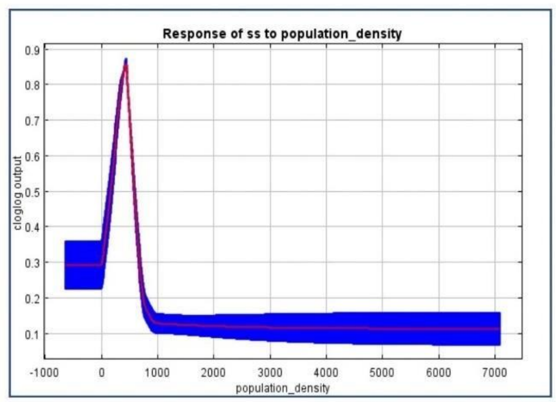
(h)


Response of ss to aspect
cloglog output
aspect

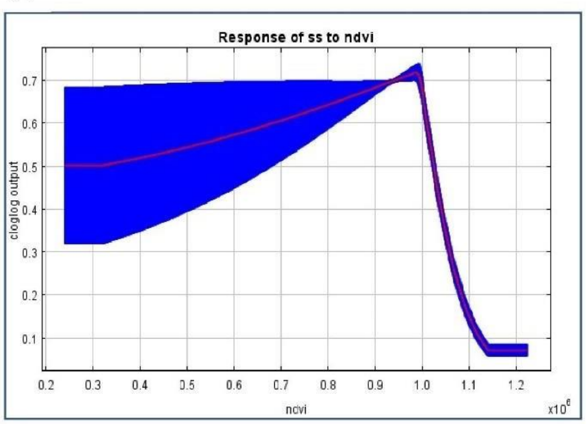
(i)


Response of ss to slope
cloglog output
slope

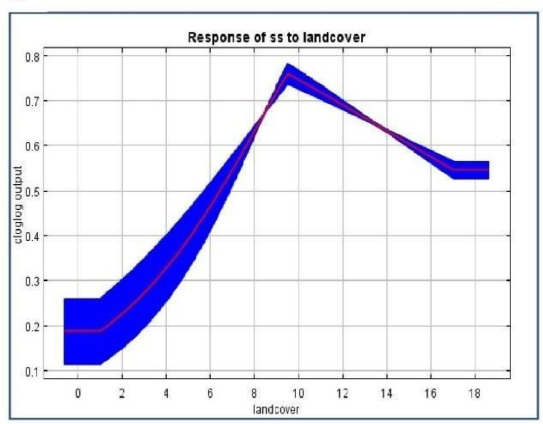
(j)


Response of ss to population_density
cloglog output
population_density

(k)


Response of ss to ndvi
cloglog output
ndvi

(l)


Response of ss to landcover
cloglog output
landcover

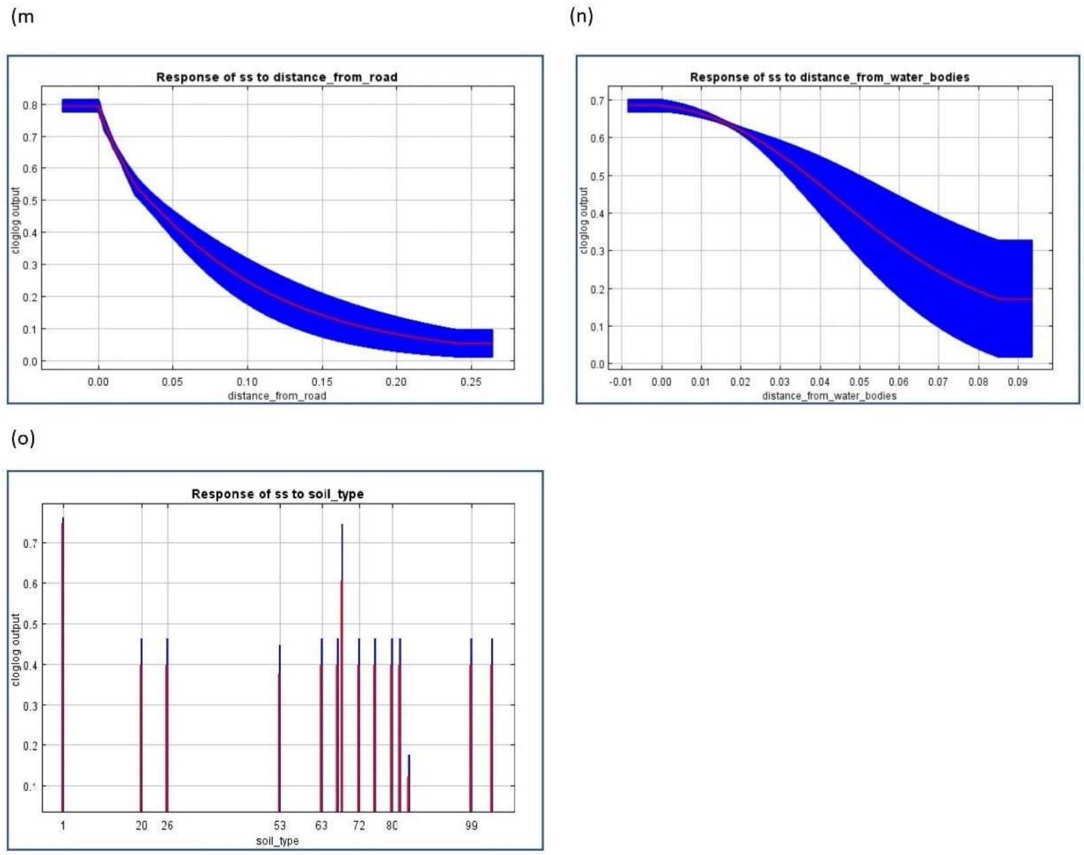


Figure 13. Response curves of variables in determining the distribution of the *S. spectabilis* MaxEnt modelling, (a). Isothermality (BIO3), (b). Annual mean temperature (BIO1), (c). Temperature seasonality (BIO4), (d). Precipitation seasonality (BIO15), (e). Precipitation of driest quarter (BIO17), (f). Precipitation of warmest quarter (BIO18), (g). Elevation, (h). Aspect, (i). Slope, (j). Population density, (k). NDVI, (l). Landcover, (m). Distance from road, (n). Distance from water bodies, (O). Soil type

4.4. Model Performance

The model output obtained was then assessed for its accuracy. Area Under Curve (AUC), True Skill Statistics (TSS), Sensitivity and Specificity were used for measuring the model performance of the current potential distribution in the study area and are shown in Table 7. below.

Table 7. Model Performance of current potential distribution of *S. spectabilis* in Wayanad using independent and dependent thresholds (AUC, TSS)

ACCURACY METRICS	**VALUES**
Training AUC	0.96
Test AUC	0.94
TSS value	0.83
AUC Standard Deviation	0.02
Overall accuracy	0.96
Sensitivity	0.86
Specificity	0.96

The accuracy metrics given in Table 8. showed that the MaxEnt model has a good performance with test AUC value 0.94 and TSS value 0.83. Furthermore, an overall accuracy of 0.96 value was showed, similarly the specificity value. Sensitivity of the model is 0.86 and showed standard deviation of 0.02. This explained that the model has a good performance.

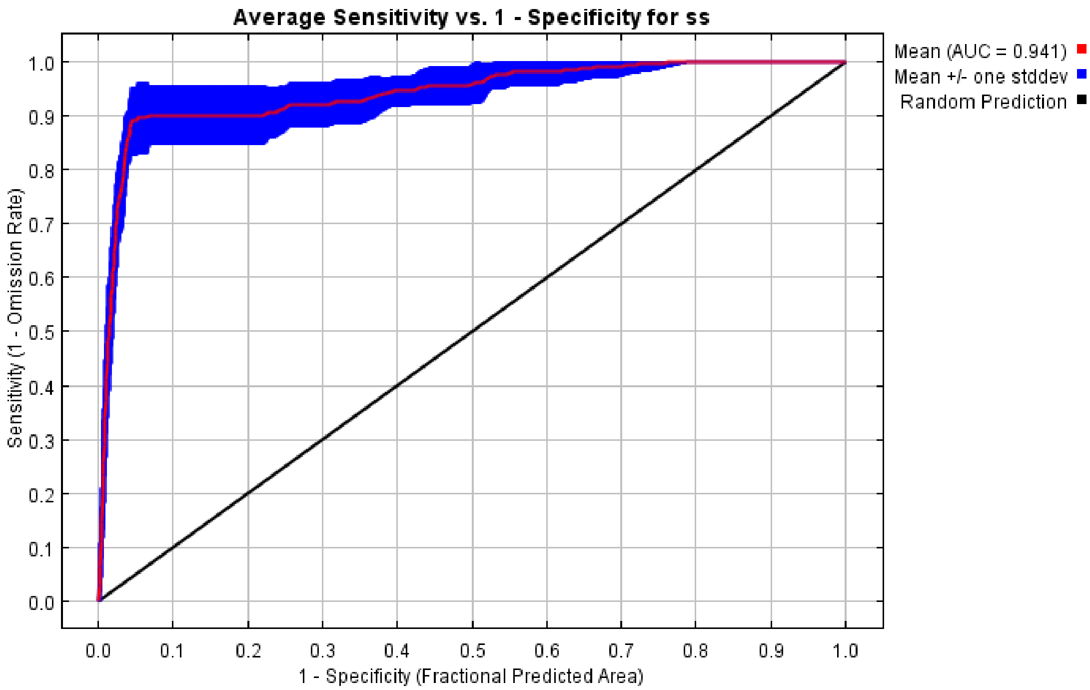


Figure 14. Receiver Operating Characteristic (ROC) curve for *S. spectabilis* averaged over the replicate runs for the current potential distribution MaxEnt modelling in Wayanad

Receiver Operating Characteristic (ROC) curve given in Figure 13. showed that there is a good fit of model to the testing data. Considering only the presence data and no absence data, fractional predicted area (x-axis) is used instead of more standard commission rate (fraction of absences predicted present). In addition, in Figure.14, the AUC line passes through the left top of the random prediction.

The omission rate and predicted area of the test data average over the 10 replicate runs is given in Figure 15. The omission on test samples (blue line) showed a very good match to the predicted omission (black line) although, the predicted omission rate is a straight line. The test omission line is observed to be well below the predicted omission line considering the test data (75%) and training data (25%) are not independent.

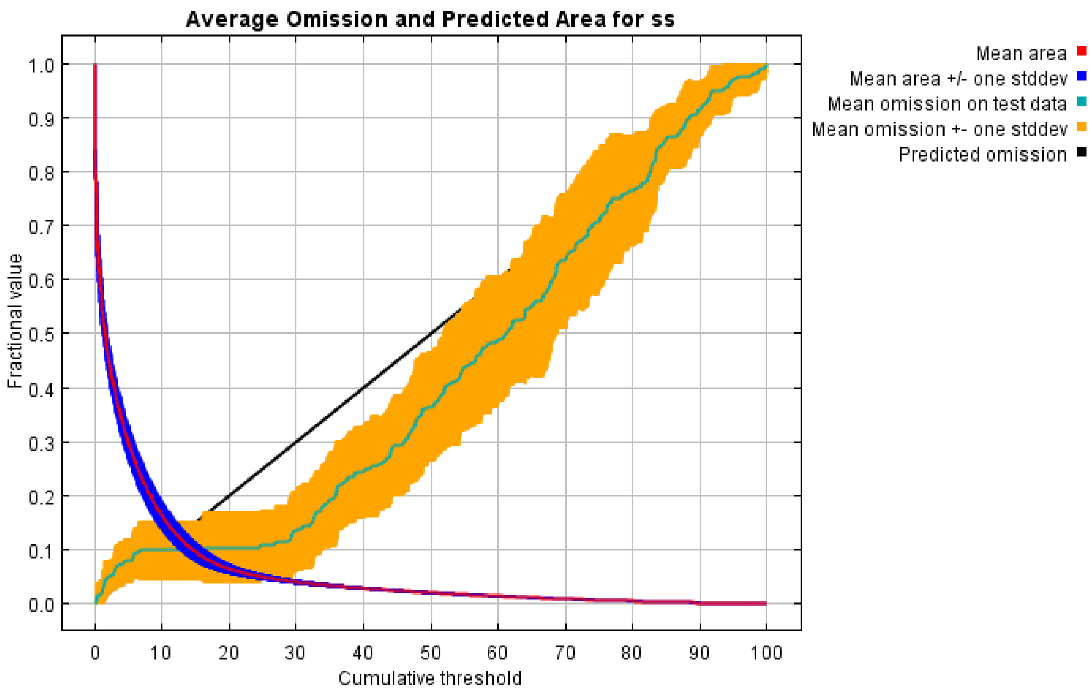


Figure 15. Test omission rate and predicted area for *S. spectabilis* in the current distribution as a function of the cumulative threshold, averaged over the replicate runs for the current potential distribution MaxEnt modelling in Wayanad

4.5. Current suitable habitat distribution of *S. spectabilis*

The currently suitable habitat of invasive alien tree species *S. spectabilis* based on the presence records as given by the MaxEnt model is given in Figure 15.

The MaxEnt output ASCII files were reclassified using ArcGIS ver.10.7.1 ESRI to obtain a logistic distribution which was then converted to binary raster for the easy interpretation of suitable and unsuitable areas based on the '*max SSS'* logistic threshold (0.52) obtained from the MaxEnt output. Out of 2364 km^2 total area, 1572 km^2 (66%) is suitable for *S. spectabilis* and the remaining 821 km^2 (34%) area is found unsuitable for its distribution. The logistic output is shown in Figure 16.

The area is classified into low suitability areas with 344 km^2 (0 – 0.2), 249 km^2 with moderate suitability (0.2 – 0.4) potential, 428 km^2 with a good suitability potential (0.4 – 0.6), high suitability potential class (0.6 – 0.8) with 572 km^2 area and very high suitability potential (0.8 – 1) area consisted about 800 km^2 for the invasive species *S. spectabilis.* The majority of very high suitability areas were distributed in the North-eastern and South-eastern parts of Wayanad. The current distribution consisted high and very high suitability areas in Tholpetty, Wayanad wildlife sanctuary, Appapara, Panavally, Irumbupalam, Kattikulam, Kuruva island, Kyasapura, Payyampally, Palvelicham, Thrishilery, Oorpally, Mananthavady, Nalloornad, Naalammile, Koolivayal, Neervaram, Pakkom, Padichira, Mullenkolly, Pulpally, Kelakkavala,Chethalayam, Kidanganad, Ottapalam, Kerala – Karnataka border, Muthanga, Muthanga Forest Range, Mathamangalam, Sulthan Bathery, Noolpuzha, Cheeral, Pazhoor, Nenmini, Chulliyode, Karachal, Muttil, Meenangadi, Purakkadi, Vakery, Kenichira, Poothadi, Bathery, Paralikunnu, Kalpetta, Chundale, Pozhithane, Vythiri, Kunnampetta, Puthurvayal, Pinangode, Vellamunda, Mattilayam, Korome, Tindumal. Furthermore, looking into the landcover of Wayanad (Figure.16), the majority of high and very high suitability areas were covered in deciduous forests, degraded/scrub forests, plantation areas, barren areas/ wasteland areas and in built up areas.

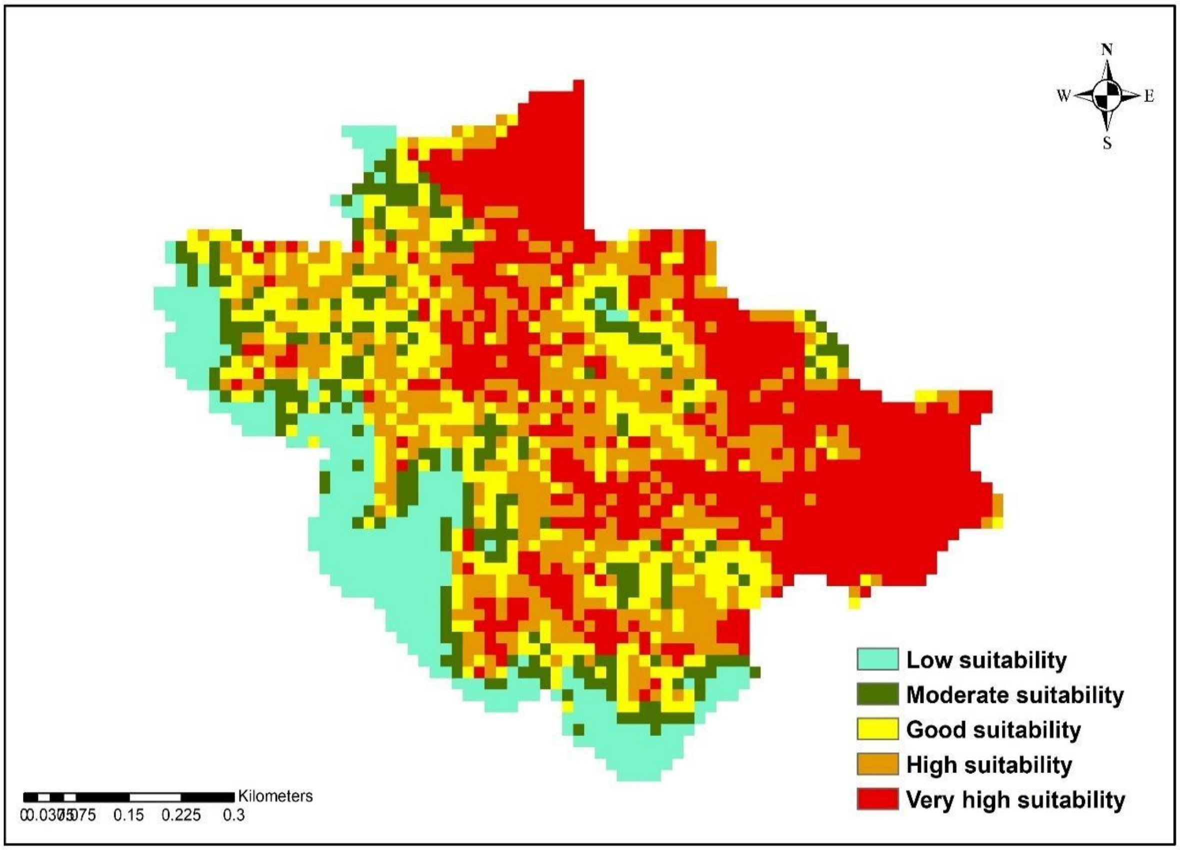


Figure 16. The logistic output and the potential distribution MaxEnt modelling of *S. spectabilis* in Wayanad district under current climatic conditions and occurrence data

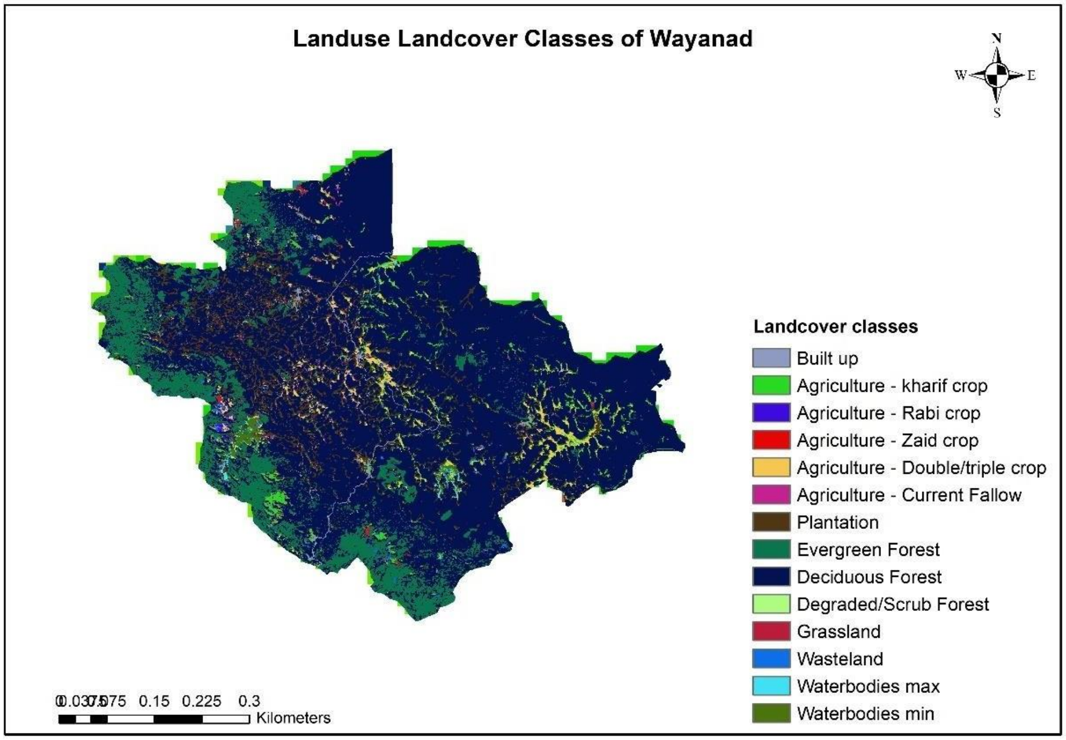


Figure 17. Landuse landcover classes of Wayanad district

4.6. Future suitable habitat of *S. spectabilis* and impact of climate change in Kerala

4.6.1. Variable contribution to the future potential distribution model of *S. spectabilis*

In the current scenario, the Isothermality (BIO3) variable has the greatest influence on the distribution of *S. spectabilis* followed by elevation. Furthermore, the Annual Mean Temperature (BIO1) showed a greater contribution however, in RCP 2.6 and RCP 6 in the distant future showed a percentage contribution lesser than Slope, which is the fourth most contributing variable. The least important variable was Aspect which showed negligible contribution. The comparison of the variable influence between current and different RCP scenarios in both 2050 and 2070 (Figure.18, 19) indicates the variation of the variable influence for the distribution of *S. spectabilis* with climate change. The influence of Isothermality (BIO3) increased in all the RCPs of both the time periods 2050s and 2070s in comparison with current scenario (37.4%) except RCP 6 2050s (37.1%) given in Table 8. Similarly, an increase in the contribution of elevation variable is showed (Table 9.) except RCP 4.5 2070s (18.6). Annual mean Temperature (BIO1) showed an increased contribution to the distribution of *S. spectabilis* except 2.6 2070s (7.1%). Slope and Precipitation of warmest quarter (BIO18) had a great contribution in all the RCP scenarios in both the time periods compared to the current scenario. Temperature seasonality (BIO4) showed a lesser contribution compared to current scenario except RCP 6 scenario in both the near and distant future. Precipitation of driest quarter (BIO17) had an increased influence in distribution of the species except RCP 2.6 and RCP 6 scenario in 2070s. Additionally, Precipitation seasonality (BIO15) had an increased contribution except RCP 4.5 and 2070s RCP 2.6. All the selected bioclimatic variables showed a significant influence to the distribution of *S. spectabilis* in Wayanad.

Table 8. A comparison between the influence of selected bioclimatic variables under the current climate scenarios and all RCP scenarios on the potential distribution of *S. spectabilis*

		RCP 2.6		**RCP 4.5**		**RCP 6**		**RCP 8.5**	
Variables	**Current**	**2050**	**2070**	**2050**	**2070**	**2050**	**2070**	**2050**	**2070**
	(in percentage)								
BIO3 (Isothermality)	37.4	42.2	39	39.9	43	37.1	44	41.8	39.1
Elevation	20.8	22.2	27.4	23.9	18.6	23.6	22.9	24.2	19.3

BIO1(Annual Mean Temperature)	7.8	11.2	7.1	10.6	12.9	10.5	8	10	14.7
Slope	6.4	10.6	10.1	10.2	10.7	9.7	9	10	10.4
BIO18 (Precipitation of warmest quarter)	3.9	5.3	4.5	4.8	4.9	7.4	4.9	3.9	6.4
BIO4 (Temperature Seasonality)	3.3	2.9	3.2	2.9	2.7	3.6	4.1	2.9	2.5
BIO17 (Precipitation of Driest Quarter)	2.7	2.9	2.4	4.8	3.7	4.1	2.6	2.7	4
BIO15 (Precipitation Seasonality)	3.6	2.6	5.6	2.6	2.9	3.5	4	4.1	3.3
Aspect	0.6	0.1	0.8	0.3	0.6	0.4	0.5	0.4	0.2

The percentage contribution of Isothermality (BIO3) is observed to increase in both the near and distant futures RCP scenarios compared to current scenario. RCP 2.6 scenario showed an increased influence (42.2%) followed by RCP 8.5 scenario (41.8%) and RCP 4.5 scenario (39.9%). Although, the greenhouse gas concentration scenario in RCP 6 has the highest percentage contribution (49.9%) in 2050. An increased trend in contribution of the isothermality from the global warming of 2.6 watts /km^2 to 6 watts/km^2 compared to current scenario is given (Table.8) except RCP 8.5 (39.1%).

Figure 18. Bar diagram representing the variability in percentage contribution of the most important variable; Isothermality (BIO3) in current and future RCP scenario in 2050s

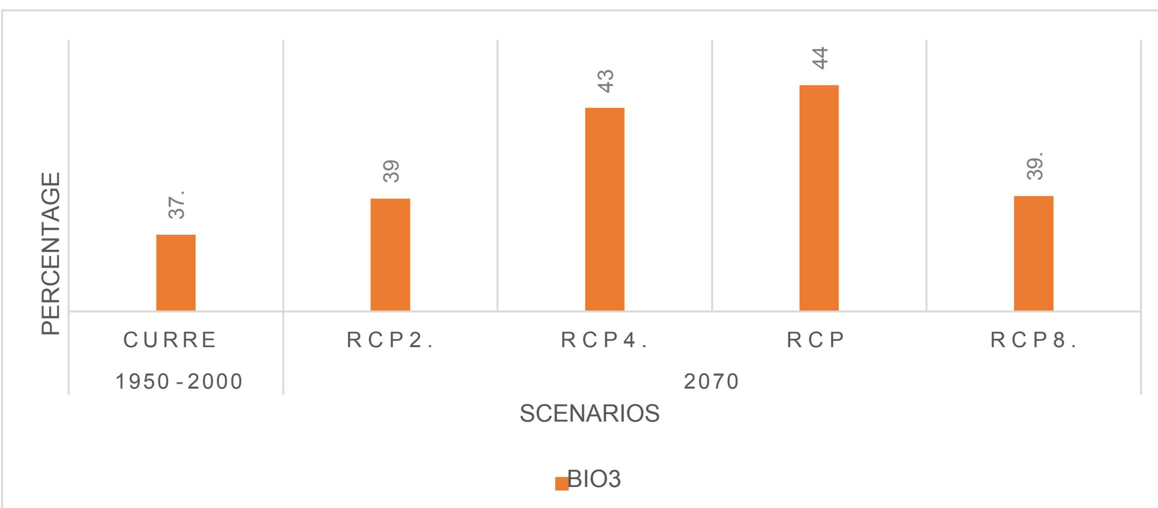


Figure 19. Bar diagram representing the variability in percentage contribution of the most important variable; Isothermality (BIO3) in current and future RCP scenario in 2070s

Table 9. Assessing the model Performance of future projection of *S. spectabilis* using independent and dependent thresholds (AUC, TSS) in Wayanad under RCP scenarios

	RCP 2.6		RCP 4.5		RCP 6		RCP 8.5	
Accuracy metrics	**2050**	**2070**	**2050**	**2070**	**2050**	**2070**	**2050**	**2070**
Training AUC	0.94	0.94	0.94	0.94	0.95	0.95	0.94	0.94
Test AUC	0.93	0.92	0.93	0.93	0.90	0.91	0.92	0.94
TSS value	0.79	0.80	0.80	0.81	0.82	0.80	0.79	0.82
AUC Standard Deviation	0.02	0.02	0.03	0.02	0.03	0.03	0.03	0.02
Overall accuracy	0.95	0.95	0.95	0.94	0.94	0.95	0.95	0.95
Sensitivity	0.83	0.85	0.85	0.86	0.87	0.85	0.83	0.87
Specificity	0.95	0.95	0.95	0.95	0.94	0.95	0.95	0.95

Model performance is explained by the dependent AUC metrics obtained from the MaxEnt modelling output and the independent TSS values given in Table 10. Considering the AUC values above 0.9 and TSS values above 0.78 in all the future RCP scenarios showed a good model performance. Additionally, the overall accuracy, sensitivity and specificity also explained a best model. Furthermore, the standard deviation of the MaxEnt future projection model is also in the range 0.02 – 0.03, showed less variations in mean AUC averaged over 10 replicate runs.

4.6.2. Distribution of *S. spectabilis* under RCP 2.6 scenario for 2050 and 2070

By 2050s, due to the rising global warming of 2.6 watts/km^2, the potentially suitable areas for *S. spectabilis* (1572 km^2) would be decreased by 31% (1077 km^2). A similar pattern was also observed in 2070s, with a decrease in the suitable area by 45% (862 km^2) compared to the current potential distribution. The logistic output of RCP 2.6 was shown in Figure 20. The low potential suitable areas for the invasive species (0 – 0.2) within Wayanad was 349 km^2 and 309 km^2 in 2050s and 2070s respectively. With the moderate suitable potential occurrence (0.2 – 0.4), there was a gain in the increase in the areas suitable for *S. spectabilis* by 26% and 23% in both 2050s and 2070s. Looking into good suitability class (0.4 – 0.6) (Table 10.) showed a significant increase in both the time periods 2050s and 2070s compared to the current suitability area (428 km^2). At a high suitability potential distribution class (0.6 – 0.8) by 2050s, the habitat suitability decreased by 7% and 22% by 2070s. Focussing on the very high suitability distribution class, about half of the suitability area is decreased in 2050s and a decrease of 62% (428 km^2) in 2070s scenario. The predicted distribution observed high (0.6 – 0.8) and very high habitat (0.8 – 1) suitability in parts of Bandipur wildlife sanctuary, Muthanga wildlife sanctuary, Mathamanagalam, Thotamoola, Puthenkunnu, Kazhambu, Pazhoor, Noolpuzha, Kuduki, Cheeral, Madakara, Chulliyode, Tharappel, Ponnamkolly, Narikkundu, Poomala, Sulthan Bathery, Kidanganad, Ottapalam, Valluvady, Chethalayam, Irulam, Padipura, Pulpally Bathery, Tholpetty wildlife sanctuary, Chekadi, Thirunelli temple road, Anjukunnu, Manjappara, Muttil, Ambalavayal, Thomaattuchaal, Naalammile.

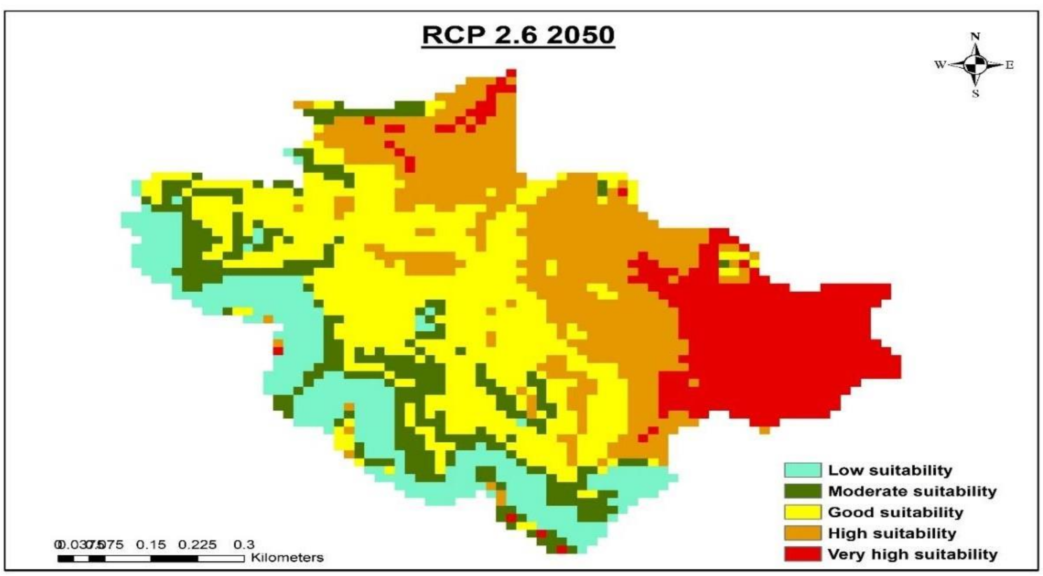


Figure 20. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 2.6 for the period 2050s

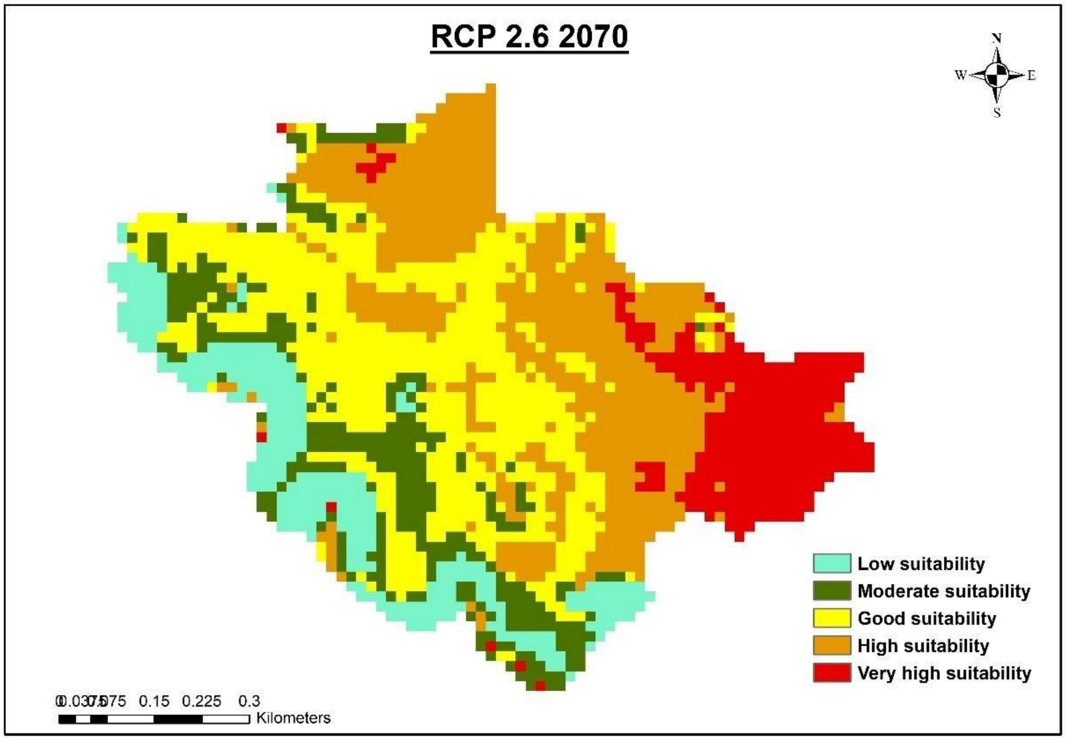


Figure 21. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 2.6 for the period 2070s

4.6.3. Distribution of *S. spectabilis* under RCP 4.5 scenario for 2050s and 2070s

The distribution of the *S. spectabilis* for the period 2050s and 2070s under the RCP 4.5 greenhouse gas concentration pathway is given in Figure 22. and Figure 23. There was a significant difference between the probability distribution of *S. spectabilis* under RCP scenario 4.5 in both 2050s and 2070s. There was a loss in suitability area in 2050s by 14% (1348 km^2) and in 2070s by 66% (532 km^2) compared to current habitat suitability (1572 km^2). The unsuitable area in both 2050s and 2070s was found to be 1047 km^2 and 1863 km^2. Low habitat suitability class in 2050s has a loss in suitability area by 12% (304 km^2) whereas, there is again in habitat suitability by 59% in 2070s. There was an enormous increase in the habitat suitability potential of *S. spectabilis* in 2070s

RCP 4.5 by 235% (835 km^2) than 2050s RCP 4.5 (363 km^2) when analysing the moderate suitability class (0.4-0.6). By focussing on the good habitat suitability class, there was a gain of suitable habitat area by 40% (599 km^2) in 2050s and by 46% (624 km^2) in the 2070s time period compared to the current distribution. The high suitability class (0.8 – 1) showed a gain in suitability by 14% in 2050s and a loss in suitability distribution by 36%. Nonetheless, the very high suitability class (0.8 – 1) exhibited a reduction in habitat suitability in both the near (2050s) and distant futures (2070s). The probable potential of very high habitat suitability was mainly observed in the north-eastern and south-eastern parts of Wayanad in both the Muthanga and Tholpetty wildlife sanctuary in both the 2050s and 2070s. In 2070s, the high habitat suitability in North and South-eastern parts contracted considerably compared to 2050s however, a good suitability is predicted in the eastern Wayanad (Figure. 23). The low suitability in the western Wayanad remained unchanged in 2050s and 2070s in comparison with current scenario. The very high suitability class (0.8 – 1) accounted 59% of the total habitat suitability in Wayanad in 2050s and observed 90% of it in South-eastern part including Muthanga wildlife sanctuary and parts of Bandipur wildlife sanctuary and Kerala Karnataka border. Whereas, only 3% of the total habitat suitability accounted for very high suitability areas, which is observed to be present in South-eastern parts of Wayanad; Muthanga and Cheeral regions.

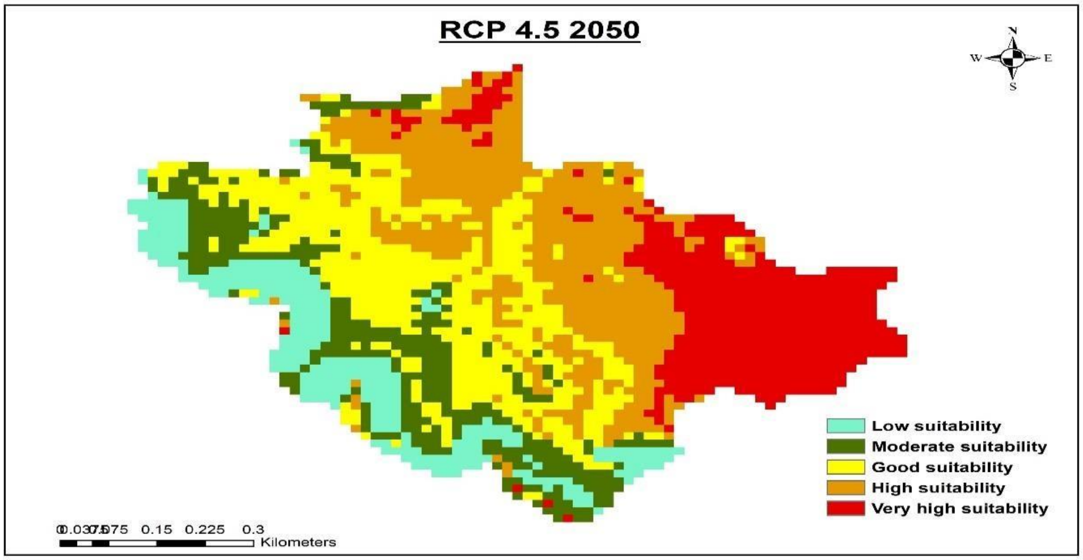


Figure 22. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 4.5 for the year the 2050s

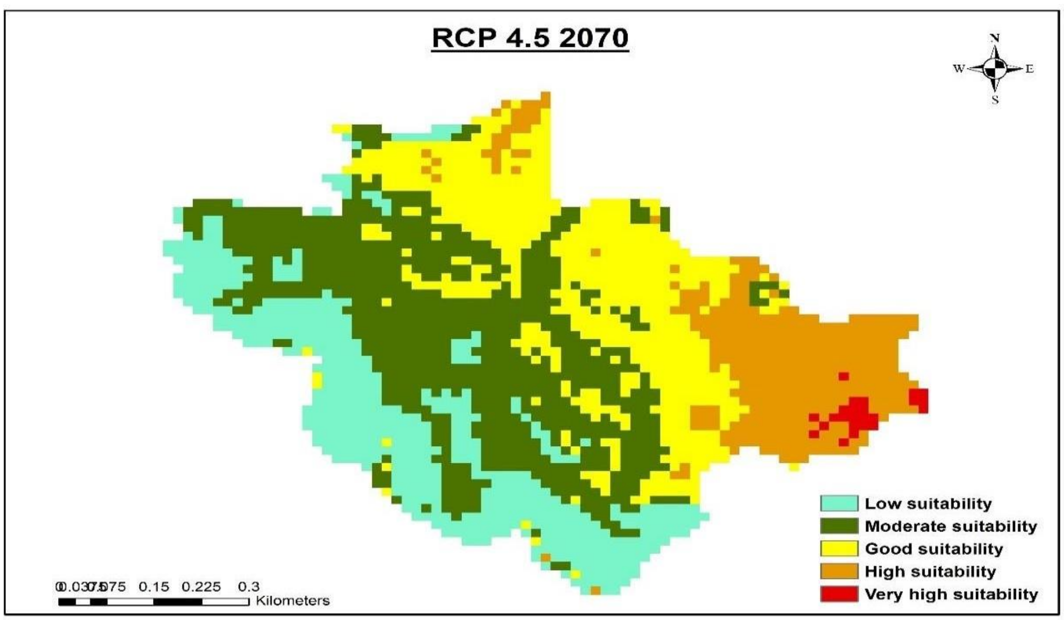


Figure 23. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 4.5 for the year the 2070s

4.6.4. Distribution of *S. spectabilis* under RCP 6.0 scenario for 2050s and 2070s

In comparison with the current suitable habitat for *S. spectabilis,* the suitable areas in both 2050s and 2070s in RCP 6 scenario is decreased. There is a decrease in habitat area by about 32% and 52% in 2050 and 2070 respectively. Focussing on the high (0.6 – 0.8) and very high (0.8 – 1) habitat suitability classes, in 2050s time period, the habitat suitability area for *S. spectabilis* is decreased compared to 2070s. Compared to the current distribution, a low habitat suitability potential (0 – 0.2) increased by 20% (412 km^2) and 16% (399 km^2) in 2050s and 2070s respectively. There is a large gain in the suitability area by 171% (676 km^2) in 2050s and 158% (642 km^2) comparing with the current distribution in the moderate suitability class (0.2-0.4). Furthermore, there is a gain in the suitability by 86% and 84% in 2050s and 2070s in good habitat suitability class (0.4 – 0.6). In the High suitability class (0.8 – 1), a reduction in suitability area is observed by 22% and 17% in 2050s and 2070s respectively compared to current scenario. Looking into very high suitability class, a decrease is observed in both the time periods. High habitat suitability (0.6 – 0.8) and very high habitat suitability (0.8 – 1) were predicted to be the north-eastern and south-eastern parts of Wayanad mainly in the Tholpetty wildlife sanctuary and Muthanga wildlife sanctuary. Muthanga wildlife sanctuary accounted 100% of very high habitat suitability of 2050s which is only 7% of the total very high habitat suitability class. In parallel, 12% of the total very high habitat suitability area is predicted to be present in Muthanga in 2070s. Nevertheless, 50% of the total suitability area in Wayanad is predicted to be under good habitat suitability class in 2050s (Figure.24). The low habitat suitability area is predicted to be in the Western parts of Wayanad and observed no change among near future and the distant future of RCP 6 scenario as well as with the current scenario

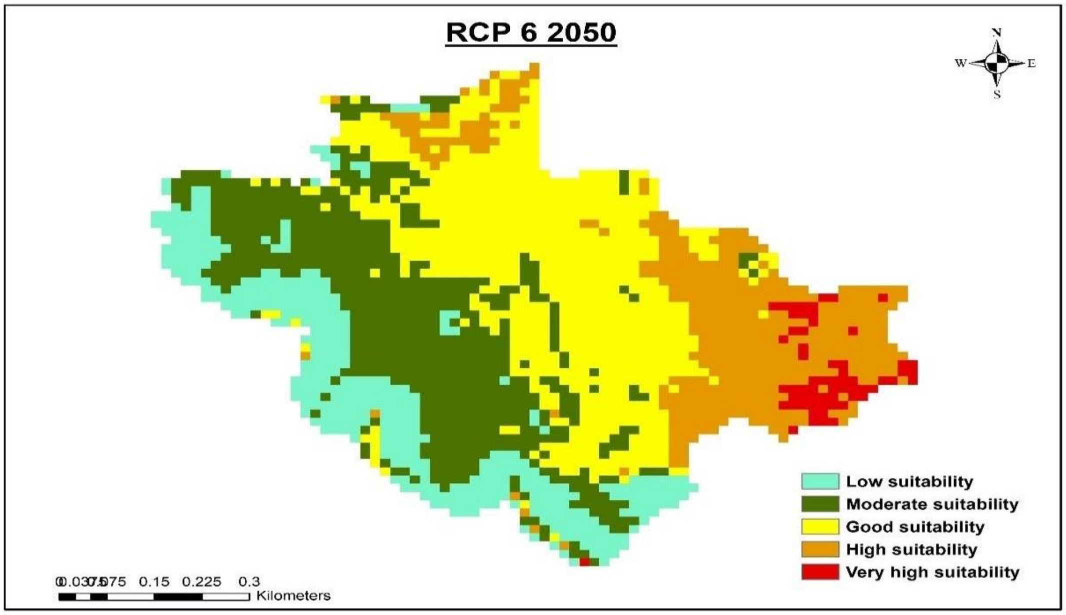


Figure 24. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 6 for the year the 2050s

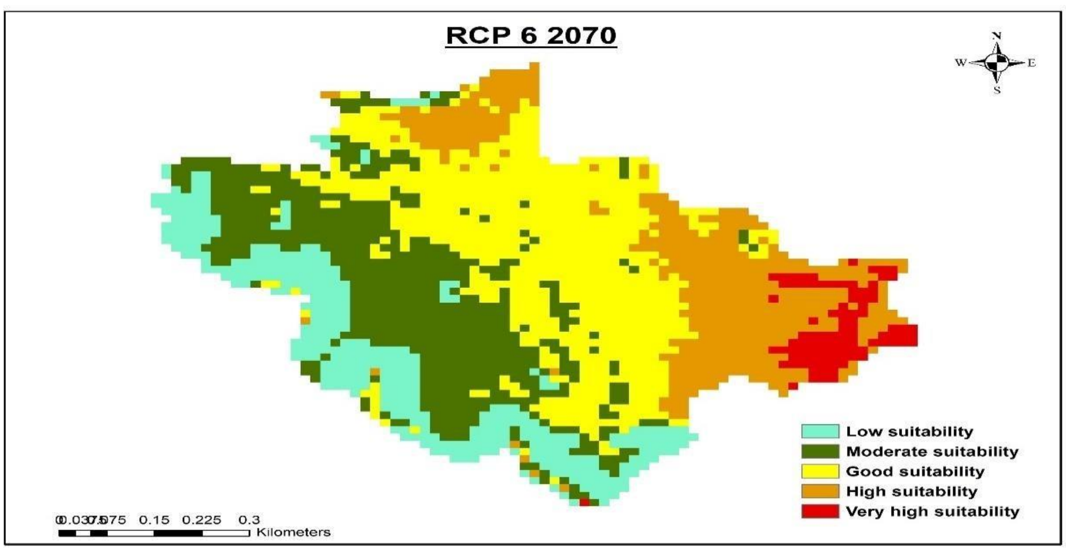


Figure 25. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 6.0 for the year the 2070s

4.6.5. Distribution of *S. spectabilis* under RCP 8.5 scenario for 2050s and 2070s

The suitability potential habitat of *S. spectabilis* is decreased in both periods 2050s and 2070s of RCP scenario 8.5 compared to the current suitability. There is a decrease of about 45% and 849% in 2050s and 2070s respectively. Looking into the habitat suitability classes, in the low suitability class (0.2 – 0.4) there is a gain in 2050s by 13% and 19% in 2070s. In the moderate suitability classes, there is an immense increase in suitability areas in 2050s (120%) and in parallel, there is an increased prediction by 124% in suitability area in 2070s. In the good habitat suitability class (0.4 – 0.6), a gain of habitat area is predicted by 79% in 2050s and 69% in 2070s. A reduction in habitat suitability is predicted in both high suitability class (0.6 – 0.8) and very high suitability class (0.8 – 1) by 14% and 76% in the near future. In the distant future, the reduction in suitability area is by 23% and 68% in the high and very high suitability class respectively. The very high suitability habitat is predicted to be only distributed in the South-eastern part of Wayanad comprising Sulthan Bathery, Muthanga forest range, Muthanga wildlife sanctuary, Noolpuzha, Cheeral, Ottapalam, Chulliyode, Nenmeni, Pazhoor, Kidanganad and Irulam in both the time periods. The predicted high suitability class (0.6 – 0.8) distribution of the invasive species in both the time periods is observed with no significant difference and distributed in the north-eastern and south-eastern parts of Wayanad. About half of the suitability is distributed in the good suitability class (0.4 – 0.6).

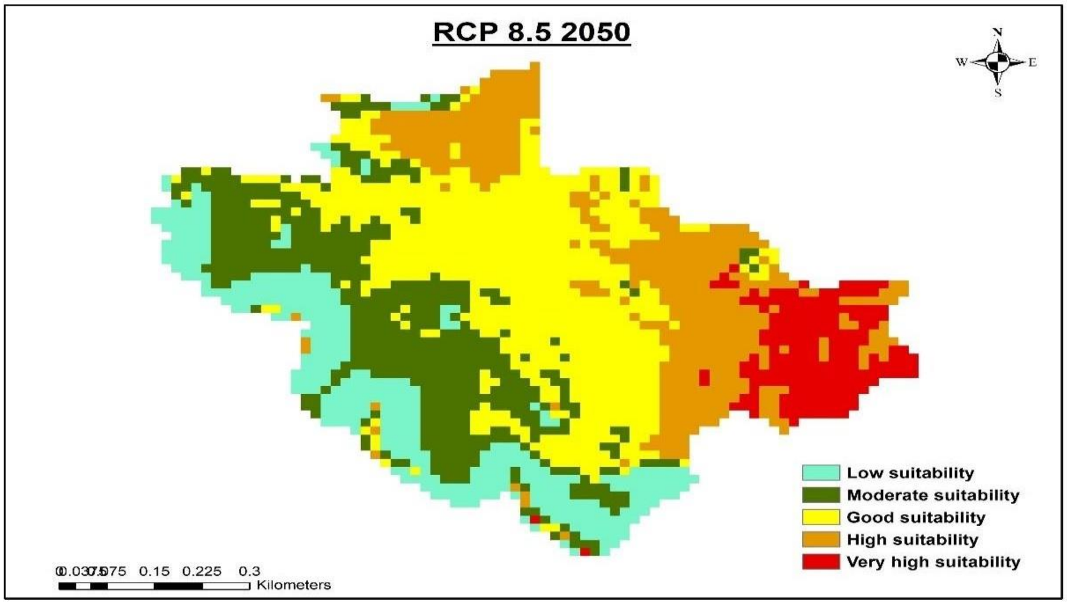


Figure 26. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 8.5 for the year the 2050s

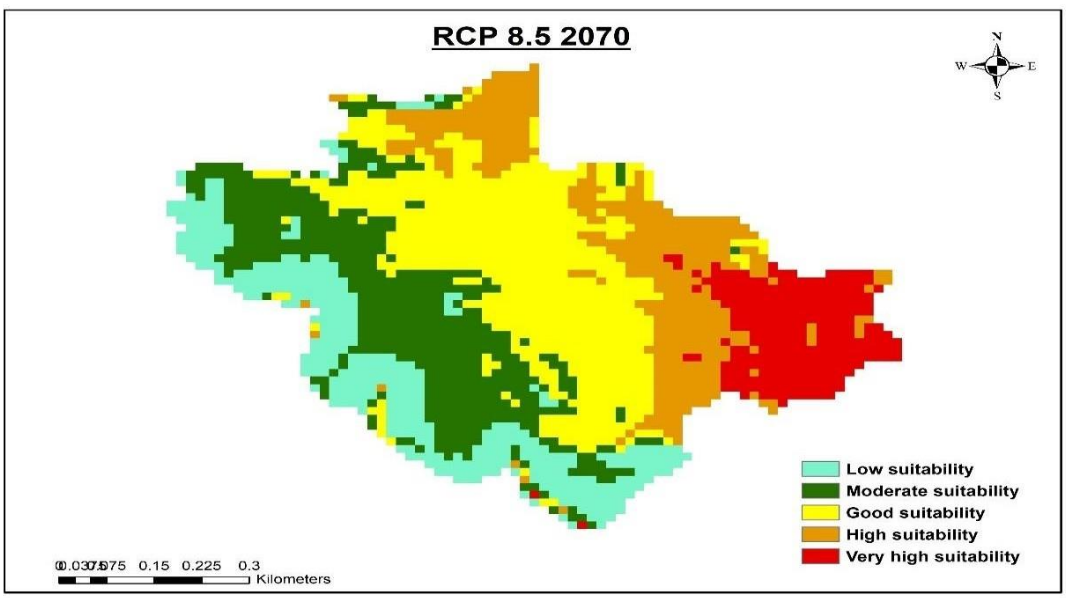


Figure 27. Predicted potential distribution of *S. spectabilis* in Wayanad for the scenario RCP 8.5 for the year the 2070s

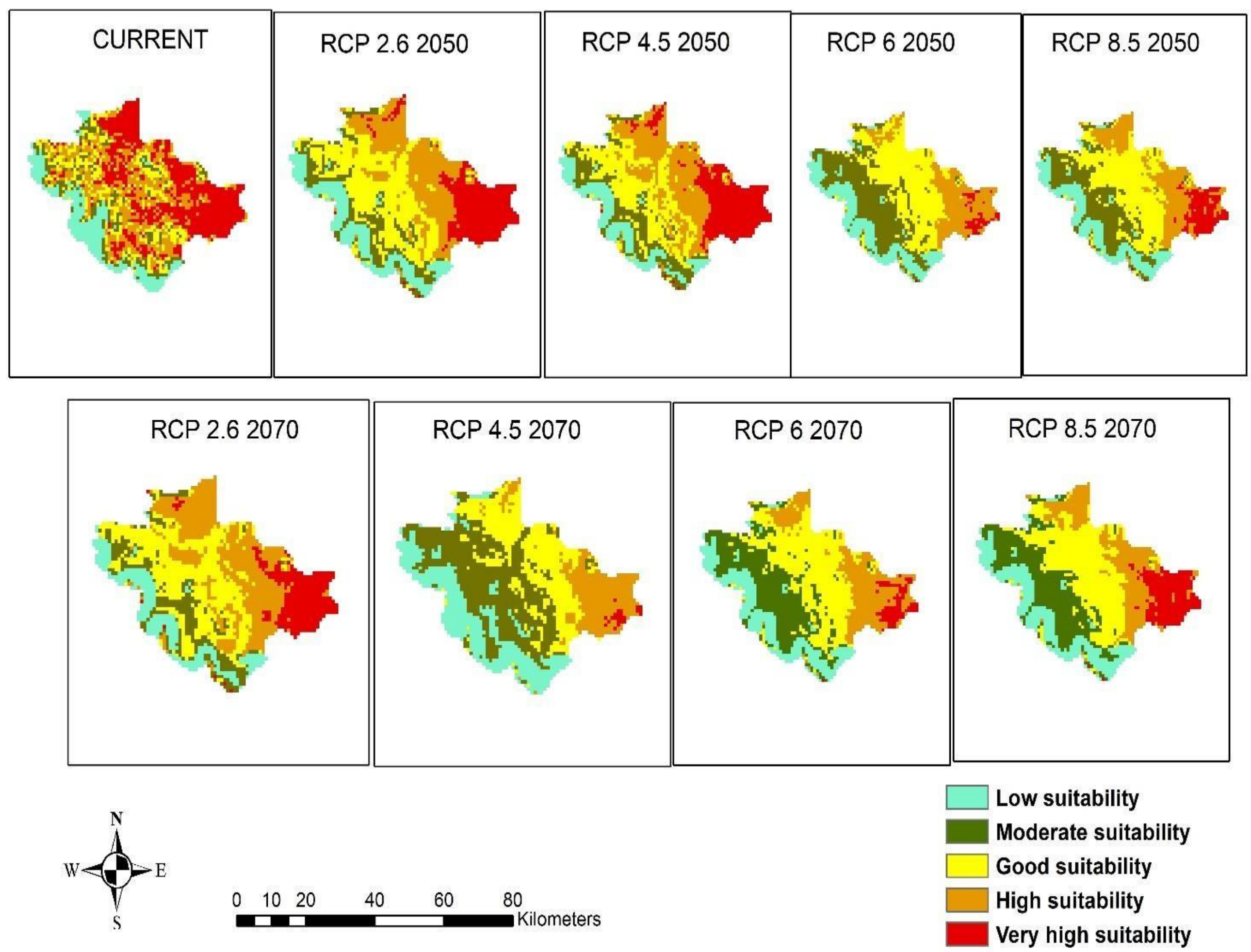


Figure 28. Predicted potential distribution of *S. spectabilis* under current scenario and various RCP scenarios for both the time periods in 2050s and 2070s in Wayanad

The very high habitat suitability of *S. spectabilis* in the Wayanad district were found to be higher in current scenario compared to all the four representative concentration pathways in both the time periods of 2050s and 2070s, which is shown in Figure.30. The very high habitat suitability of current scenario is observed to reduce to moderate and good suitability habitat areas. The low suitability habitat areas are found to be seen in the western parts of Wayanad and also the model showed a probable prediction of low suitability areas in western parts of Wayanad in future as well. The eastern parts of Wayanad especially Wayanad wildlife sanctuary are predicted to be under very high and high habitat suitability areas.

Table 11. Suitability class distribution for *S. spectabilis* under various RCP scenarios with their area of distribution in km^2 for both the time periods in Wayanad

Suitability class	Distribution area (km^2)								
		RCP scenario 2050s				RCP scenarios 2070s			
	current	2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Low	344	349	304	412	389	309	547	399	409
Moderate	249	314	363	676	549	325	835	642	559
Good	428	717	599	797	767	720	624	786	725
High	572	613	654	447	494	735	365	472	442
Very high	800	402	475	63	196	306	24	96	260

The suitability distribution classes comprising low (0 – 0.2), moderate (0.2 – 0.4), good (0.4 – 0.6), high (0.6 – 0.8) and very high (0.8 – 1) of all the four RCP scenarios are given in the bar diagram. The suitability class distribution of *S. spectabilis* in 2050s indicates that the very high suitability (0.8 - 1) is in the RCP 4.5 scenario (475 km^2) compared to other RCP scenarios however, the current scenario is found to be highest in the very high suitability area (800 km^2) for *S. spectabilis* than RCP 4.5 scenario. The predicted high habitat suitability (0.6 – 0.8) is observed to be higher in RCP 4.5 scenario in 2050s and lower in RCP 6 scenario. A good habitat suitability is predicted to be higher in RCP 6 scenario whereas, lower in RCP 4.5 scenario. Moderate habitat suitability and low habitat suitability for the probable distribution of *S. spectabilis* is predicted to be greater in RCP 6 scenario among other RCP scenarios and lower in RCP 4.5 scenario. In 2070s, the predicted habitat suitability areas of the RCP scenarios varies from 2050s. The very high suitability class is higher in RCP 2.6 (475 km^2) than the other representative concentration pathways. In general, there is a decreasing trend in the high habitat suitability class among RCP scenarios from 2.6 to 8.5 watts/km^2 although RCP 4.5 scenario has the least habitat suitability area. Comparing the good habitat suitability area among all the RCPs, RCP 6 scenario has the highest suitability area and RCP 4.5 has the least suitability. The moderate habitat suitability (0.4 – 0.6) and the low suitability (0 – 0.2) is predicted to be higher in the RCP 4.5 scenario and lower in RCP 2.6 scenario.

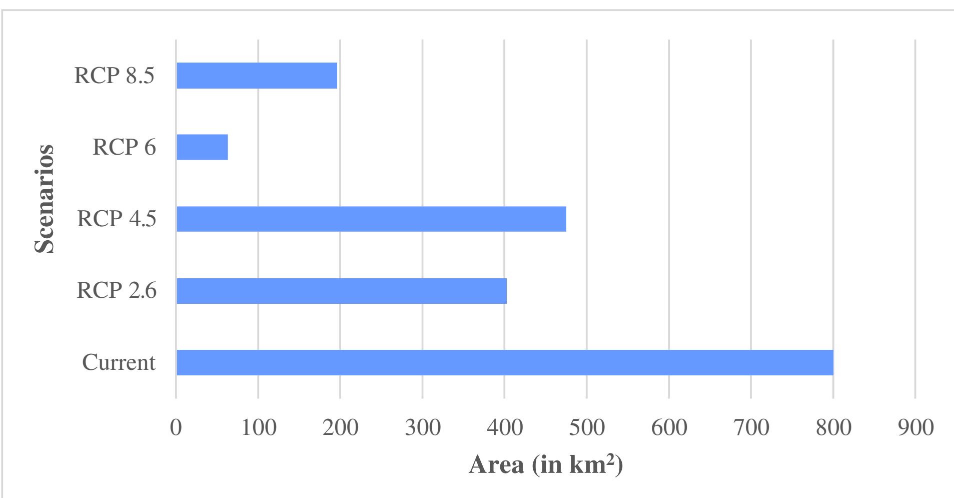


Figure 29. The chart illustrating the predicted very high habitat suitability area of *S. spectabilis* under all the RCP scenarios and current scenario in 2050s in Wayanad

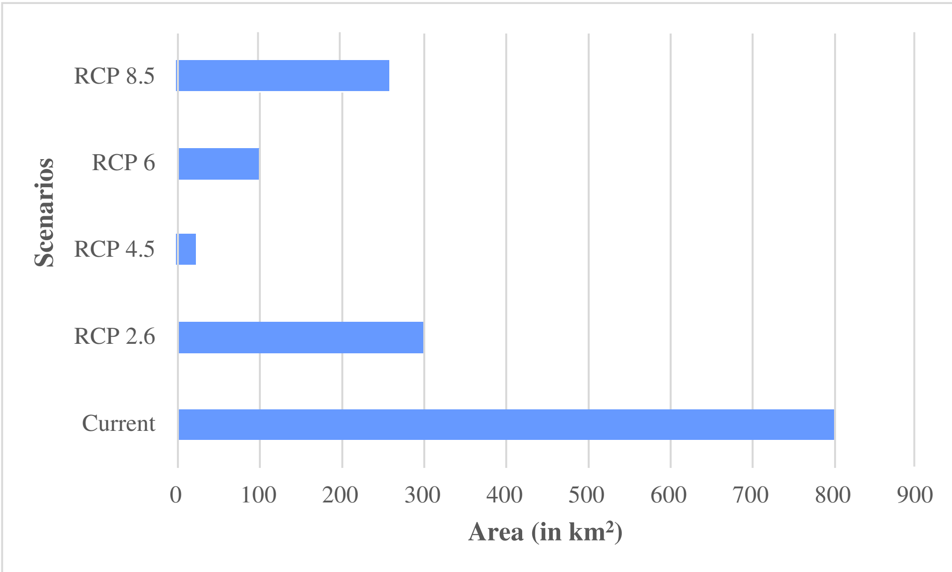


Figure 30. The chart illustrating the predicted very high habitat suitability area of *S. spectabilis* under all the RCP scenarios and current scenario in 2070s in Wayanad

The higher area suitability is predicted to be in RCP 4.5 (475 km^2) among the RCP scenarios in 2050s compared whereas, RCP 2.6 scenario is higher in 2070s. The lowest suitability is in the RCP 6 scenario (63 km^2) in 2050s and RCP 4.5 (24 km^2) in 2070s.

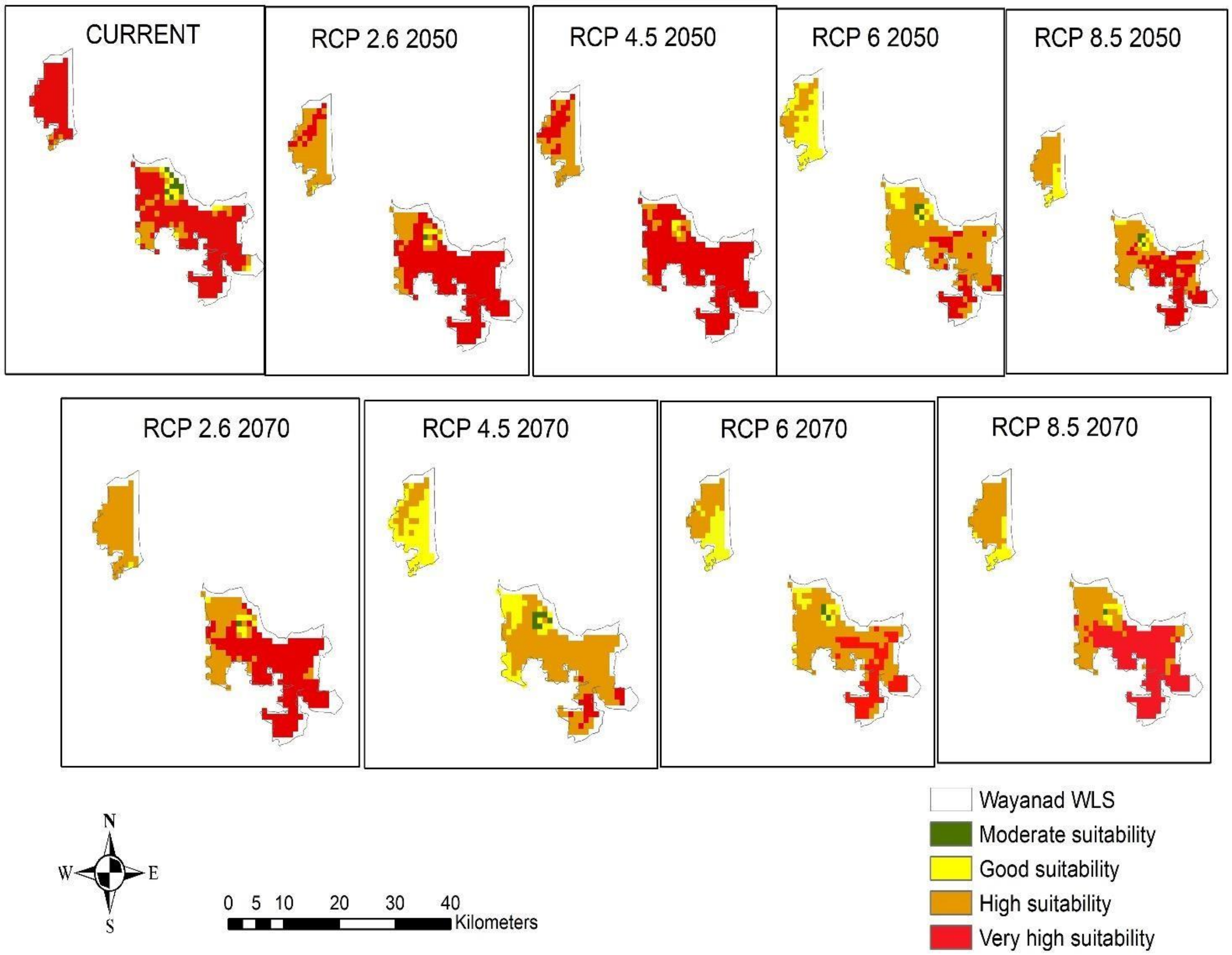


Figure 31. Predicted potential distribution of *S. spectabilis* under current scenario and various RCP scenarios for both the time periods in 2050s and 2070s in Wayanad wildlife sanctuary

Habitat suitability of all the four RCP scenarios in both time periods 2050s and 2070s is shown in Figure 31. In the current scenario, the very high habitat suitability area accounted for 83% potential compared to the potential area of Wayanad wildlife sanctuary (344.44 km^2). Moreover, the high habitat suitability is observed to be 14% of the potential area of Wayanad wildlife sanctuary. The abundant distribution of *S. spectabilis* are found to be covered in Tholpetty range, Kurichiat range, Sulthan Bathery range and Muthanga range. In comparison with the current scenario, there is a decrease in very high habitat suitability all the four RCP scenarios in both the time periods. Additionally, in comparison to 2050s time period future prediction, very high habitat suitability is decreased considerably in 2070s time periods.

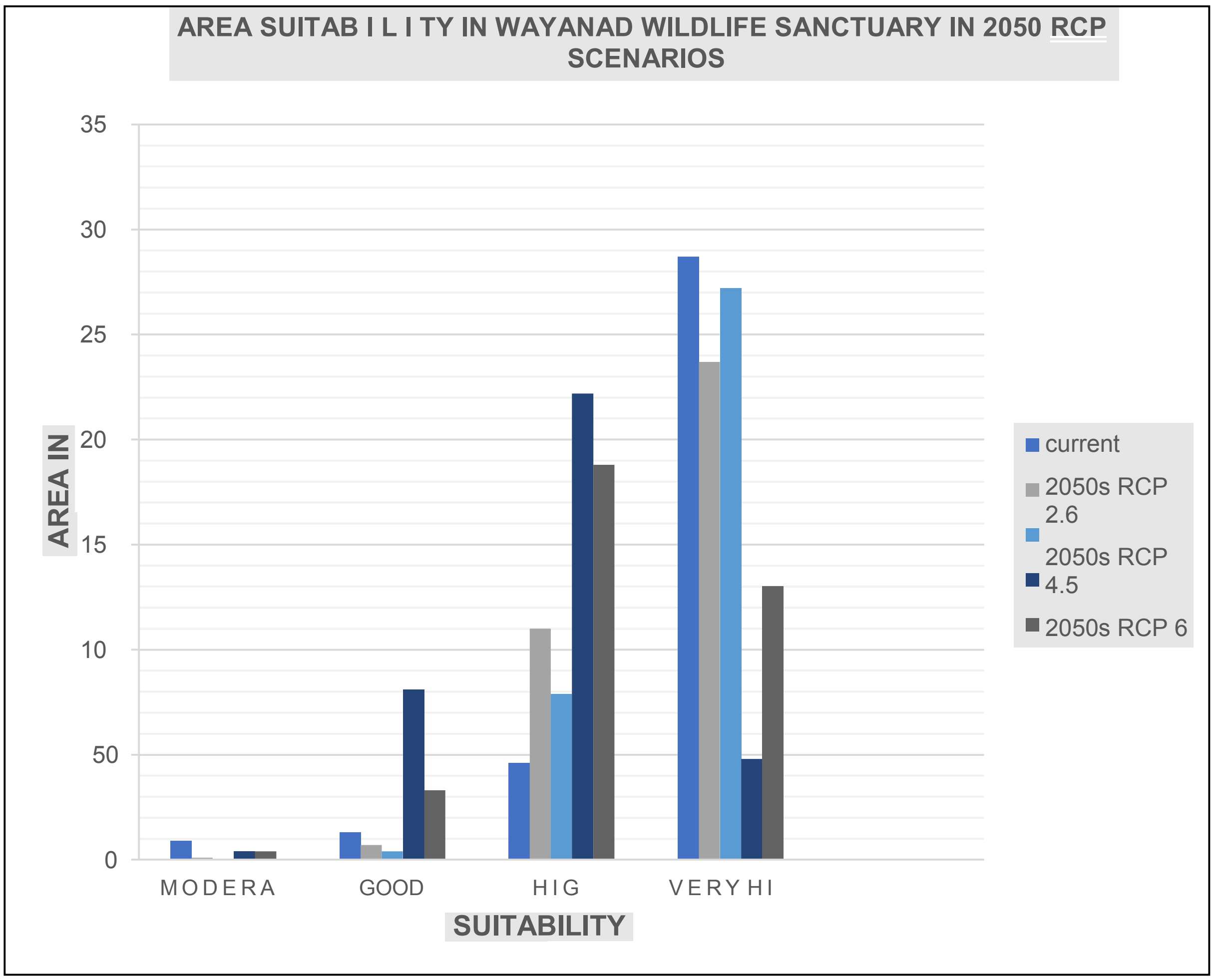


Figure 32. Bar chart illustrating the area suitability in Wayanad wildlife sanctuary under all RCP scenarios and current scenario in time periods 2050s

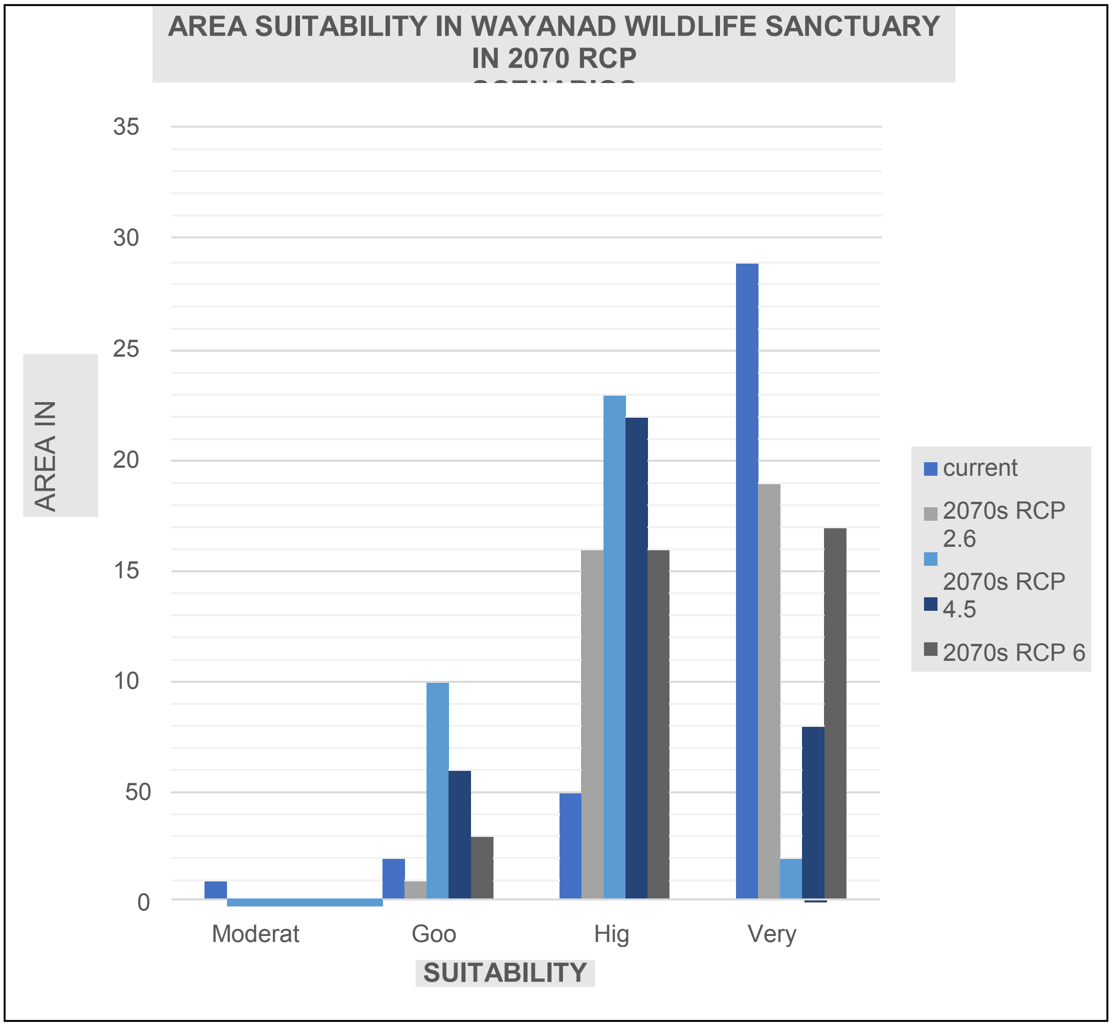


Figure 33. Bar chart illustrating the area suitability in Wayanad wildlife sanctuary under all RCP scenarios and current scenario in time periods 2070s

The habitat suitability of *S. spectabilis* in Wayanad wildlife sanctuary under all the representative concentration pathways and current scenarios is shown in Figure. 32 and Figure. 33. The very high habitat suitability is observed to be higher in the current scenario compared to other time periods 2050s and 2070s. In 2050s, the very high habitat suitability is highest in RCP 4.5 among all the RCPs followed by RCP 2.6, RCP 6 and RCP 8.5 Figure 36. High habitat suitability is higher in RCP 6 and RCP 8.5 followed by RCP 2.6. The least is predicted to be in RCP 4.5. The good habitat suitability areas are comparatively higher in RCP 6. The habitat suitability in 2070s time period is shown in Figure 37. in which current scenario is observed with the highest suitable habitat. Among the other representative concentration pathways, RCP 2.6 showed a highest suitability whereas, RCP 4.5 showed the least suitable habitat. Focussing on the high suitability class, RCP 4.5 showed the highest suitability followed by RCP6. In the good suitability class, there is found to be a considerable suitable potential area in RCP 4.5 compared to other RCPs. Followed by RCP 6 with second most suitable habitat areas.

4.7. Range Expansion

By estimating the difference between current and future binary distribution maps, the relative changes in the future potential species distribution and the impact of climate change were observed. The criteria used for change analysis were; range expansion, range contraction, no change (presence in both), no occupancy (absence in both).

Table 12. Area distribution changes (km^2) of *S. spectabilis* in Wayanad based on the change in binary distribution of RCP scenarios for 2050s and 2070s and current scenarios

Distribution changes (km^2)	**2050s**				**2070s**			
	RCP scenarios							
	2.6	**4.5**	**6.0**	**8.5**	**2.6**	**4.5**	**6.0**	**8.5**
range expansion	138	189	132	99	89	20	68	77
no occupancy	683	632	689	722	732	801	753	744
no change	937	1157	930	758	771	510	678	718
range contraction	635	415	642	814	801	1062	894	854

The distribution changes in 2050s under the four RCP scenarios are given in Figure 38. The range expansion is highest in the RCP 4.5 scenario (189 km^2) and followed by the RCP 2.6 scenario (138 km^2), and there is no significant trend. The range contraction is predicted to rise in RCP 8.5 scenario (814 km^2) followed by RCP 6 scenario (642 km^2) in the near future. The lowest range contraction is in the RCP 2.6 scenario. The no change (presence in both the current and RCP scenarios) is predicted to be greater in RCP 4.5 scenario. The no occupancy (absence in both current and RCP scenarios) is greater in RCP 8.5 scenario followed by RCP 6 scenario. Among the four criteria used (Table.16), no change (presence in both current and future scenarios) is predicted to be higher in area distribution.

The range expansion distribution area is comparatively negligible with the other three categories; range contraction, no occupancy, no change. However, the highest range expansion is 89 km^2 in RCP 2.6 scenario, followed by the RCP 8.5 scenario (77 km^2), and there is no significant trend. The highest range contraction is predicted in the RCP 4.5 scenario (1062 km^2) followed by the RCP 6 scenario (894 km^2). The lowest range contraction is in the RCP 2.6 scenario (801 km^2). The no change (presence in both the current and RCP scenarios) is predicted to be greater in RCP 2.6 scenario. The absence in both current and RCP scenarios (no occupancy) is predicted to be greater in RCP 4.5 scenario and lower in RCP 2.6 scenario. Comparing both 2050 and 2070 RCP scenarios (Table.12), the range expansion is highest in the near future (2050s) than distant future (2070s) and RCP 4.5 with the highest. The highest range contraction is in 2070 RCP 4.5. Comparatively, the range contraction is higher in 2070s than 2050s. The no change area (presence in both) is higher in 2050s whereas, no occupancy is higher in 2070s time period.

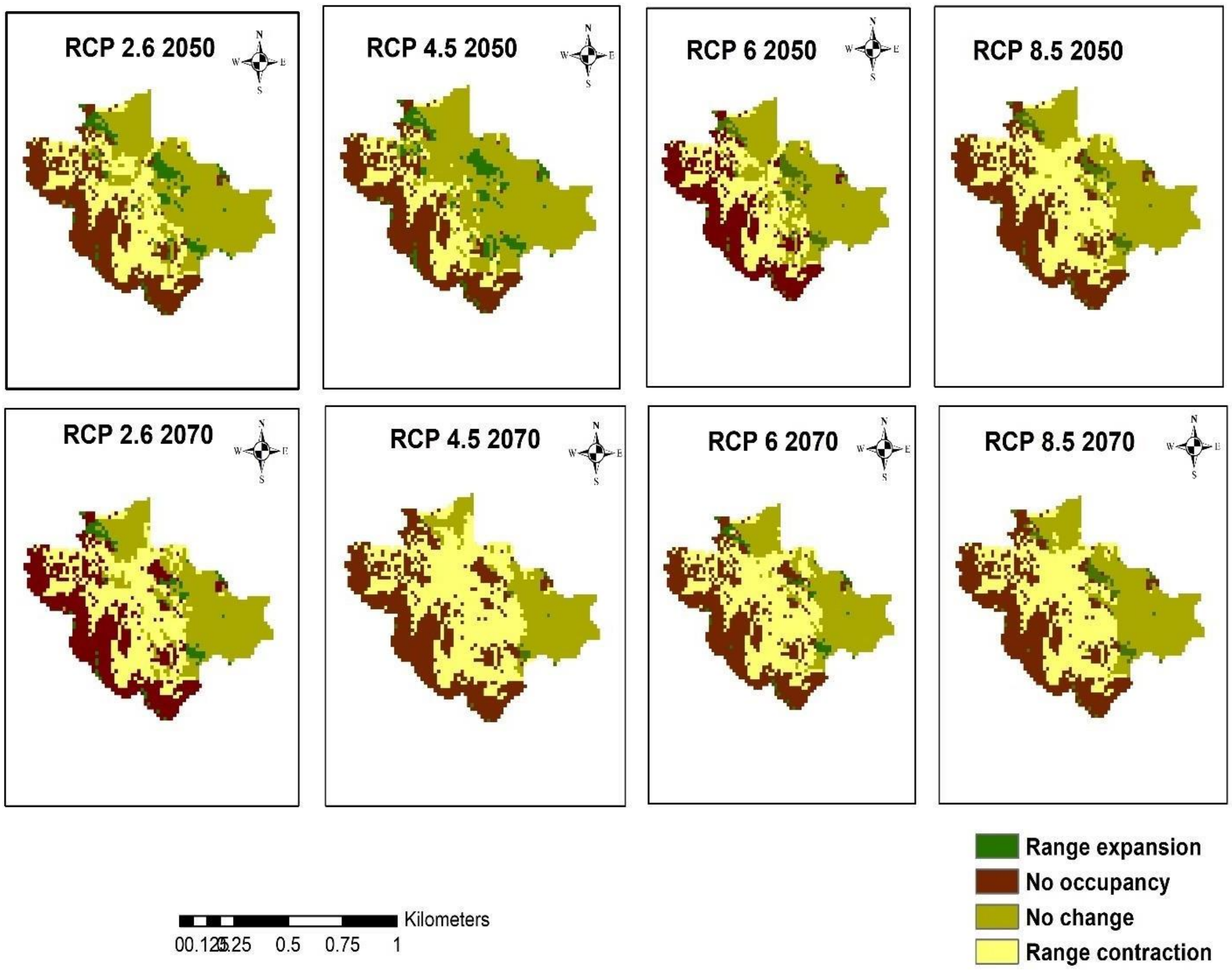


Figure 34. Distributional changes of *S. spectabilis* in Wayanad under RCP scenarios in the near future (2050s) and the distant future (2070s)

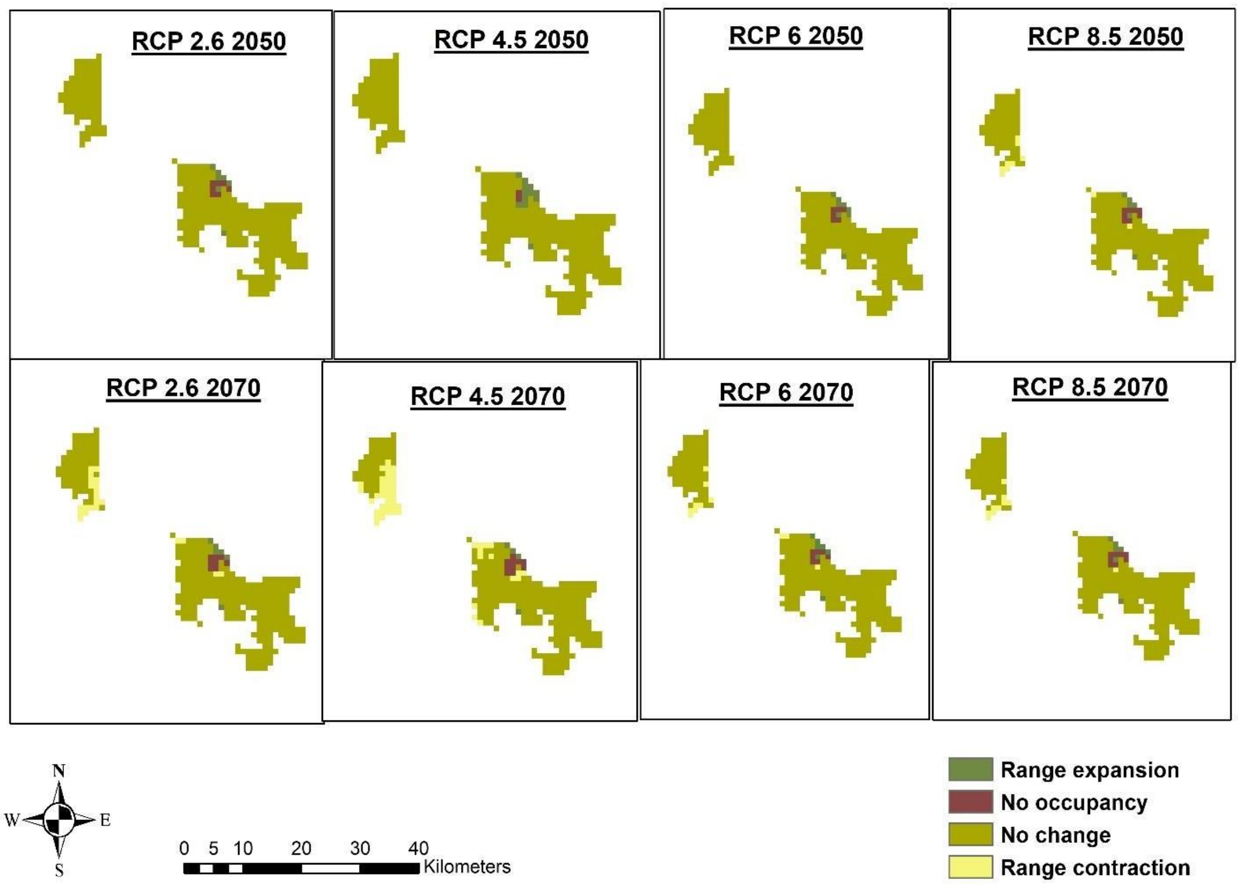


Figure 35. Distributional changes of *S. spectabilis* in Wayanad wildlife sanctuary under RCP scenarios in the near future (2050s) and the distant future (2070s)

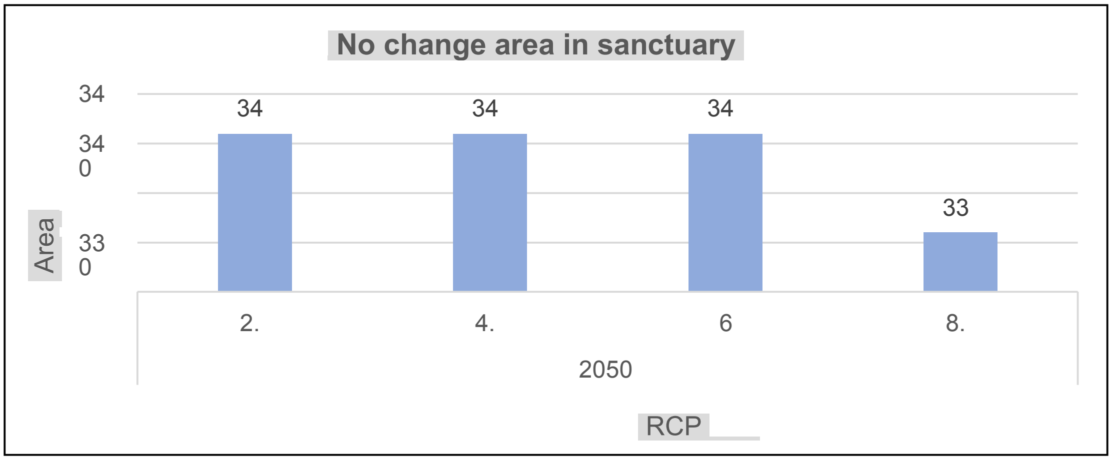


Figure 36. Bar diagram showing the no change area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2050s

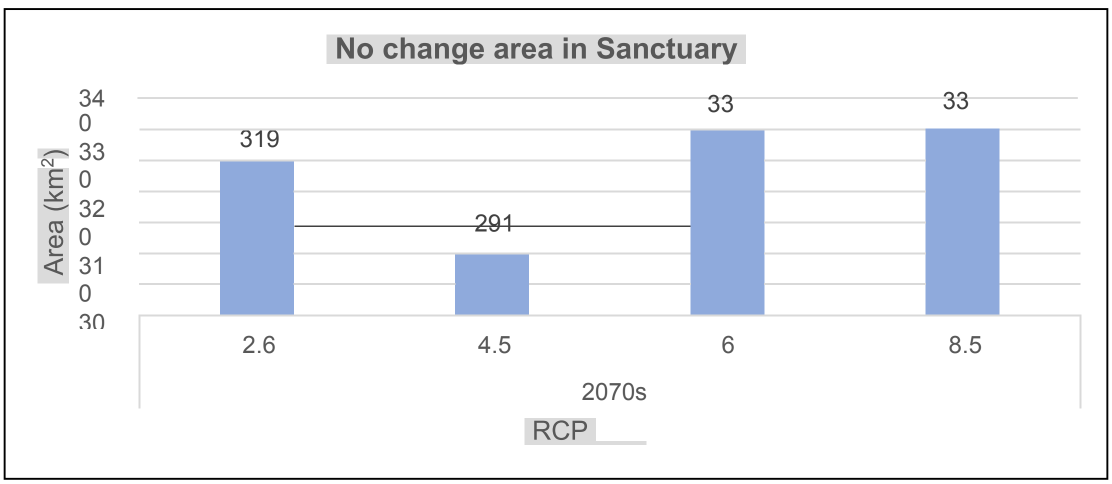


Figure 37. Bar diagram showing the no change area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2070s

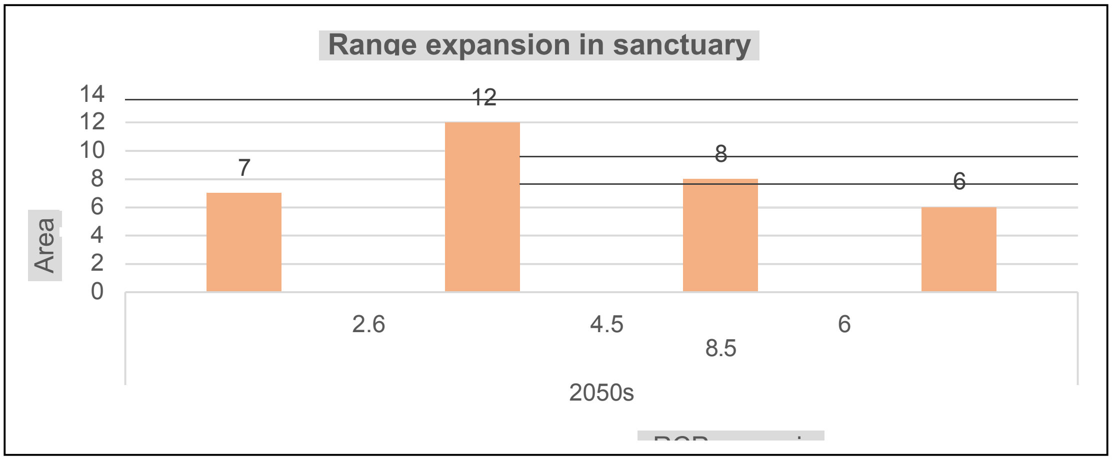


Figure 38. Bar diagram showing the range expansion area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2050s

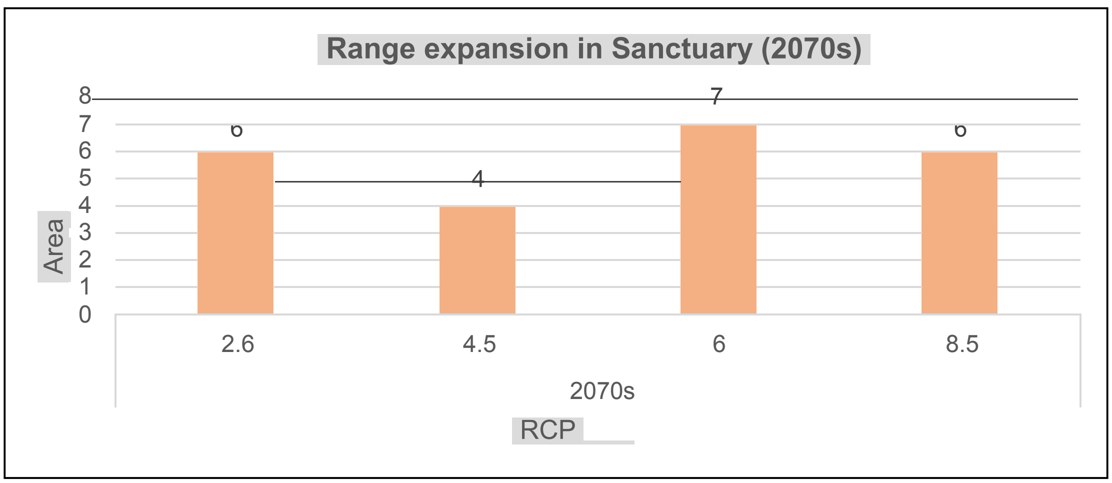


Figure 39. Bar diagram showing the range expansion area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2070s

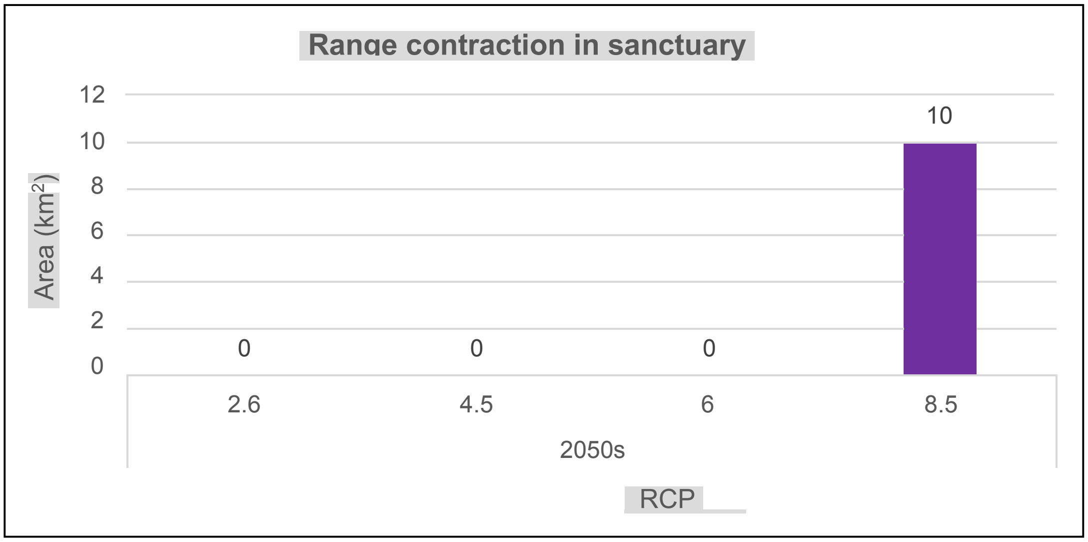


Figure 40. Bar diagram showing the range contraction area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2050s

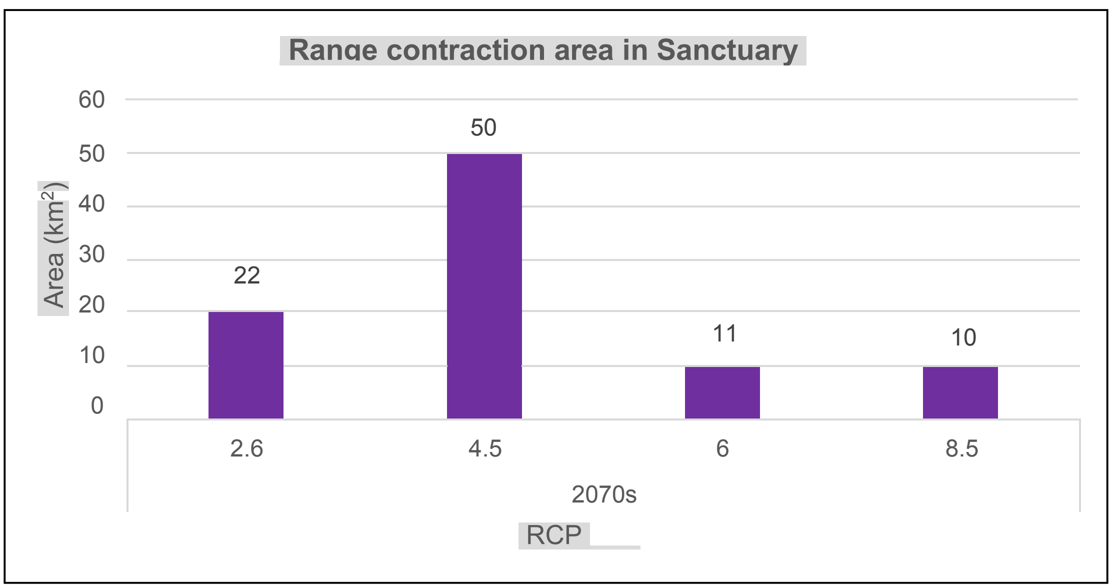


Figure 41. Bar diagram showing the range contraction area changes in distribution of the *S. spectabilis* in Wayanad wildlife sanctuary in all the RCP scenarios in 2070s

The distributional changes in future RCP scenarios for both the time periods 2050s and 2070s is shown in Figure 35. The given Figure 36 and Figure 37. illustrated the no change distribution change areas in 2050s and 2070s respectively. In 2050s, RCP 4.5 and RCP 6 has same no change area whereas, there observed a reduction in the no change area in RCP 8.5. However in 2070s, RCP 8.5 is predicted with highest no change area followed by RCP 6 and RCP 2.6. Comparing the range expansion of *S. spectabilis* in Wayanad wildlife sanctuary, the range expansion area in 2050s is predicted to be very less compared to no change habitat suitability area (Figure 38.). The highest habitat suitability area is observed in RCP 4.5 with 12 km^2 suitability area and the least range expansion was observed in RCP 8.5 with 6 km^2 . The range expansion in time period 2070s (Figure 39.) is predicted with RCP 6, the highest (7 km^2) and the least expansion seen in RCP 4.5. However, the range expansion in RCP 4.5 in 2050s, which is the highest among other RCPs is found to be reduced to least range expansion in 2070s time periods. The given figure 40. and figure 41. Illustrated the range contraction in the wildlife sanctuary in 2050s and 2070s respectively. In 2050s, the range contraction is predicted to be absent in RCP 2.6, RCP 4.5 and RCP 6 and in RCP 8.5 with the highest range contraction (10 km^2). However, in 2070s, the highest range contraction is observed in RCP 4.5 and the least range contraction in RCP 8.5.

CHAPTER 5

DISCUSSION

Climate change is one of the major challenges of our time and it intensifies the terrestrial plant invasion in non – native habitats (Colautti and Barrett, 2013) and thus posing a great threat to native biodiversity. Moreover, Climate change alters species interactions, population demographics, germination, recruitment, establishment, and distribution, all of which affect the ecosystem. Besides, the magnitude, rate and impact of climate change are intensified by invasive species and thus alters the ecosystem functioning, structure and composition. (Pysek and Richardson 2010; Smith et al. 2012). Additionally, a study by Pantoja *et al*. (2018) concluded the adaptive ability of invasive species to new environments indicating that the behaviour of invasive plants changes temporally. This study was one of the first studies and attempted to investigate the impact of climate change on the potential distribution of *S. spectabilis* in Wayanad.

S. spectabilis which has been regarded as the medium risk invasive species (Sajeev *et al*., 2012) is now spreading at an alarming rate in parts of Western Ghats. Currently, the occurrence of the invasive species is mostly confined to Wayanad and is a great concern for ecologists, biological conservationists, forest departments and natural resources managers. The spread of this exotic plant in Wayanad has increased to about 23% in the sanctuary area more than 10% from 2015 (Anoop *et al.,* 2021). Therefore, it becomes essential to model and identify the expansion of plant invasion in future under projected climate change in Wayanad which is undertaken in this study.

Species distribution modelling is particularly a valuable tool in addressing these issues and predicting the potential distribution of invasive species across space and time (Srivastava *et al*., 2020). Maximum Entropy (MaxEnt) species distribution modelling was employed in the study of the distributional changes of the *S. spectabilis* with the presence of data points to the prevailing climatic and non-climatic conditions. The study used the primary and secondary data on occurrence points of the *S.*

spectabilis and climate data from 1950-2000 for current conditions and the years 2050 and 2070; non-climate data were downloaded from various other reliable sources. For the future prediction distribution in 2050 and 2070, the coupled model HadGEM2-ES of 30-second resolution under four different Representative Concentration Pathways (RCPs); RCP 2.6, RCP 4.5, RCP 6, RCP 8.5 was used. The findings were examined and analysed in detail in this chapter.

5.1. Variable optimization in the model

The studies showed that the distribution and number of invasive species were subsequently favoured by the rising temperature, altered precipitation and other human disturbances (Easterling *et al*., 2000; Hellmann *et al*., 2008; Walther *et al*., 2009). According to Tripathi *et al.* (2019), when the mean temperature increased, it was convenient for the invasive species as the increase in mean temperature escalated the growing season length and thus creating many vacant spaces where invasive species successfully adjust. A shift in the flowering of invasive species with respect to inter-annual variation in the temperature of North American systems were noticed in the studies of Wolkovich *et al*. (2013). A study by Eskelinen and Harrison (2014) suggested that increased rainfall could create constraints in soil nutrients and competition for the invasive species. Therefore, bioclimatic variables which were derived from monthly temperatures and rainfall were used in the model. The other non-climatic variables viz., Population density, Distance from water bodies, Distance from the road, soil type were chosen in regard to its influence on the invasive species. In the studies of Adhikari *et al*. (2015), he identified invasion hotspots with the diverse signature of the anthropogenic disturbance. Kosaka *et al*. (2010) proposed that the recent construction of roads nearby could assist in the establishment of the invasive species. Moreover, *S. spectabilis* invades; forest margins, savanna, riverbanks, roadsides, waste ground and plantations (Irwin and Barneby, 1982). The influence of edaphic variables on *S. spectabilis* was important as it preferred a well-drained, deep, moist, sandy or loamy soil but flourishes even in poor, black cotton soil and additionally, its established plants were drought tolerant (Tropical Plants Database, 2021). Besides, Velazco *et al.* (2017) recommended that the addition of edaphic features to the model significantly affected the model performance and model accuracy compared with the model construction with only climatic variables. Therefore, variable selection was a big deal in model building. However, the high correlation of bioclimatic variables among each other were well known (Brown, 2014). The contribution of each input variable to the species *S. spectabilis* was difficult to interpret when autocorrelated variables were not removed. The highly correlated variables can lead to overprediction (quality of prediction), masking effect (limits inference of influence of correlated variables), which can cause a poor-quality model output (Rogerson, 2001; Dormann et al. 2013; Weldemariam and Dejene, 2021). Therefore, in this study correlation among variables were tested by using Pearson correlation matrix |r|. The result is shown in the Table. 2.

The threshold value of Pearson correlation coefficient |r| was chosen to be 0.7 (Weldemariam and Dejene, 2021). The correlation will be at its minimum when the lesser number of independent variables explains the model. Considering that most of the bioclimatic variables had a high chance of correlation with each other, the model with a Pearson correlation coefficient less than |0.7| certainly will have lesser variables and the model used variables of high permutation importance having |r| > 0.7. In addition, the variables among correlated variables were chosen after an investigation of the influence of these variables on the species. The greater influencing variables among the other correlated variables were kept and others excluded which was a major decision in the variable and the model optimization. The remaining non - correlated variables were selected viz., Slope, Aspect, Landcover, Soil type, distance from water bodies, distance from the road, NDVI and population density. Additionally, the most important bioclimatic variables were chosen from the two correlated variables based on its influence on the species. Besides collinearity, the variability criteria of the bioclimatic variables under different RCP scenarios were also analysed based on the mean values in the study area shown in Table. 3. All the selected variables showed a significant variability which enhanced the credibility to the variable optimization in the model building process. Furthermore, these variables were then compared with other similar studies as well. Considering, *S. spectabilis* grows in dryland forests, most commonly in open formations as well as moist and dry seasonal forests, disturbed or secondary woodlands and savannah. Although, *S. spectabilis* was a tropical/subtropical tree and highly adaptive, the temperature and precipitation ranges are well defined (Tropical Plants Database, 2021), annual mean temperature (BIO1), precipitation of driest quarter (BIO17), precipitation of warmest quarter (BIO18) was selected (Weldemariam and Dejene, 2021). Along with the isothermality (BIO3), temperature seasonality (BIO4), precipitation seasonality (BIO15) was also selected. The current and future prediction models were built upon these variables.

5.2. Variable contribution to the model distribution of the *Senna spectabilis*

It was important to assess the contributions of environmental variables given by MaxEnt output as it was the keystone in the construction of the distribution model of *S. spectabilis*. The coefficient of a single feature was changed and the gain of the model was increased in each step of the MaxEnt algorithm. Further, for obtaining the percentage contribution, these increased gains of each variable were converted into percentage at the end of the training process. From the analysis (Table. 5), temperature related bioclimatic variables BIO3 and BIO1 (Isothermality and annual mean temperature) have highly contributed to the distribution with a cumulative contribution of 45.2%. This indicated that the temperature was an inevitable factor in determining the distribution of this invasive species. Similarly, Weldemariam and Dejene (2021) confirmed that temperature variables were the most important variables for the establishment of the *Senna* spp. Averett *et al.* (2016) established that the temperature variables are the most influencing predictor variables that limit the distribution of non-native species richness. Whereas, the precipitation variables; precipitation of the warmest quarter (BIO18), precipitation seasonality (BIO15), precipitation of driest quarter (BIO17) have a cumulative contribution of 10%. In comparison with the other temperature variables, temperature seasonality (BIO4) lower percent contribution (3.3%). Elevation was the second most influencing variable with a contribution of 20.8%. Other than these variables, slope, landcover and distance from the road had a significant role in the distribution of *S. spectabilis* as they contribute 6.4, 6 and 4.3 percent respectively. NDVI, aspect, soil type, population density had less than one percent contribution whereas distance from water bodies has contribution of 2.1% to the distribution model. Nevertheless, these percentage contributions defined were based on a probabilistic algorithm. Following different algorithms, they would differ when the path changes (path-dependent) in accordance with different algorithms even though the same solution was achieved. Besides, correlations among variables could also affect the percent contribution of variables to the model. The permutation importance of the variable in the model was path independent and depends only on the final MaxEnt model. However, it would be more advisable to measure the contribution of each variable. Among bioclimatic variable, precipitation of warmest quarter (BIO18) showed higher importance whereas, temperature seasonality (BIO4) and isothermality (BIO3) had very less permutation importance. The Jack-knife test (Figure. 10, 11) of variable importance depicted the importance of environment variable (a) when used in isolation (consisting of the most useful information) with the highest test gain and (b) the environment variable which has the least test gain when it is omitted (consists of the most information that is not present in the other variables). The most contributed variable can be easily identified individually with the help of Jack-knife testing. Isothermality (BIO3) provided a very good fit (>1) to the test data and had the most useful information. The environment variable that decreased the gain the most when it is omitted is the distance from road. The non-climatic variables had a very less test gain which concluded that these variables were of less significance to the model and consisted any substantial amount of useful information that was not already obtained from other variables. Additionally, the variable influence on the distribution model was established by the jackknife of AUC. The jackknife of AUC with only isothermality was 0.93. The response curve of each variable (Figure.12) showed the response curve of each variable when other variables were at their average values. The variables which showed a positive response in favour of the distribution of *S. spectabilis* in Wayanad were BIO15 (Precipitation seasonality), BIO4 (Temperature seasonality). The environmental variables which showed negative response curves were the distance from water bodies, distance from the road, BIO3 (Isothermality), BIO18 (Precipitation of warmest quarter), aspect. These variables lowered the chance of potential distribution of *S. spectabilis* in Wayanad when the values of these variables increased. Annual mean temperature (BIO1), precipitation of driest quarter (BIO17), elevation, landcover, slope, NDVI, population density had a rise and fall. These variables increased the distribution to a value and then declined suddenly in further increase of the variable.

The response curve of *S. spectabilis* to annual mean temperature (BIO1) predicted that the highest probability of the distribution of the *S. spectabilis* was seen when the annual mean temperature (BIO1) was at its peak 22.5° C and then declines gradually (Figure 12.b.) which was a well-grounded result as the ideal annual mean temperature range of *S.spectabilis* is 19-22° C (CABI, 2021). *S. spectabilis* distribution increased with increasing temperature seasonality (BIO4) were at the range of 90-165% (Figure 12.c). The higher the isothermality (BIO3), the lower the probability of the presence of *S. spectabilis.* There was no presence of the invasive species when the isothermality was 65%. However, it revealed only a smaller level of temperature variability within an average month relative to the year as the isothermality value was less than 100. When the precipitation of warmest quarter (BIO18) was in between the range 130-200mm, the probability presence of *S. spectabilis* was higher with 100% probability (Figure 12.f.), as the required annual precipitation of the species was 800-2000mm (CABI, 2021). The response curve of precipitation of the driest quarter was reliable as it indicated that the presence probability was higher when the range was between 15-23mm and the probability percent was around 90. The probability of *S. spectabilis* presence increased (>75%) when landcover was a deciduous forest or degraded/Scrub Forest, indicating that the areas with these forests were under greater threat of invasion (Figure 12.e.). The response curves of the climatic variables suggested that the invasive species has a higher probable occurrence in a dryland climatic condition although it had different distribution ranges and adaptive capacity (Tropical Plants Database, 2021).

5.3 Accuracy assessment of distribution modelling of *Senna spectabilis*

The model output demonstrated that the distribution model of both current and future habitat suitability of *S. spectabilis* had a good performance. For model evaluation, the area under the curve (AUC) and true skill statistics (TSS) were used. Model accuracy could be best described by both omission curves and AUC curves (Philips *et al.,* 2006; Elith *et al*., 2011). The correctly predicted presence records were defined as sensitivity whereas specificity could be defined as the correctly predicted absence. For example, If the correctly predicted presence recorded the number ofcells = a, the number of cells for which species not found but there was a predicted presence = b, c = number of cells for which model predicted species was absent, d = number of cells where model correctly predicted absence. Therefore,

Sensitivity = a/(a+c) = True Positive / (True Positive + False Negative)

Specificity = d/(b+d) = True negative / (True negative + False positive)

From which, 1 – specificity defined incorrectly predicted absences.

By plotting the sensitivity (1- omission rate) against the fractional predicted area (1-sensitivity) across different thresholds, the receiver operating curve/ area under the curve was obtained. The predicted omission should be close to the predicted omission in the graph. Even though the AUC value was independent of the prevalence, this accuracy measurement index was widely questioned as it avoided a real prediction by equally weighing the commission and omission errors (Lobo *et al*., 2008).

Additionally, the models could not be described as highly informative even though a high AUC value was obtained (Phillips *et al*., 2006). Therefore, relying on the AUC score alone for model evaluation could be unreliable (Austin 2007; Lobo *et al*., 2008). Therefore, both AUC (threshold independent) and TSS (threshold dependent) indices were applied to evaluate the model performance (Adhikari *et al*., 2019). Unlike AUC, TSS values were not affected by the size of the study region and the prevalence of the occurrence records (Allouche *et al*., 2006).

The model performance of the current potential distribution of *S. spectabilis* was found to be good with a test AUC value above 0.94 ± 0.02 and TSS value 0.83, indicating that the model performed well in predicting the species distribution of *S. spectabilis*. This finding fitted with both the primary and secondary occurrence records (Sankaran *et al*., 2013 and Sajeev *et al*., 2012) indicating that the results were reliable. The future projection models also obtained high AUC indices and TSS values in each RCPs in both the periods 2050 and 2070 (Table.10) thereby concluding that model performance was in the acceptable range as recommended by Allouche *et al*. (2006). This could be considered good and indicated that the MaxEnT model's predictions and observations were in good agreement. Yet again, the model predictive capacity was better explained by mean omission and predicted omission for the selected species averaged over the 10 replicate runs. The omission rate was close to the predicted omission, thus signified the climate prediction result. Additionally, the little differences in the test and training AUC values indicated a very low overfit in the prediction results as suggested Pramanik *et al*. (2018) (Table.10). The standard deviation of AUC also suggested that the overall performance of the model was excellent and very close to the approximation of the true probability distribution (Deb *et al*., 2017).

5.4. Change in the Spatial Distribution under Climate Change

The report of Sajeev *et al.* (2012) indicated the insurgence of invasive species in Kerala by identifying 38 high impacting invasive species in the forests of Kerala through a risk assessment protocol. Along with the anthropogenic pressure which promotes bioinvasion (Pauchard *et al*., 2016), climate change amplifies the wide distribution of the invasive species (Adhikari et al. 2015; Panda et al. 2018). In this context, climate change in Kerala has promoted the spread of many invasive species (Rekha *et al.* 2015). Kerala's climate has shifted from B4 to B2, going from wetness to dryness within the humid type of climate, as a result of changes in heat and moisture regimes throughout the year (Rao *et al*., 2009). A new suitable habitat emerges that will be suitable for invasive alien species when the climate changes (Hellmann et al., 2008). The potential impact of current and future climate on the distribution of *S. spectabilis* in Wayanad was modelled for the first time by the MaxEnt model. The current habitat suitability distribution of *S. spectabilis* in Wayanad is shown in Figure.16 based on fifteen variables including bioclimatic and non – climatic variable in the selected model (Table.4). Under the current climatic scenarios, high and very high habitat suitability for the invasion was observed in regions of Tholpetty, Wayanad wildlife sanctuary, Appapara, Panavally, Irumbupalam, Kattikulam, Kuruva island, Kyasapura, Payyampally, Palvelicham, Thrishilery, Oorpally, Mananthavady, Nalloornad, Naalammile, Koolivayal, Neervaram, Pakkom, Padichira, Mullenkolly, Pulpally, Kelakkavala,Chethalayam, Kidanganad, Ottapalam, Kerala – Karnataka border, Muthanga, Muthanga Forest Range, Mathamangalam, Sulthan Bathery, Noolpuzha, Cheeral, Pazhoor, Nenmini, Chulliyode, Karachal, Muttil, Meenangadi, Purakkadi, Vakery, Kenichira, Poothadi, Bathery, Paralikunnu, Kalpetta, Chundale, Pozhithane, Vythiri, Kunnampetta, Puthurvayal, Pinangode, Vellamunda, Mattilayam, Korome, Tindumal . Considering the total study area, the very high habitat suitability accounted for 34% of the potential area, followed by 24% high suitability potential area. On the contrary, Tariyod, Koroth, Mukki and other western most parts of

Wayanad bordering Western Ghats were modelled as the low suitability habitat for *S. spectabilis* invasion under climatic conditions and accounted about 14% potential area compared to the study area (2364 km^2). Additionally, the current distribution model result concurs with that of the report made by Sajeev *et al.* (2012) and Satynarayana and Gnanasekaran (2013), Singh, (2001), who put *Senna* spp. as among the most occurring alien invasive species in many habitats of Peninsular India as well as categorised under the medium risk category. Besides, our current invasion distribution model result was in parallel with studies conducted in Wayanad (Anoop *et al.*, 2021) by reason of that the model predicted that 66% of the total area of the Wayanad district (1572 km^2) is currently suitable for *S. spectabilis.* According to Anoop *et al.* (2021), 23% of the Wayanad wildlife sanctuary area is covered with this invasive species in 40 years since the 1980s. Moreover, the model performance indicated that the model performed well in predicting the current habitat potential species of *S. spectabilis* with a good test AUC value above 0.94 ± 0.02 and TSS value 0.83. The very high habitat suitability area in the Wayanad wildlife sanctuary in the current scenario accounted for 83% potential area compared to the area of Wayanad wildlife sanctuary (344.44 km^2) followed by a high habitat suitability area with 14% potential area in the wildlife sanctuary that included Tholpetty range, Kurichiat range, Sulthan Bathery range, Muthanga range. The very high habitat suitability area in Wayanad is contributed by the most influencing environmental variables; mean annual temperature (BIO1) and isothermality (BIO3) shown in Figure.4 and Figure.5. The species distribution was at the highest (85%) when the mean annual temperature was at 22.5° C (Figure 12.b). The mean annual temperature (BIO1) in the Wayanad district under the current scenario was found to be 22.23° C which found to be highly suitable for distribution of *S. spectabilis* (CABI, 2021). Besides, isothermality (BIO3) was found to be 59.46 shown in figure.6, which seemed to increase the species distribution about 98% (Figure 12.a) although the response of isothermality to *S. spectabilis* distribution was a negative relationship. The isothermality variable was the most influencing variable given in Table.5, besides the test gain values were the highest for the isothermality variable which gave the most useful information by itself (Figure.11). Most abundant distribution in the Wayanad district was seen in the deciduous forest shown in Figure.17. which was found to be favourable for 86% of the potential suitability area in the district. However, a low suitability habitat distribution was seen in the evergreen forest, part of southern western ghats in the western Wayanad. This is because that the *S. spectabilis* could not establish under full canopy forest (PIER, 2014). *Majority* of modelled high habitat suitability of *S. spectabilis* in the current scenario was seen in the elevation range between 500 – 750 m, which is the eastern and central parts of Wayanad including Wayanad wildlife sanctuary. The response of elevation to the invasive species *S. spectabilis* distribution increased with the increased elevation reaching the peak of distribution at the elevation 750m and further, increased elevation had a decreased response in species distribution reaching no change at 2400m shown in Figure.12.g. However, the IAS had been seen in the coastal areas and Andes regions of its native region, South America. *S. spectabilis* is highly competing and adaptive tree species which could grow and establish in any condition. Additionally, elevation is the second-most important contributing variable in percentage shown in Table.5. Disturbances create corridors thereby, acting as outlets to fragmented or undisturbed landscapes (Tripathi *et al.,* 2019), also creating 'vacant spaces/ecological opportunities' (Moles *et al.,* 2008). This is proved by the study of McDougall *et al.* (2018), as roads also facilitate the expansion of invasives which will significantly increase with human mobility, tourism, trade etc. Although, distance from road and distance from water bodies showed a negative response to *S. spectabilis* distribution in the Wayanad district as predicted by the MaxEnt model in the study given in Figure.12.m,n. The high habitat suitability potential of current climatic condition was found in the low disturbance area additionally, distance from roads had the most information that isn't present in the other variables shown in Figure.10. Furthermore, the model predicts that the influence of distance from road would play an important role in the distribution of *S. spectabilis* (Table.5). The cumulative contribution of the contributing precipitation variables; precipitation of warmest quarter (BIO18), precipitation seasonality (BIO15), precipitation of driest quarter (BIO17) was found to be 10%. The distribution of *S. spectabilis* showed an increase when the precipitation seasonality (BIO15) increased and moreover, the precipitation seasonality seemed to be higher value (Figure.8). Furthermore, precipitation of driest quarter (BIO17) found to be in the range (30mm), where the distribution of *S. spectabilis* was at the highest (Figure.12,e). Similarly, current scenario showed a highly suitable range of precipitation of warmest quarter (BIO18) (Figure.10), where the distribution of *S. spectabilis* seemed to be at the peak about 100%. Temperature seasonality (BIO4) in the current scenario in the Wayanad district also contribute the high habitat suitability as it was under the suitable range about 140.8 (Figure.70 for distribution of *S. spectabilis,* additionally it showed a positive J-shaped response curve (Figure.12,c). The abundance of the *S. spectabilis* was mainly because of its high adaptive capacity in any conditions including its high coppicing ability, high allelopathic effect, high seed viability and lack of natural enemies. Moreover, the study of Anoop *et al.* (2021) suggested that the native mammals specifically elephants transport *S. spectabilis* to a considerable distance and thereby could play a role in the current and future distribution of the species. Furthermore, a co-occurrence of the fruiting of the seeds of *S. spectabilis* and the high density of elephants in the Nilgiri biosphere reserve were reported by the studies (Anoop *et al*., 2021). Thus, the dispersal mechanisms also played a major role in the distribution of *S. spectabilis* in the regions of Wayanad wildlife sanctuary apart from the dispersal pathways. The profuse growth of the IAS in the Wayanad district especially in the Wayanad wildlife sanctuary was due to the lack of quarantine of the ornamentals as the species was accidentally introduced as ornamentals which caused the great havoc. The invasiveness of the species is found to be in the wildlife sanctuary rather than the human inhabited areas. The study also focussed on the objective of finding the future distribution of *S. spectabilis* to understand whether the future climatic conditions could promote the distribution and invasiveness. The decrease in the temperature profiles; BIO1 and BIO3 favoured the distribution. However, the temperature seasonality increase between the range 90 - 165^{o} C favoured the distribution. Looking into the precipitation variables; BIO17, BIO15 increased precipitation in the specified range favoured the current distribution. BIO18 however unfavoured as it increased. Accordingly, the results of the model provided by this study have an important implication in the management measures.

The study modelled using the optimized variables under four different Representative Concentration Pathways (RCP) such as RCP2.6, RCP4.5, RCP6 and RCP8.5 predicted the future distribution of the Indian Peafowl in Kerala for the years 2050s (average for 2041 – 2060) and 2070s (average for 2061 – 2080). The distribution change of the *S. spectabilis* showed that in all the greenhouse gas pathways compared to the current scenario, majority of parts of the Wayanad district and mostly Wayanad wildlife sanctuary had no change in distribution. In the time period of 2050s, RCP 4.5 scenario showed nearly half of the suitability area had no change compared to current scenario, followed by 40% of no change distribution potential in parts of Wayanad in RCP 2.6 scenario. RCP 6 and RCP 8.5 scenario also had considerable no change distribution potential with 39% and 32% respectively (Figure.31). Focussing the protected areas, it gave a shocking result as the entire Wayanad wildlife sanctuary had 99% no change distribution potential compared to current in RCP 2.6, RCP 4.5, RCP 6 scenarios and 96% in RCP 8.5 scenario. It could be regarded as an alarming call for action as in the earlier studies (Anoop *et al.*, 2021), reported that 23% of the Wayanad wildlife sanctuary is found to be distributed with *S. spectabilis* and moreover, this study showed that very high suitability for the invasive species accounted for 86% of the sanctuary. This could hamper the biodiversity and lead to species extinction of both the flora and fauna as it would create imbalance in the ecosystem. Although in Wayanad district, the very high habitat suitability area in all the RCP scenarios decreased compared to current scenario, the high, moderate and good suitability area showed an increase compared to current scenario (Figure.31), however the moderate suitability area decreased in the wildlife sanctuary. Wildlife sanctuary showed chiefly high and very high habitat suitability area and compared to the current scenario, the high suitability would increase whereas, very high suitability would decrease in all the RCPs (Figure.33). This could be chiefly attributed by the decrease in the isothermality variable (BIO3) which outperformed by far the rest of the contributed variables (Figure.19,20). There was 100% distribution response to *S. spectabilis* in the area when isothermality is the lowest (Figure.12.a). The increase in the temperature seasonality, precipitation seasonality, precipitation of driest month also favoured the distribution of *S. spectabilis* although the increase in precipitation of warmest quarter and annual mean temperature not favoured (Table.9). The distribution change in no occupancy would be comparatively greater than range contraction in the RCP scenarios except RCP8.5 scenario. The no occupancy distribution regions would be mainly the western parts of Wayanad with the evergreen forests and agricultural regions in the western ghats which were classified under the low habitat suitability area for the *S. spectabilis.* The model predicted highest range contraction in the RCP 8.5 scenario with 34% potential area compared to the current scenario in the 2050s. Similarly, the RCP 8.5 scenario to be highest in the wildlife sanctuary. The rise in the annual mean temperature (BIO1) and increased annual precipitation (BIO12) (Table.3) increased range contraction in RCP scenarios as the idea temperature for *S. spectabilis* is 19 - 22^{o} C and the precipitation range between 800 – 2000mm (CABI, 2021). The report by Kerala State Action Plan on Climate Change, (2014) predicted a negative change in variation of rainfall in Wayanad district in 2050s. The range expansion in the Wayanad district and as well as in wildlife sanctuary was predicted to be very less compared to range contraction. However, range expansion in wildlife sanctuary would be greater than no occupancy distribution change under RCP scenarios in 2050s. The highest range expansion would be found in RCP 4.5 scenario in both the sanctuary and Wayanad district and the lowest in RCP 8.5 scenario. The greater range expansion in RCP 4.5 scenario among other RCPs could be attributed to the favourable range of isothermality, precipitation seasonality, precipitation of driest quarter and temperature seasonality for the distribution of *S. spectabilis.* Therefore, for the time period 2050s, RCP 4.5 scenario has the highest habitat suitability for *S. spectabilis* in both the wildlife sanctuary and

Wayanad district whereas, RCP 8.5 scenario would be unfavourable for habitat suitability leading to greater range contraction in both the wildlife sanctuary and Wayanad district in the time period 2050s.

Unlike 2050s, the model projection of *S. spectabilis* in all the four RCP scenarios in the time period 2070s showed that the range contraction would be greater than the no change, no occupancy, range expansion distribution change areas in the Wayanad district whereas, in the Wayanad wildlife sanctuary, the no change distributional change would be greater than range contraction followed by no occupancy and range expansion. Range contraction was found to be higher in RCP 4.5 scenario about 45% in the 2070s and the higher range expansion with RCP 2.6 scenario among the RCP scenarios in the Wayanad district (Table.16). Similarly, the range contraction in the wildlife sanctuary found highest in the RCP 4.5 scenario and with the highest range expansion in RCP 2.6, RCP 6 and RCP 8.5 scenario. Moreover, RCP 4.5 also showed highest no occupancy distributional change in area in the sanctuary. Furthermore, 96% of potential area of wildlife sanctuary would be no change distribution area in RCP 6, RCP 8.5 and RCP 2.6 while, there would be decrease in RCP 4.5 scenario. The very high suitability was found to be higher in RCP 2.6 among other scenarios. The sole reason for less distribution of *S. spectabilis* in RCP 4.5 scenario could be the higher isothermality (BIO3) among other RCP scenarios (Figure.5.b). The isothermality response to *S. spectabilis* distribution showed a negative relationship (Figure.12.a). Furthermore, the temperature seasonality (BIO4) was very low in RCP 4.5 (Figure.6.b.) compared to other RCPs. The suitable range of the temperature seasonality for the distribution of *S. spectabilis* is given in Figure.12.c. Moreover, the increased precipitation of driest quarter (Figure.8.b.) and precipitation of warmest quarter (Figure.9.b.) beyond the suitable range given in Figure.12, contributed to lower suitability compared to other RCPs in 2070s. The most favourable habitat in RCP 2.6 scenario could be attributed to low precipitation of driest quarter which lies in the suitable range between 15 – 23 mm, higher temperature seasonality among the RCPs and also the isothermality values of RCP 2.6 in the suitable range.

Eventhough, the future projected model showed variability among RCPs and among the time periods of 2050s and 2070s, it predicted a decrease in habitat suitability compared to current scenario. However, there found to be no significant change in the Wayanad wildlife sanctuary which is an alarming call for action. The predicted results of climatic suitability in the future scenario in Wayanad have broader similarities with the results of Adhikari *et al.* (2015) who found high climatic suitability in Wayanad despite the study carried out was on combined model projection from all five continents. According to Shreshta *et al.*(2012), the impact of climate change is likely to be more drastic at high- elevation regions, possibly due to greater change of temperature in those areas compared to lowlands as well as midlands. Furthermore, there are studies accounting for the species invading higher altitude areas currently than in the past (Shrestha *et al.*, 2015; Tiwari *et al*., 2005). However, the high and very high habitat suitability areas in Wayanad tend to decrease in future scenarios compared to current scenario. Additionally, it was visualized that very high suitable areas under current climate conditions are prone to lose their suitability into good, moderate and low suitability ranges under the future climatic condition (Figure.31, 32) which was in line with the study of Weldemariam and Dejene (2021) predicting the invasion hotspots of *Senna didymobotrya* in Africa. Biological invasion of *S. spectabilis* will enhance pressure and add risks to vulnerable ecosystems in future in eastern parts of Wayanad especially Wayanad wildlife sanctuary as it is already vulnerable to climate change and experiencing its repercussion. Furthermore, the high coppicing ability, allelopathic nature and the viability of the seeds of *S. spectabilis* that turns into a great advantage for establishment in the invaded region and aids in ecosystem destruction.

Although climate change created some novel climatically suitable habitat for *S. spectabilis*, the model predicted large contraction, no occupancy and no change areas in Wayanad which had an upper hand compared to range expansion in future scenarios in both the time periods. Furthermore, the very high habitat suitability decreased compared to current scenario. Additionally, there was no significant shift in the future range. Therefore, the undertaken study articulated that there was no large range of new invading areas in Wayanad. The hypothesis put forward in the study, as the climate change would likely increase its occurrence probabilities was thus proven wrong. There was no profuse expansion due to increase in temperature and rainfall instead there was large range contraction and no change areas. The protected areas (Tholpetty range, Muthanga range, Sulthan Bathery range and Kurichiat range) were in stake of danger due to invasion risk in both current and future scenarios although there would be less expansion.

5.5. Uncertainty of the Results of the model

There were uncertainties in the model output, as in any other model due to the complexity of the real world. Prediction errors were possible due to differences in the correlation structure of future climatic conditions and current conditions (Shreshta and Shreshta, 2019) and besides, model outputs were developed from the extrapolation of current distribution in time and space to forecast potential suitable habitat niches under future climate, however, did not address non-analogous climatic space issue (Fitzpatrick and Hargrove, 2007). Range expansion of species range involves multiple ecological processes such as dispersal, physiology, biotic interactions (e.g., facilitation and competition) and evolution as described in Urban *et al*. (2016) and Martin *et al.* (2013). Inclusion of projected landuse and landcover change variable and the edaphic variables to the model could provide a more accurate prediction and lessen the uncertainties. Despite the uncertainties, considering the conservation and ecological management aspect in a changing climate, some amount of model extrapolation was essential for practice (Mahony *et al*, 2006). To lower the level of uncertainty, the present study employed the HadGEM2-ES GCM, which includes a terrestrial dynamic vegetation scheme that depicts changes in vegetation distribution also as the study was focused on an invasive species (Collins *et al.*, 2011). Moreover, MaxEnt models were effective for indicating the climate suitability of species across a broad geographic range, but they had limits that can be uncertain (Elith *et al*., 2006).

5.6. Implications with the distribution model study

The results of this study can act as a precautionary note in a situation where there is a lack of information base in invasive species distribution and ecology. With this result, management measures can be focused on the areas of predicted habitat suitability. To tackle the aggressive growth of the invasive species *S. spectabilis* there should be a short term and long-term management action plan implementation. The distribution modelling can aid in the risk assessment measures and thus the eradication procedures. Besides the distribution modelling, to prevent the profuse growth and colonization of the invasive species, species traits, dispersal pathways and the mechanism of the natural filters should be better understood. The result emphasized on the very high suitability of the *S. spectabilis* in the current scenario in Wayanad and the wildlife sanctuary. Currently, 86% of potential area of wildlife sanctuary is found to be under the very high habitat suitability category. The astonishing result is that eventhough there is no considerable range expansion, there would be about greater than 90% potential area of wildlife sanctuary under the habitat suitability remained as such in future scenario as that of current scenario. Looking into Wayanad district there is a considerable range contraction, and in western Wayanad, part of western ghats with no occupancy or low suitability areas for *S. spectabilis* which is a relief. But the distribution of *S. spectabilis* could lead to extinction risk of many flora and fauna if not taken right measures at the right time. The legislatives, scientists, laymen should involve in the process of eradicating the species since it is an invasive species with high potential and competitiveness, which could survive in any conditions. Providing Awareness to the public is also a crucial step.

CHAPTER 6

SUMMARY

Climate change caused by humans had a tremendous impact on physical and biological systems all around the world. All the levels of biodiversity from species to ecoregions had been anticipated by the multiple components of climate change. Climate change and bioinvasion were the two main drivers of species extinction and hampering natural evolutionary processes worldwide. A single loss of species will lead to cascading effects since each organism were connected by food webs and other biological interactions. The extent and intensity (invasion hotspots) of the suitability potential regions for IAPs would increase as a result of climate change. The present study was a supporting element for the above statement. The distribution of the invasive tree species *S. spectabilis* was studied to the changing climate. The widely used species distribution model Maximum entropy-based model (MaxEnt) was used. It gave robust output and high performance for a small set of presence data. Using these, SDMs it was possible to delineate the invasion hotspot areas and thus helped in devising better management plans. Using the primary and secondary occurrence data collected, the present distribution was worked out. The subsampling method was chosen as a replication type because of less collinearity among variables and the exclusion of noisy variables. Linear-Quadratic-Hinge-Product model features with regularization multiplier four was chosen. The testing percent was 75 and the remaining iterations of 25 percent were used for training. Future projection of the distribution of the invasive species made by converging it to the maximum entropy probability distribution when utilizing the current distribution analysis. The same current environmental layers, as well as future predictor layers for different RCPs such as RCP 4.5, RCP 6.0, and RCP 8.5 and the HadGEM2-ES were used to carry out the modelling process for future prediction of *S. spectabilis*. The nature of the relationship between the environmental variables and the selected invasive species were analyzed from the model output. The variable which showed the highest percentage contribution in the construction of the

model for the distribution of *S. spectabilis* was Isothermality (BIO3) followed by elevation and annual mean temperature (BIO1), additionally, the precipitation variables; precipitation of warmest quarter (BIO18), precipitation seasonality (BIO15), precipitation of driest quarter (BIO17) also showed significant contribution. The variation in the influence of the isothermality variable was observed with an increased contribution in RCP 2.6 scenario in 2050s and RCP 6 scenario in 2070s. Non-climatic variables have less significance in the distribution model of *S. spectabilis*. Nevertheless, the permutation importance of precipitation of warmest quarter (BIO18) was the highest and isothermality (BIO3) with the least. The variables that had a positive response to the distribution of *S. spectabilis* were BIO4 (temperature seasonality), BIO15 (precipitation seasonality). A higher presence probability was observed when the annual mean temperature was at 22.5° C. The results of the study revealed that the protected areas in Wayanad is at a high stake of danger in every RCP scenario. Both the periods (the 2050s, 2070s) showed an increase in range contraction with RCP 8.5 scenario in 2050s and RCP 4.5 scenario in 2070s. The no occupancy region and no change distribution areas remained unchanged which will hamper the native flora and fauna community of the area. The majority of the range expansion is expected to be in the inhabitant areas where the population density was around 500 persons per km^2. The high and very high suitability area for *S. spectabilis* showed a decreasing trend with the RCPs in both periods whereas, a good habitat suitability showed an increasing trend. Therefore, observed habitat suitability of *S. spectabilis* from the study calls for urgent action in the management of areas where biodiversity is at a higher risk of danger.

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IMPACT OF PROJECTED CLIMATE CHANGE ON THE SPREAD AND DISTRIBUTION OF THE INVASIVE ALIEN SPECIES *Senna spectabilis* (DC.) H. S. Irwin & Barneby IN WAYANAD DISTRICT OF KERALA

by

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THESIS ABSTRACT

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ABSTRACT

Climate change has exacerbated the threat of biological invasions, particularly by increasing the range of climatically suitable regions for invasive alien species. Many native and invasive species' distributions are anticipated to change as the future climate changes. Species distribution models may be particularly useful in risk analysis of recently arrived invasive species. Preventive management is required in areas where invasion is a danger. *Senna spectabilis* is a rampantly spreading recent invasive of Kerala posing a major threat to the native species in ecologically important areas like Wayanad wildlife sanctuary. The present study attempted to model the potential habitat suitability of *S.spectabilis* under current and future climate conditions and understand the effects of climate change on the distribution of *Senna spectabilis.* The study used Maximum Entropy (MaxEnt) species distribution modelling utilising the primary and secondary presence-only occurrence records. A total of fifteen environmental variables including both bioclimatic and non-climatic variables were used for model parametrisation. Annual mean temperature (BIO-1), Isothermality (BIO-2), Temperature seasonality (BIO-4), Precipitation seasonality (BIO-15), Precipitation of warmest quarter (BIO-18), Precipitation of driest quarter (BIO-17), elevation, slope, aspect, distance from road, distance from water bodies, soil type, landcover, aspect and population density were the optimized variables after excluding the autocorrelation among the bioclimatic variables and analysing the climatic variability in future representative concentration pathways. The best model for species distribution modelling was chosen with ENMeval algorithm using R language. A High average Area Under Curve (0.92 ± 0.02) and True Skill Statistics (0.84) suggested that the model developed had a good prediction accuracy. The study identified that the temperature variables had a higher contribution with a cumulative contribution of 45.2% and will be the major factors which determine the distribution of *Senna spectabilis* whereas, the precipitation variables had a cumulative contribution of only

10%. Elevation contribute (20.8%) higher than other non-climatic variables. The current distribution model estimates that about 66% of potential area of Wayanad is a very high climatically suitable habitat for the profuse growth of *S.spectabilis*. The reclassified five habitat suitability classes suggested that 34% of potential area of Wayanad is under very high suitable habitat, 24% potential area under high suitability. The low suitability accounted for 14% of the potential area which is in the western parts of Wayanad. Eastern Wayanad and Wildlife sanctuary are the major invasion hotspots of *S.spectabilis.* The study also forecasted the future distribution patterns of *S.spectabilis* for the time period 2050s (2041–2060) and 2070s (2061–2080), based on the four RCP scenarios viz; RCP 2.6, RCP 4.5, RCP 6, RCP 8.5 using the HadGEM2-ES general circulation model. The projected model predicted that nearly half (49%) of the potential area of Wayanad and 99% in Wayanad wildlife sanctuary will have no change (presence of invasive species in both current and future scenarios) in species distribution in 2050s RCP 4.5 scenario compared to current scenario and 34% of area under range contraction in RCP 8.5 in Wayanad district. The model predicted that in 2070s, there would be a decline in range expansion and increase in range contraction compared to 2050s time period and with highest range contraction in RCP 4.5 scenario with 45% and 34% of potential area under range contraction in Wayanad and Wayanad wildlife sanctuary respectively. Additionally, RCP 8.5 with 96% no change species distribution area in wildlife sanctuary in 2070s. The model predicted that an increased mean annual temperature (BIO-1) and precipitation of warmest quarter (BIO-18) would not favour the species distribution in Wayanad district whereas, the decrease in the most influencing variable isothermality (BIO-3) and the precipitation of driest quarter (BIO-17) would significantly favour the distribution in the future. This would enhance pressure and risks to vulnerable ecosystems of eastern Wayanad including Wayanad wildlife sanctuary which calls for urgent action at the earliest to prevent from further biodiversity loss.