PREDICTING HOTSPOTS OF FOREST INVASIVE SPECIES (FIS) IN INDIA USING SPECIES DISTRIBUTION MODELING

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CERTIFICATE

This is to certify that **Mr. Utsav Bahuguna**has carried out his project entitled **"Predicting Hotspots of Forest Invasive Species (FIS) in India using Species Distribution Modeling",** in partial fulfilment for the award of degree of **Master of Technology in Remote Sensing and GIS**. The project has been carried out in **Forestry & Ecology Department** and is original work of the candidate under the guidance of **Dr.HitendraPadalia**, Scientist/Engineer-SE, at Indian Institute of Remote Sensing, Dehradun, India.

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Abstract

Biological invasion is the second-greatest threat to biodiversity, after habitat destruction. Pre-emptive management is necessary for the regions under severe threat of invasion. In the present research, the hotspots of forest invasive species (FIS) has been modelled in India using species distrituion model. The occurrence records of 105 FIS gathered from natural vegetation (comprising forests, shrublands, grasslands) regions of the country over past one decade were used for predicting hotpots of invasion. The species distribution model (i.e. MaxEnT) was trained with climatic, topographic and landscape variables and occurrence data to predict potential distribution for each of FIS. The high average Area Under Curve (AUC) (0.94 ±0.5) and True Skill Statistics (TSS) (0.74 ±0.5) value was obtained for all FIS suggesting good prediction accuracy. The high to medium invasion risk are predicted in the north-eastern part of Deccan Peninsula, semi-arid biogeographic zones. The foothills of Himalaya and Western Ghats are also under medium invasion risks. The mixed forest, woody savannahs, grasslands and open shrub lands are the potential habitats of most of tropical FIS. The potential habitats of most of FIS are distributed in the low canopy density habitats and low phytorichness areas. The study reveals that forest areas with high canopy density, rich in native plant diversity and located in the relatively complex terrain have less probability of getting invaded by most number of FIS presently introduced in India.

The behaviour of most widespread and noxious FIS has been studied in terms of changes in their potential geographic range under the projected climate change scenario. Ensemble of three widely used climate models namely: CGCM2, CSIRO-mk2 and HADCM3 were used to predict range shift for 15 FIS. The ensemble forecast projection was found effective in overcoming minor contradictions in the prediction by individual model. Study alarms expansion in potential invasion range of FIS such as *Ageratum conyzoides, Bidens pilosa, Cassia occidentalis, Cassia tora, Chromolaena odorata, Eupatorium adenophorum, Mikania cordata, Lantana camara* and *Parthenium hysterophorus*. Whereas other species such as *Prosopis juliflora, Euphorbia hirta, Hyptis suaveolens, Cyperus rotundus, Eclipta prostrata* would shrink in their potential invasion range offering opportunities for ecosystem restoration.

Present research provides valuable spatial knowledge about major areas of concentration of potential habitats of FIS or hotspot of invasion in India. Study also provides knowledge about distribution of most noxious and widespread FIS of India under climate change. Study has been successful in prioritizing forests and phytorichness zones susceptible to FIS invasion. Overall, the spatial knowledge about distribution of FIS would be useful for developing surveillance and control strategies and devising efficient conservation and management strategies to preserve biodiversity.

Keywords- Invasion, species distribution modelling, climate change, hotspots, range shift.

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ABBREVIATIONS

ASCII:	American Standard Code for Information Interchange
AUC:	Area Under Curve
BioCLIM:	Bioclimatic envelope
CART:	Classification and Regression Tree
CSV:	Comma Separated Value
DBT:	Department of Biotechnology
DEM:	Digital Elevation Model
DST:	Department of Science and Technology
ENM:	Ecological Niche Model
FIS:	Forest Invasive Species
GARP:	Genetic Rule Set Prediction
GCM:	General Circulation Model
GLCF:	Global Land Cover Facility
IAS:	Invasive Alien Species
ICFRE:	Indian Council of Forestry Research and Education
LULC:	Landuse/Landcover
MaxEnT:	Maximum Entropy
MODIS:	Moderate-resolution Imaging Spectroradiometer
NBSS&LUP:	National Beureo of Soil Survey and Land Use Planning
ROC:	Receiver Operating Characteristic
SDM:	Species distribution model
SRES:	Special Report on Emissions Scenarios
SRTM:	Shuttle Radar Topographic Mission
TSS:	True Skill Statistics
UNEP:	United Nation Environment Programme
UNFCCC:	United Nation Framework Convention on Climate Change
USGS:	United State Geological Survey
VCF:	Vegetation Continuous Field

Chapter-1 Introduction

Biological invasion have intrigued ecologists for decades. Elton "Father of Invasion Ecology" coined the term invaders and invasion in ecological context (Elton 1958). Forest invasive species may include plants, animals and even micro-organisms that are non-native to a specific ecosystem and are capable of establishing a self-sustaining population causing significant ecological destruction. Kolar and Lodge (2001) defined invasive species as "a non-indigenous species that spreads from the point of introduction and becomes abundant". These species may be introduced by humans into places out of their natural range of distribution either accidently or deliberately, where they establish themselves, disperse and out-compete the existing native species (Richardson *et al.*, 2011). Forest invasive species includes introduced and non-native species specific to forested ecosystems having tendency to spread causing significant damage to the forest structure, composition including regeneration.

Biotic invasion is considered as one of the most important environmental issues of the 21st century (Miller *et al.*, 2010). Invasive FIS are the second-greatest threat to biodiversity, after habitat destruction and the cause of substantial economic damage (Ficetola*et al.*, 2007). The invasive species are known to affect the ecosystems in a number of ways e.g. displacement of the native species; effecting the ecosystem processes; reducing the native wildlife habitats; degradation of recreation lands; reducing the forest health and productivity (False-brome Working Group 2003)

The invasive species bear certain traits which help them to colonize and establish populations in the new environment. The spread of invasive species depends upon several factors including the physiological traits , ecosystem properties (Bazzaz 1986) and landscape structure (Richardson *et al.*, 2000) The associated physiological traits of invasive plant species includes: extensive growth, high reproductive capacity, good dispersal mechanism, high competitive ability, wide range of ecological amplitude, unique ability to adapt physiologically to new environmental conditions, high phenotypic plasticity coupled with hybridization capacity, wide range of ecological strategies and strong allelopathic potential (Bazzaz 1986). The lack of natural enemies and suitable growing conditions helps an invasive species to spread (Sutherst 2000). Landscape structure including disturbance facilitates the spread of invasive species (With and King 1997; Richardson *et al.*, 2000).

The ongoing climate change is a major factor which can dramatically influence the spread of invasive. Intergovernmental Panel for Climate Change (IPCC) defines climate change as any change in the average climatic conditions over a long period of time, whether due to any natural variability or as a result of human activities. The rate of global climate change is accelerating, and global mean surface temperatures is projected to increase by 2.4 to 6.4 ºC between 1990 and 2100 (Solomon *et al.*, 2009), along with various changes in rainfall patterns (increases, decreases and changes in seasonality) (Taylor *et al.*, 2012) Climate change has complex effects on the potential distribution of non-native weed by altering current climatic habitat (Roura-Pascual, 2004; Peterson, 2008), expected to exacerbate non-native species invasions as conditions at any given site become less suitable for existing species and may become more suitable for invasive species (Dukes and Mooney, 1999).

Prudent management of biological invasions requires information about the expected potential distribution and relative abundance of invasive species under current and future climate change scenarios. Such information is necessary for risk assessment as well as the formulation of appropriate long-term management strategies (Taylor *et al.,* 2012).

Species distribution models (SDMs) have become the extensively useful tools to determine the relationships between species and their environments (Robertson *et al.,* 2004; Guisan and Thuiller, 2005, Yang *et al.,* 2013), and are used to predict drastic impacts of climate change, biogeographic studies, assisting in reserve selection, improve species management and answer conservation biology questions (Guisan and Zimmerman, 2000). SDMs are a set of computer algorithms that are used to predict the species distribution in geographic space basing on mathematical representation of their known distribution in ecological niche (environmental space). These models are developed to meet the current challenges of predicting the future geographic distributions of the invasive alien species ranging from genetic algorithm, maximum entropy, neural network and multivariate regression algorithm (Babar *et al.,* 2012). Few examples of SDMs include MaxEnT, GARP, and BioCLIM etc.

The countries located in tropical and sub-tropical climatic regions particularly have been invaded by more number of alien invasive species. It may not be possible keep track of each of invasive species rather focusing on ecosystems which have high suitability for large number of FIS for adopting management practices. Information about major areas of concentration of forest invasive plant species (hereafter referred as FIS) or hotspot is useful in identifying the emerging threats posed by the invaders on the native vegetation at larger scale and help in devising conservation and management strategies and efficient decision making. SDMs can be very effective tools to identify such hotspots areas at different scales.

1.1 Motivation and Problem Statement

India has a major proportion of exotic species, however, a significant number of them have become invasive and posing negative impacts on natural ecosystems. Though species survey on some of the widespread invasive species is feasible yet for majority of invasive species field data collection is difficult at regional and national level. In absence of a nation-wide database on occurrence of invasive, so far explicit knowledge on areas of major concentration of invasive plants lacking. These gaps in knowledge about the major areas plant invasion in the country can be met by generating potential hotspot distribution scenario using reasonably good occurrence records which have been recently become available. This research would provide valuable information about major areas of concentration of invasive species or hotspot under current scenario and their range shift under future climate projections. This information would be useful in identifying threats on the native vegetation and biogeographic zones at larger scale. The research would help in development of understanding about the probable impact of climatic changes on the potential niches of invasive species. It would provide information about major hotspots and future range shift, which would be useful for recognizing threat on various forested ecosystems and help forest managers and policy makers in devising efficient conservation and management strategies

1.2 Aim and Objectives

The aim of this study is identifying the potential hotspots of plant invasion in the terrestrial natural ecosystems of India.

1.2.1 Objectives

1. To model the potential hotspot of alien forest invasive species (FIS) in India using species distribution modelling.
2. To predict the potential distributions of most aggressive and widespread FIS in the future climate change scenarios.
3. To assess the geographic range shift of FIS for major natural vegetation types and biogeographic zones in country in future climate scenarios.

1.2.2 Research Questions

1. What is the levels of uncertainty associated climatic data models, and thresholding techniques used for predicting invasion?
2. Does an ensemble overcome the predictive uncertainties of future climate change projections?
3. Does inclusion of landscape heterogeneity and soil characteristics help SDM in improving prediction of potential spread of invasive?

1.3 Innovation

The present study is a first ever attempt to identify potential hotspots of alien species in India. The study has considered unprecedented field information on major proportion of FIS distribution to demonstrate the applicability of SDMs for prioritizing potential invasion hotspots in India. Study relates potential concentration areas of alien species with affected natural vegetation and native plant species diversity. The climate envelopes of geographic zones under the various levels of threats from FIS have been characterized. The study has analysed agreement/disagreement in the spatial predictions of three different climate model projections and their influence in modelling future suitability of most widespread FIS in India.

Chapter -2 Literature Review

2.1 Status of Invasive Plants in India

Invasive alien species (IAS) have become a major environmental concern in India. Reddy *et al.*,(2008) has listed 176 as species in India based on published literature. Indian Council of Forestry Research and Education (ICFRE) organised a national workshop at Dehradun and documented the status of plant invasive species affecting the structure and composition of forests in the country. ICFRE (2005) listed 111 plants as species of immediate attention. The selected species include a range of weeds, vascular plants, fungi etc. 75 number of species (including herbs, shrubs, trees and climbers) are mentioned in world's top 100 most noxious species (http://www.issg.org/database/species/reference_files/) database mentioned by World Invasive species Database.

2.2 Species Distribution Modelling (SDM)

Species distribution model (SDMs) are used to predict the potential distribution of the species in space and time against various bio climatic and biophysical parameters. Most of the SDMs are based on following major environmental niche assumptions (Wiens*et al.*, 2009):

- The species under study are in dynamic equilibrium with their environment factors drive species distribution.
- The niche is coincident with climate change.
- Reported evidences for species dying and not reproducing due to change in the climate.
- There exists co linearity between the variables used in SDMs.

The usefulness of Species distribution models can be summarized under two categories; firstly these models can be used to detect the occurrence of the rare species at remote regions (Pearce *et al.*, 2001) secondly, the habitat change mapping can be very useful in accessing the direct impact of anthropogenic pressure in terms of land use land cover change, and the climate change on the existing habitats (Johnson *et al.*, 2004). The species distribution models are based on presence-absence data (e.g. GAM (Generalized Additive Model), GLM (Generalized Liner Model), CART (Classification and Regression Tree etc.), presence only (e.g. BioClim (Bioclimatic envelope)), presence-pseudo absence data (e.g. Genetic Rule Set Prediction (GARP)) and presence-background data (e.g. Maximum Entropy (MaxEnT)).

2.2.1 MaxEnT (Maximum Entropy)

MaxEnT was introduced by Phillips, *et al.*, (2006) for modelling the species geographic distribution; it is a general purpose machine learning method with precise mathematical calculations. It is based on the maximum entropy approach for modelling species habitat. MaxEnT takes as input, a set of environmental variables e.g. 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 geographic dataset with respect to the ‘background’ environmental layers (Phillips *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. According to Elith (2006), MaxEnT is observed to have outperformed other modelling methods, since it can also work well when the number of occurrence record is less. Pearson *et al.*, (2006) also advocated the better performance of the model with small sample size data. MaxEnT models the suitability of each grid cell as a function of environmental variables in the grid cell. The grid with high value is considered to have been predicted with suitable conditions to favour the species occurrence. Elith*et al.*,(2006) and Ortega- Huerta and Peterson (2008) commented on the better performance of MaxEnT over rest of the modelling approaches.

2.3 Plant Invasion vis-a-vis Environmental Linkages

The environmental conditions (climatic and non-climatic), plays an important role in defining the ecological niche of any species. Climate is the most important factor which influences on environmental processes. It accelerates invasion from the introduction to its establishment and spread (Walther *et. al.*, 2009). IPCC has reported recently about the severe impact of climate change on the species range shift and the consistent response of species towards the growing temperature conditions (IPCC, 2007b). Other environmental factors include topography and landscape heterogeneity etc. 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 the biodiversity and its functions; as it is known to enhance or retard the disturbance in the landscape. Many studies have analysed the positive as well as negative association between the landscape heterogeneity and species richness (Tews*et al.*, 2004; Benton *et al.*, 2003).In addition to climate change, landscape heterogeneity etc., the 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).

2.4 Prediction of Hotspots of Invasion

Duursma*et al.*, (2013) predicted the hotspots of invasion in Australia, using MaxEnT over 292 species under continental as well as regional scale. Wulff*et al.*, (2013) carried our hotspot analysis 283 narrow endemic species in the north and south province of New Caledonia using maximum entropy approach. Liang *et al.*, (2014) stressed upon the importance of hotspot analysis to control the invasion and better decision making. The probability of invasion was accessed using MaxEnT and Mahalanobis distance technique, while the hotspots were predicted for North America. The ensemble technique was considered to have provided better results for predicting hotspots. Miller *et al.*,(2010) modelled the suitable habitats for eight invasive alien plants. Catford*et al.*, (2011) carried out hotspot analysis and claimed its usability in identification of regions of high risk of invasion.

2.5 Landscape Change vis-a-vis Plant Invasion

Change from forest into non-forest has tremendous impact on the ecosystem through destruction of the existing habitats, change in the competitive regimes of the species etc. (Monney and Hofgaard 1999). As the forest changes to non-forest, the products and services associated with forest changes. Few examples of impacts of forest change include habitat fragmentation changes in the transportation corridors and change in the native species habitats (Echaverria 1996). The changes within the forested ecosystems also promote introduction and spread of invasives. Various modelling techniques are available to predict the changes in the landscape patterns (Cheong *et al.,* 2012). Markov models are generally used to generate the landscape scenarios; it is easy to develop with minimal data requirement (Brown *et al.,* 2004). Other models that are now being used for predicting the change in the landscape includes logistical models (Brown *et al.,* 2008), non-linear fitting models (Hastie *et al.,* 1986) and models based on artificial neural network (Tewolde*et al.,* 2011).

2.6 Climate Change vis-a-vis Plant Invasion

The change in the climatic regimes can be majorly understood with the change in the temperature and precipitation conditions and CO2 and aerosol levels in the atmosphere. Climate change may impact the overall invasion process by affecting three major constraints: Invasive species source pools, the dispersal pathways and the process of invasion in the new host ecosystem (Sutherst*et al.,* 2000). The climate change can lead to extreme conditions of droughts, floods, forest fires etc. and may thereby trigger new opportunities for the species to invade new regions by creating extreme disturbance events. Climate change may affect the natural ecosystems, communities and habitats in several ways (Parmeason and Yohe 2003) but most remarkable is the shift in their natural ranges. Environmental gradient have profound impact on the suitable habitat shift of the species therefore more stress should be laid upon the environmental variables that are responsible for the current spread of the invasive alien plant species and the loss of the native species population (Zhang *et al.,* 2014). Buckley *et al.,* (2010) observed that the range shifts from the lower to upper climate-change scenarios, with several invasive species that notably underwent some degree of range shift. It was found that changing climate conditions the expansion in the range of the invasive alien species is more as compared to the contraction due to effects of physical barriers, limited dispersal and potential life history of the species. Sutherst*et al.,* (2000) on the other hand advocated that the climate change may impact the overall invasion process by affecting three major constraints: Invasive species source pools, the dispersal pathways and the process of invasion in the new host ecosystem.

2.7 Climate Scenarios

The future prediction of spread of invasive species demands development of climate scenarios (present and future) considering CO2 emission levels, the factors associated with depletion of ozone layer, landuse changes and globalization etc. (Parry 2007). IPCC (Intergovernmental Panel on Climate Change) a scientific body active under United Nations provides guidelines on emission scenarios (SRES). IPCC was established in 1988 by World

Meteorological Organization (WMO) and United Nation Environment Programme (UNEP). IPCC publishes reports in favour of United Nation Framework Convention on Climate Change (UNFCCC) with the aim to reduce the greenhouse gas emissions to considerable level so as to discourage the impact of human interference on climate change. SRES discusses the possible future emission scenarios, for example the AR4 focuses on scenarios namely A1- marked with homogenous world and global rapid economic growth, and B1- associated with global environmental sustainability, A2-describes a heterogeneous world with regional economic development, B2- focuses on local environmental sustainability.

2.7. 1 Climate Models

2.7.1.1 HadCM3 (Hadley Centre Coupled Model)

HadCM3 was developed in 1999 and has been the first unified climate model that does not require flux adjustments. Flux adjustments are the adjustments applied to climate model simulations which prevents it from drifting into unrealistic climate state i.e. the model climate remains stable. It is a general circulation model (GCM) which has atmosphere-ocean coupling. In case of this model there is always a good match between ocean and atmosphere components and is known to capture the time-dependent footprints of historical climate change in response to anthropogenic and natural forcing. It has an improved ocean mixing scheme over other climate models that are used in climate related studies. The atmospheric model consists of 19 vertical levels with a resolution of 3.75 degree, which approximates to around 300 km resolution. While the ocean model consists of 20 levels with a resolution of 1.25 degree.

2.7.1.2 CSIRO-mk2 (Commonwealth Scientific and Industrial Research Organization)

CSIRO-mk2 is a combination of global ocean, atmosphere, biospheric and sea-ice sub models. It consists of a diagnostic cloud scheme and is a fully flux corrected climate model. The model combines the effect of all radiatively active trace gases into equivalent CO2 concentrations. It is quite similar to Hadley experiments on negative forcing from atmospheric sulphate-aerosol. The forcing found missingare solar variability, sulphate indirect impacts and influence of soot. The atmospheric model consists of 9 vertical levels. While the ocean model consists of 21 levels and the resolution of data provided by the model is 5.6 degree X 3.2 degree (latitude x longitude).

2.7.1.3 CGCM-2 (Canadian Global Coupled Model)

CGCM-2 stands for in this model the ocean mixing parameterization has been changed from horizontal/vertical diffusion scheme to ispycnal/eddy stirring parameterization. This model is used to produce ensemble climate change projections. The model uses radiative forcing equations are used to convert greenhouse gas emission into effective CO2 concentration. The model takes into account linearly interpolated data and includes the direct impact of sulphate. To reduce the climate variability alternate runs of GHG + A1 and GHG + A2 scenarios are made. The atmospheric model consists of 10 vertical levels with a resolution of 3.75 degree, which approximates to around 300 km resolution. While the ocean model consists of 29 levels with a resolution of 1.8 degree.

2.8 Uncertainties in SDM; Occurrence data, Algorithms and Climatic Scenarios

Species distribution modelling is affected by a number of uncertainties arise due to insufficient occurrence data, difference in species distribution algorithms (e.g. presence/absence or presence only), sensitivity of modelled continuo suitability outputs to techniques used for binary (presence and absence) predictions and due differences in climatic projections.

Several studies stress upon the effect of sample size on the predictive accuracy and the model simulation results. Generally with larger sample size the model accuracy increases until the maximum accuracy is reached (Harnendez*et. al.,* 2006). Kumar *et al.,* (2014) highlighted the problems associated with the lack of precise coordinates of species occurrence at regional level to be used a inputs in the species distribution models; therefore he emphasised on the use of the occurrence data even at a coarser district level. Different SDMs differ in terms of their conceptualization e.g. MaxEnTis based on the maximum entropy approach. It provides a probability distribution of species habitat. On the other hand GARP is a fuzzy envelope model using genetic algorithm for determining the ecological niche for the spread of the species and maintain a viable population. One of the majorly faced uncertainties is the selection of rule to obtain binary predictions of the species potential spread from a continuous result. Selection of appropriate threshold may result in eliminating major biasness in species distribution modelling (Phillips *et al.,* 2008). Liu *et al.,* (2013) observed 13 different threshold selection methods (e.g. Fixed cumulative value 1, Fixed cumulative value 5, 10 percentile training presence, Equal test sensitivity and specificity etc.) working with presence-only data and discovered that Maximum training sensitivity and specificity to have been giving better results with presence-only data. Major uncertainties in the predicted outputs arise due to differences in climate models used for prediction. Bellard*et al.,* (2013) modelled the future hotspots of world's top 100 noxious species using three different climate models namely, HADCM3, CSIRO-mk2 and CGCM2 and exclaimed the usability of multiple models and the ensemble forecast projections for better predictions. Zhang *et al.,* (2014) studied the change in woody plant species range in Yunan using the three climate models and reported similar predictions with less uncertainty amongst them.

2.9 Ensemble Modelling

Ensemble modelling techniques are employed to obtain a robust estimate of the suitability of the habitat for the potential spread of the invasive species under study at given time period. Ensemble models are employed to reduce the uncertainty of single model by combining the predictions of all the models and therefore reduce the weakness of single model prediction. Ensemble model is therefore a model which involves combining model outputs from different models (Stohlgren*et al.,* 2010) and is reported to have outperformed the predictions from other individual models (Crossman and Bass 2009). Ensemble models makes use of various algorithm e.g. PCA (Thuiller 2004; Araújo*et al.,* 2006) and statistical criteria (Johnson and Omland 2004), or on basic mathematical functions such as averages and medians of ensembles of predictions (Gregory 2001; Araújo and New 2007).

Chapter-3 Study Area

3.1 Geographical Location

India occupies a strategic position in Asia; surrounded by China, Tibet, Nepal and Bhutan in north. In the South, it is surrounded by Sri Lanka by a narrow channel of sea called Palk Strait and the Gulf of Mannar. India is located to the north of the equator between 8°4' and 37°6' north latitude and 68°7' and 97°25' east longitude. The total land area of the country is around 328.7 million hectares (mha) which forms 2.4% of the world's total area. Fig. 1 represents the study area map of India with different biodiversity hotspots shown with black shaded area.

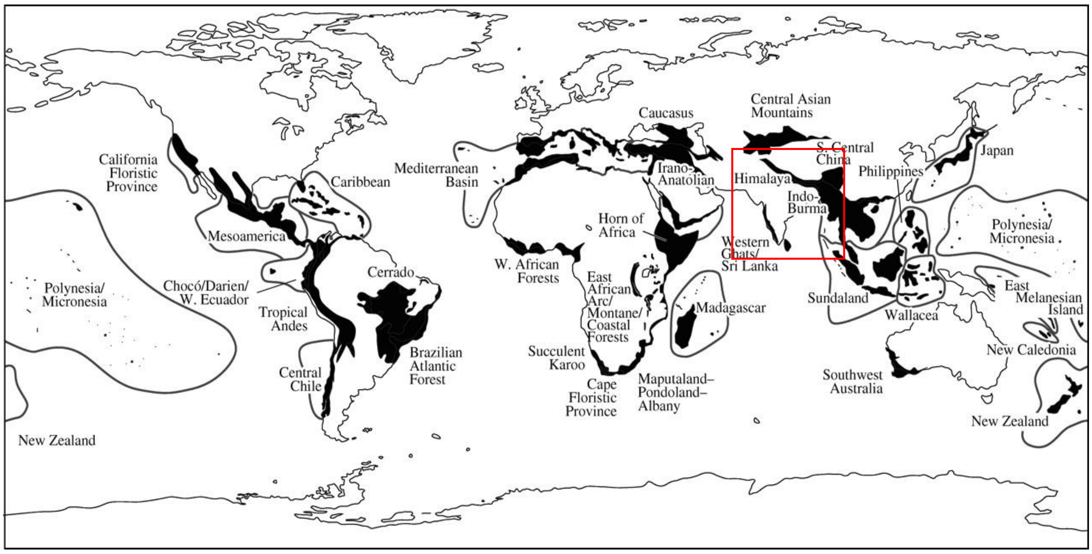


Figure 1: Location of study area i.e. India (in square box) (**source**:www.biodiversity.sg)

3.2 Climate

India being mainly a tropical country, however due to variations in the altitude varying climatic conditions ranging from hot deserts to cold deserts prevails. In India there exists total of four seasons in a year namely: a) Spring (January-March) b)Summer (April-June) c) Monsoon (July-September) d) Winter (October-December). Though the monsoons in the winter months provide some precipitation, around 80% of the precipitation of the country is received from the south west monsoon (summer monsoon).

3.3 Physiography

India consists of four major geographical landforms namely:

a) **The Northern Mountains-** Corresponding of the Himalayan mountains alongside country's northern boundary including Jammu & Kashmir, Himachal Pradesh, Uttarakhand, North-West Uttar Pradesh, Sikkim, Assam, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura and Meghalaya.

b) **The Indo-Gangetic Plains-** Formed by basins of three river systems including the Indus, Brahmaputra and Ganges. The Indo-Gangetic Plains marks their extension from Rajasthan in the west to Brahmaputra valley in the east.

c) **The Deccan Peninsula-**It covers the southern region of India including Tamil Nadu, Karnataka, Andhra Pradesh and Kerala. Also includes the sates of Madhya Pradesh and parts of Bihar.

d) **The Coastal Plains and Islands-**Covered by Eastern and Western Ghats on two sides. The region is marked by very high population density.

3.4 Soil and Geology

India bears a wide range of soil types that are locality specific. The two most important soil types found in India are the alluvial covering about 78 million ha (24%) of the total land and black cotton soil covering 51.8 million ha and are considered as important soil types required for agriculture. Alluvial soil is considered good for the production of rice, pulses, wheat, oil seeds, potatoes etc. The black cotton soil supports cotton, cereals, pulses; oil seeds etc. The other soil types found in India includes red soil (51.8 million ha), laterite soil (12.6 million ha) and desert soil (37 million ha).

3.5 Flora

India hosts four biodiversity hotspots namely: the Western Ghats, the Himalayas, Indo-Burma region and Sundaland (Conservation International, 2012). According to the 2003 State Forest Report, the total forest cover in India is around 67.82 million hectare constituting around 20.64% of its geographical area. The total tree cover in India is estimated to be nearly 9.99 million hectare which is about 3.04% of its area. The major forest types of India used in the study includes: evergreen needle leaf forest, evergreen broad leaf forest, deciduous needle leaf forest, deciduous broadleaf forest and mixed forests.

3.6 Fauna

India is rich in fauna. It has been estimated that 500 species of mammals, more than 200 species of birds and around 30,000 species of insects are present in India in addition to this India reports the presence of a hundreds of species of fishes and reptiles. The invasion of exotic plant species in natural ecosystems has already started exerting negative impacts on native fauna.

3.7 Socio-Economy

The statistics of the National Census (2001) recorded the total population of the country to be 1027 million which was about 21.34% above the population recorded between 1991 and 2001. As per the latest 2011 census the population of India is 1.221 billion. It has increased by 1.21 billion with a decadal growth rate of 17.64%. The population density is reported to be 382 persons per km^2.India is considered as one of the world's largest economies and ranked fourth with the present GDP of 1.877 trillion USD (2013). India as a growing economy is going to develop cities, linking of rivers, transportation corridors and other spatial infrastructure with reduction in natural habitats. All of these processes brings spatial changes in landscape and thus would influence the spread of invasive plant species.

Chapter-4 Materials and Methods

4.1 FIS Occurrence Data

The majority of FIS occurrence data was compiled from the species database of the national project "Biodiversity Characterisation at Landscape Level using RS and GIS" carried out by the Department of Science and Technology (DST) and Department of Biotechnology (DBT) between 1998 and 2010. In total 105 FIS (including 94 herbs, 8 shrubs, 1 tree and 2 climbers) were found having well-distributed and sufficient number of occurrence records (Appendix-1). These FIS were included because they were found during sampling in the forested areas during biodiversity project. After having identified the FIS, the occurrence data was collected from the Global biodiversity Information Facility Database (GIBF).

The most widespread and invasive plant species of ecological and economical concern was identified based on published research articles, reports and consultation. The 15 most noxious FIS were selected and considered for modelling the distribution under projected climate change scenarios. Table in Appendix-2 give the details of these FIS and their occurrence records.

4.2 Environmental Database

4.2.1 Climatic Variables

The global climate data at 30 arc-second (approx. equal to 1 km^2) grid size was downloaded from World Climatic Research Centre (Hijmans*et al.,* 2006; http://worldclim.org/ bioclim.htm). The climate data comprised of monthly maximum temperature (tmax), monthly minimum temperature (tmin) and monthly precipitation (prec). DivaGIS software was used to derive19 Bioclimatic variables that are biologically significant for defining the eco-physiological tolerances of different FIS, for present as well as for the future climate scenarios. The Bioclimatic variables coding is included in Appendix 3. Fig. 2 represents the selected climatic variables used as inputs in the study.

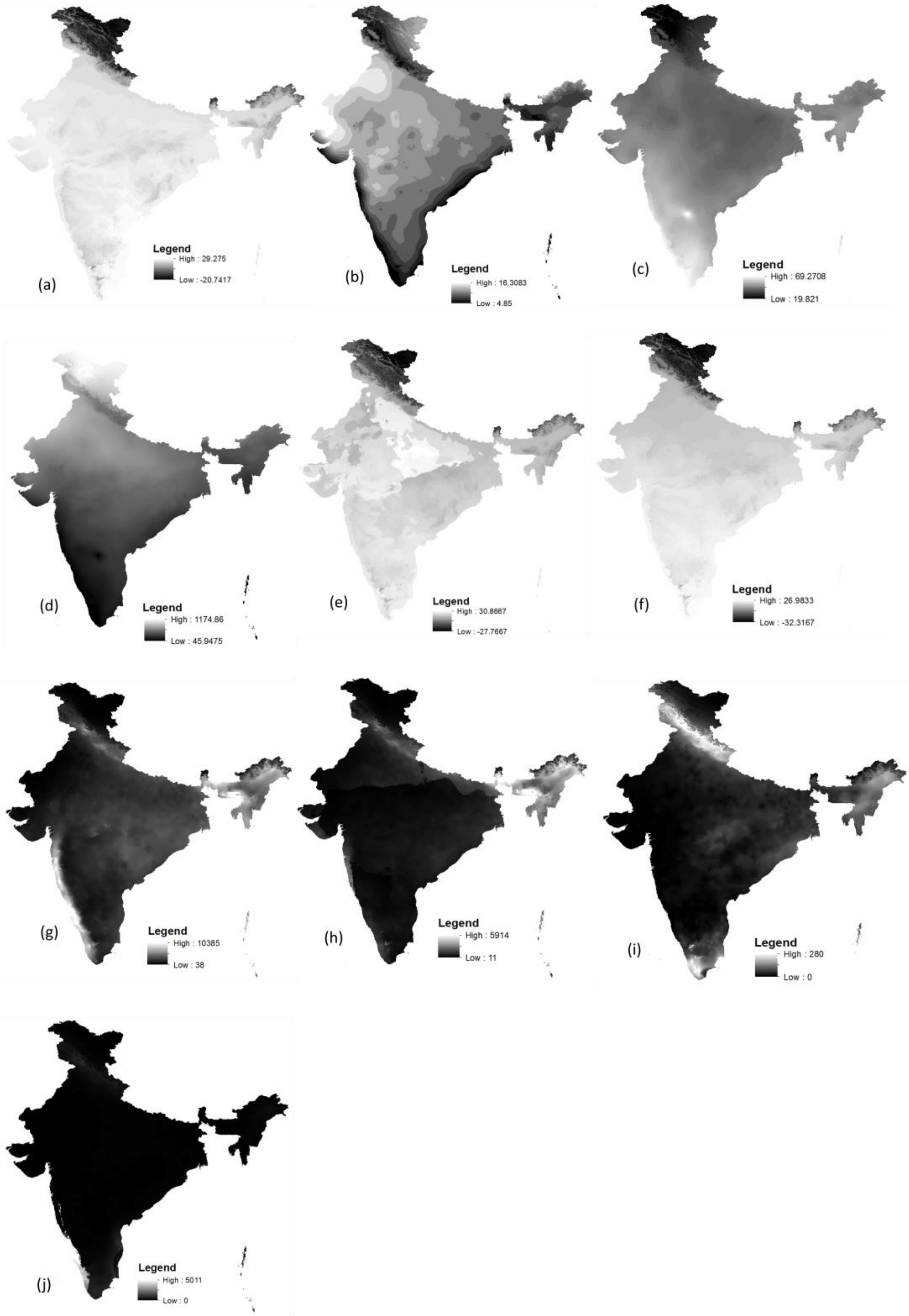


Figure 2: Selected climatic variables namely (a) annual mean temperature (b) mean diurnal range (c) isothermality (d) temperature seasonality (e) mean temperature of driest quarter (f) mean temperature of coldest quarter (g) annual precipitation (h) precipitation of wettest quarter (i) precipitation of driest quarter (j) precipitation of coldest quarter at 1 km spatial resolution

4.2.2 Non-Climatic Variables

Three non-climatic variables namely topography (elevation, slope and aspect), forest density and soil were considered for defining geographic distribution of FIS. The elevation map generated from Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) downloaded from United State Geological Survey (USGS) website (http://earthexplorer.usgs. gov/) available at 90 m spatial resolution. The slope and aspect maps were derived from the DEM using surface tools in ArcMap 10.1.The forest density layer was obtained from Global Land Cover Facility (GLCF) (http://www.landcover.org) at 30 m pixel size. The forest density layer is based on Landsat Vegetation Continuous Fields (VCF) tree cover prepared for the year 2000. The soil type information was obtained from the vector database prepared by National Beureo of Soil Survey and Land Use Planning (NBSS&LUP) at 1:1 million scale. The soil type classes (in total 13) were generalised to order level (7 classes) representing Mollisols, Ultisols, Aridisols, Vertisols, Alfisols, Entisols and Inceptisols. The vector soil order map was rasterized to 1 km spatial resolution. Fig. 3 represents the non-climatic variables used as an input in the study.

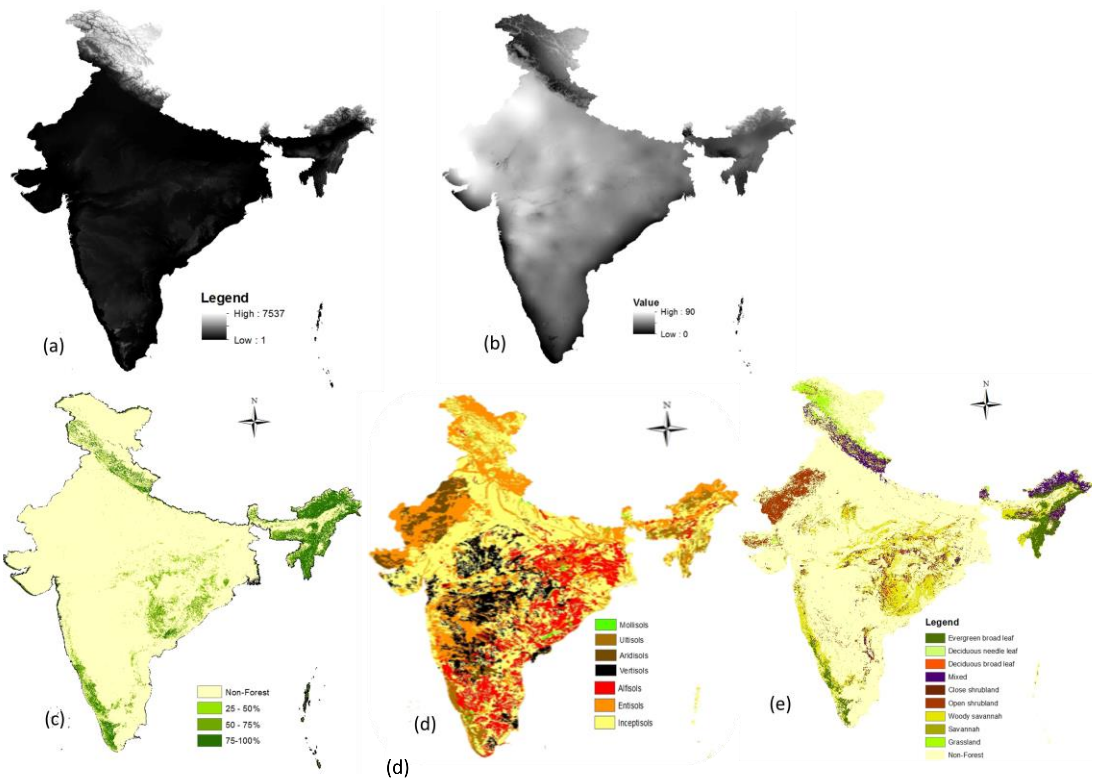


Figure 3: Selected non-climatic variables namely (a) elevation (b) slope (c) forest density (d) soil (e) forest type at 1 km spatial resolution

4.2.3 Biogeographical Zones

FIS range shift in the climate change scenarios was assessed for different biogeographic zones of the country. The biogeographical classification of India (Rodger *et al.*, 2002) comprises 10 classes*viz*., Trans Himalayan zone, Himalayan zone, Desert zone, Semi-Arid zone, Western Ghats zone, Deccan Peninsula zone, Gangetic Plain zone, North-

East zone, Coastal zone and Islands. Each biogeographic unit represents distribution of flora and fauna and their ecosystem in geographic space through geological time.

4.3 Model Design

4.3.1 Selection of Optimal Environmental Variables

Considering the large number of environmental variables (24 viz., climatic (19), topographic (3), landscape heterogeneity (2), the variables were tested for multi-collinearity using ENM (Ecological Niche Model) tool v. 1.3. Amongst every two highly correlated variables (Pearson's correlation coefficient r> 0.90) one was selected keeping the importance of variable in determining ecophyisiological requirement of the FIS. The Pearson's correlation coefficient between the variables is shown in Appendix 4. The correlation values shown with highlighted text represent highly correlated variables and the highlighted variables are the ones that are discarded for their less usefulness in the study. In the next step, the variables selection was further optimized by calculating the percentage contribution of above selected variables for prediction of potential invasion range for different FIS.

4.3.2 Model Selection

The most accepted species distribution modelling technique was used to work with presence-only data namely, MaxEnT (Phillips *et al.,* 2006; Phillips and Dudík 2008), based on its better performance while working with presence-only data. The model was used to predict the potential habitat suitability for invasion of the FIS in present scenario and was used to generate hotspot prediction maps. It was also used to model the future suitability and distribution of the selected invasive species under CGCM2, CSIRO-mk2 and HADCM3 A2a and B2a climate change scenarios for 2050.

The model was generated using the standard of 75% occurrence records randomly selected for the purpose of training dataset and remaining 25% a test dataset. The FIS occurrence data was prepared in .CSV (Comma Separated Value) and environmental layers in ASCII (American Standard Code for Information Interchange) format for model execution.

4.3.2.1 Model Training

An auto feature limiting function was used to train the MaxEnT model. The multiplier value was set very low at 1 along with the default set of parameters with convergence limit set to 0.00001. Logit rule was applied to observe the binary predictions and the number of iterations was set to 500 and replicates equal to 10. The replicate run type was selected as cross validate which is also known as k fold technique as it breaks the sample into k subsets and it runs the model k number of times and withhold the kth subset in each model run which in turn is used for model testing.

4.4 Model evolution

4.4.1 Accuracy Assessment

4.4.1.1 Threshold Independent ROC AUC

The receiver operating characteristic (ROC) curve is obtained by plotting the sensitivity (1- omission rate) against fractional predicted area (1-specificity) across the range of varying thresholds. Sensitivity is defined as the correctly predicted presence records and specificity on the other hand is defined as the correctly predicted absence records.

Sensitivity = a/(a + c) = True Positive / (True Positive + False Negative)
Specificity = d/(b + d) = True negative / (True negative + false positive)

Where, a = number of cells for which the presence was correctly predicted, b = number of cells for which FIS was not found but the model predicted presence, c = number of cells for which the FIS were found but the model predicted absence, d = number of cells for which the absence was correctly predicted, Therefore 1-specificity defines the absences that are incorrectly predicted.

The Area Under Curve (AUC) value above 0.90 shows high accuracy of the model suggesting that the model is able to discriminate well between the FIS presence and FIS absence, value ranging between 0.7 – 0.9 shows good accuracy, 0.5 – 0.7 shows low accuracy while the AUC value below 0.5 is equivalent to random chance. AUC value is correlated to the size of the study area and the prevalence of the occurrence points and the spread of the FIS and ignores the predicted probability values and the goodness-of-fit of the model. It weights omission and commission errors equally (reliable if presence/absence model is used).

4.4.1.2 True Skill Statistics (TSS)

It is another method to examine the goodness of model fitting and is used in the study. The TSS technique also accounts for the omission and commission errors.

TSS = Sensitivity + Specificity – 1

The range of this index falls in between -1 to +1. On one hand +1 is indicative of the perfect fit whereas -1 on the other hand represents a random fit (Allouche*et al.*, 2006).TSS values are not affected by the prevalence of the occurrence point or the size of the study region. It uses a threshold dependant measure and can be used to overcome the problem in the previous technique, in this approach weights can easily be provided to sensitivity and specificity.

4.4.2 Sensitivity Analysis

The sensitivity of the MaxEnT model was tested using the jack-knife technique. It was used to determine the relative importance and training gain of each of the predictor variable that was used to train the model considering the model being run for each variable in isolation, to the training gain considering all the variables at a time.

4.5 Thresholding of MaxEnT outputs

MaxEnT model was run for selected three thresholding techniques namely Minimum training presence; Fixed cumulative value 1and 10 percentile training presence. Although there are four other techniques, but those were not taken into account because of their less usability in previous studies. The selection of method was based on results pointing to lower threshold values i.e. greater fractional predicted area, and the omission error nearing 0 values or 0 itself. Since, if the omission error is not low, the wide range and long lived FIS like *Lantana camara* would definitely find suitable conditions to spread within the total predicted area; which would result in incorrect prediction. The AUC values were also considered and the technique which resulted in higher AUC values was selected to overcome the uncertainty associated with different thresholding techniques. Therefore for threholding the maps, minimum training presence threshold values were used.

4.6 Potential Invasion Hotspots Modelling

The invasive species hotspot map represented the areas with potential number of invasive plant species concentration. It highlighted the regions where the invasion risk would be high (i.e. more than 65 noxious FIS found together), moderately high (45-65 FIS), medium (25-45 FIS), low (5-25 FIS) and least (<5 FIS). The hotspot analysis was used in the study to identify the regions having high suitability for the potential spread of the FIS in forested ecosystems of the country and in each of the biogeographic zones. The MaxEnT produced continuous outputs of potential habitat suitability ranging from 0 to 1, which was further reclassified into two classes 0-0.25 (unsuitable) and 0.25-1 (suitable). The threshold was selected as per the 'minimum training presence' threshold technique limits. The hotspots were calculated by summing up the thresholded binary maps all the 105 FIS and reclassifying the grid cells with the habitat suitability based on the percentile at 25% bands. It highlights the zones where the invasion risk would be very high (> 75%), moderately high (50-75%), medium (25-50%) and low (<25%). This technique was chosen for its robustness while working with a large number of FIS.

4.7 Characterisation of Hotspots of Invasion

The identified potential hotspots of invasion were characterised in terms of their climate envelope, geographic distribution in various forest ecosystems, canopy density classes and vascular species diversity. The phytorichness map is from the Biodiversity Characterisation Landscape Level Study carried by Department of Space and Department of Biotechnology (Roy *et al.,* 2012).

4.8 Potential Distribution under Future Scenario

The impact of climate change on the potential distribution of the selected invasive species was accessed using MaxEnT modelling for the projected CGCM2, CSIRO-mk2 and HADCM3 A2a and B2a climate change scenarios for 2050. The model was trained with the environmental variables and occurrence records of species. This was done by projecting the future environmental variable over a set of present environmental variables. Along with the future climate, the Landscape heterogeneity variables i.e. forest-nonforest change were also projected for future and used as an input to train the model.

Forest-nonforest maps (2001, 2006 and 2011) based on MODIS 250m LULC layers were used to generate a scenario for 2050 using artificial neural network (ANN) in Land Change Modeller module in IDRISI Taiga software. The MODIS product with 16 categories was reclassified into forest/grasslands, non-forest, snow/glaciers. The model training accuracy for the year 2011 based on forest-nonforest for the year 2001 and year 2006 was found 93%. The trained ANN model was used to simulate forest-nonforest scenario for the year 2050 that was used for future analysis. The final MaxEnT model output of potential habitat suitability ranged from 0 to 1, which was further reclassified into two classes based on the 'minimum training presence' threshold values.

Ensemble maps were generated for each FIS under A2a and B2a scenario. This was achieved by combining the binary suitability maps obtained from the individual climate models using the AUC weighted mean. The outputs obtained from the models were continuous values ranging between 0 and 1. A threshold value was selected to convert the continuous binary maps from, showing the habitats that are suitable for the potential spread of the invasive alien species and the no habitat for the spread. This ensemble map for each FIS was used for further analysis.

4.9 FIS Range Shift

The ensemble outputs were used to generate the change maps (suitable to unsuitable and vice-versa) between present and future for each of the 15 selected invasive FIS. These change maps were used to generate a range shift plot for A2a and B2a climate change scenarios. The range shift plots represented x axis as the biogeographic zones or forest types respectively and y axis as potential invasion area in km^2. It represented the positive (expansion in the suitable habitat) or a negative (reduction in the suitable habitat) shift in the FIS range under future climate projection.

The overall methodology is shown in Fig. 4.

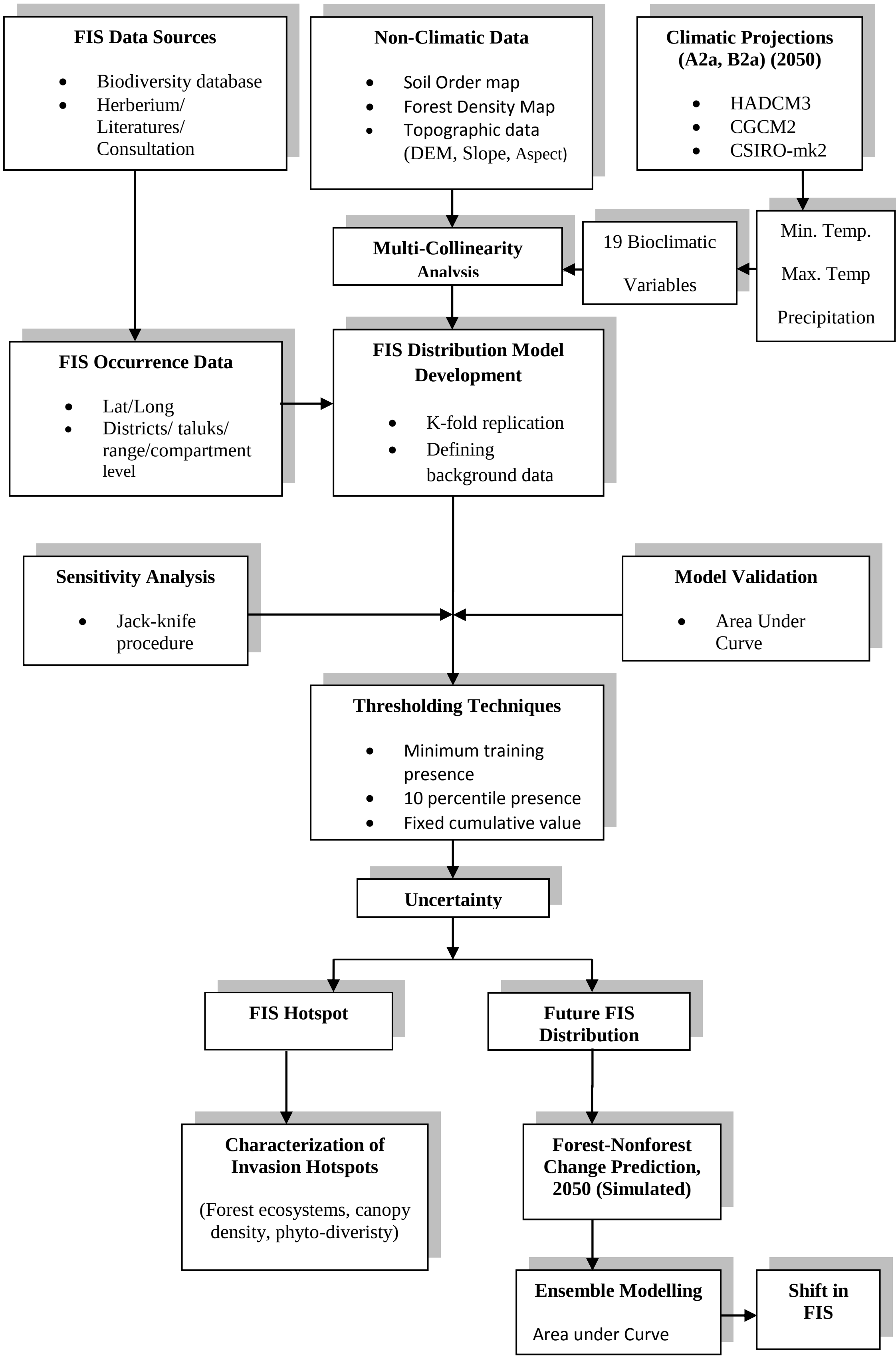


Figure 4: Methodology Flowchart

Chapter-5 RESULTS& DISCUSSION

5.1 Potential Hotspots of Invasion

5.1.1 FIS Concentration

The potential geographic distribution of 105 alien plant species (constituting approx. 80% of total FIS identified in the country) was predicted using MaxEnT algorithm. The modelling was performed for the geographical areas represented by the natural ecosystems (forests, savannah and alpine pasture) in the country excluding areas under agriculture, snow/glacier and barren /rocky areas and water body. Fig. 5 represents summation of potential distribution surfaces of 105 FIS in the country. The summed output has been further categorized into the areas with high, moderately high, medium, low and least number of potential distribution surfaces of FIS.

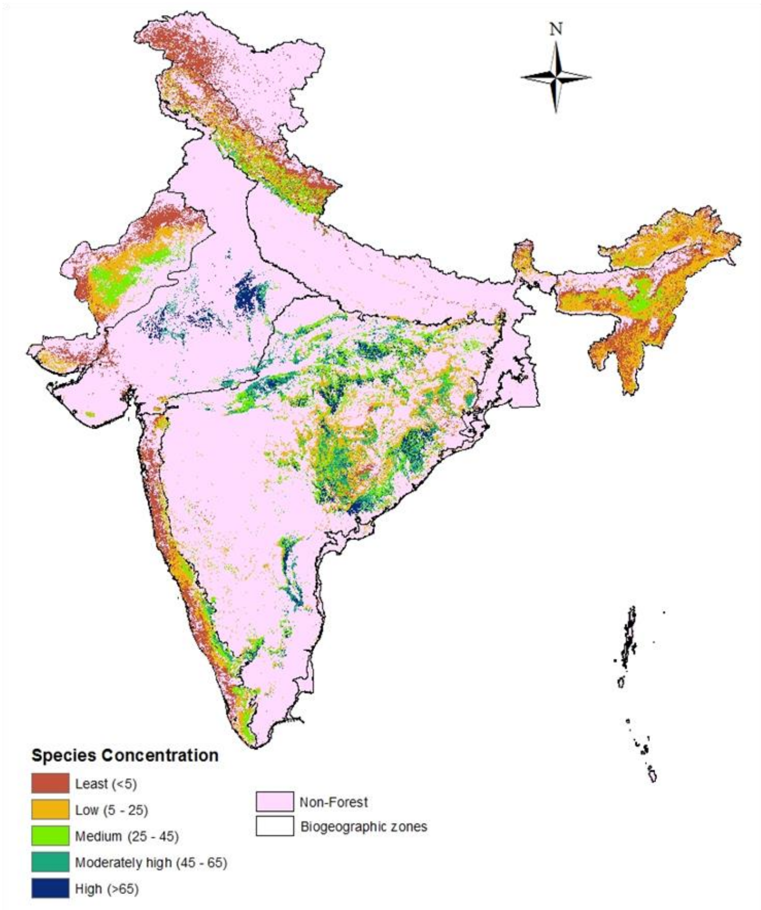


Figure 5: Potential number of FIS

It was observed that a majority of the FIS were concentrated in mixed forests, woody savannahs, evergreen broad leaf forest, open shrubland and grasslands. Fig. 6 represents the potential FIS richness in each of the forest ecosystem category.

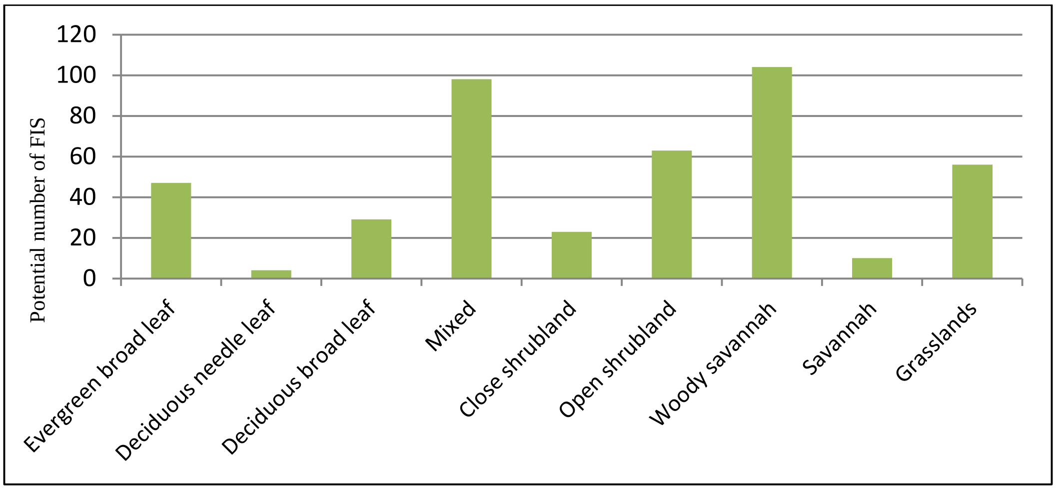


Figure 6: Potential FIS richness in different forest categories

5.1.2 Environmental Variables

The statistical analysis of multicollenarity among variables helped in reducing number of climatic variables to be used for potential distribution modelling of FIS. Further, selection of climatic variables for modelling potential distribution of each FIS was decided based on % contribution of variables (also considering topographic and landscape heterogeneity variables). In general, annual mean temperature, isothermality, temperature seasonality, mean temperature of driest quarter and precipitation of wettest quarter, canopy closure and elevation showed largest influence (% contribution) in modelling potential distribution. While climatic variables such as mean temperature of coldest quarter, precipitation of coldest quarter, precipitation of driest quarter and soil, showed least % percentage contribution in predictions.

5.1.3 FIS Potential Distribution Model Accuracies

The average AUC score for the 105 FIS was calculated 0.94 (± 0.5) with the values ranging from 0.88 to 0.99. Whereas the average TSS score for the all the FIS was calculated 0.74 (± 0.5) with the TSS scores ranging from 0.64 to 0.83. AUC scores indicate that the area predicted suitable for the FIS distribution was correlated with a random 10% of observation data, which was not considered for species training and used to test the models. The high AUC and TSS scores suggest that good prediction accuracy and stronger prediction was achieved using MaxEnT model.

5.2 Hotspot of Invasion Risk

The hotspots of FIS at country level were modelled by reclassifying the grid cells with the habitat suitability based on the percentile at 25% intervals (Fig. 7). The percentage quantile has been depicted in the regular interval of 25% in categories namely very high (> 75%), moderately high (50-75%), medium (25-50%) and low (<25%). The forested areas distributed in the semi-arid regions and some parts of Deccan peninsula of the country were represented by very high invasion risk with risk varying from (75 – 100%). Such areas were observed of having at least 73 FIS represented at least once within the area. The moderately high and medium risk hotspots extended in semi-arid, Deccan peninsula, north-east, Western Ghats and part of Himalayan foot hills. The low FIS risk zones were found distributed in the temperate Himalaya, high rainfall region of Western Ghats and north-east India as well as the warm and cold desertic regions of the country.

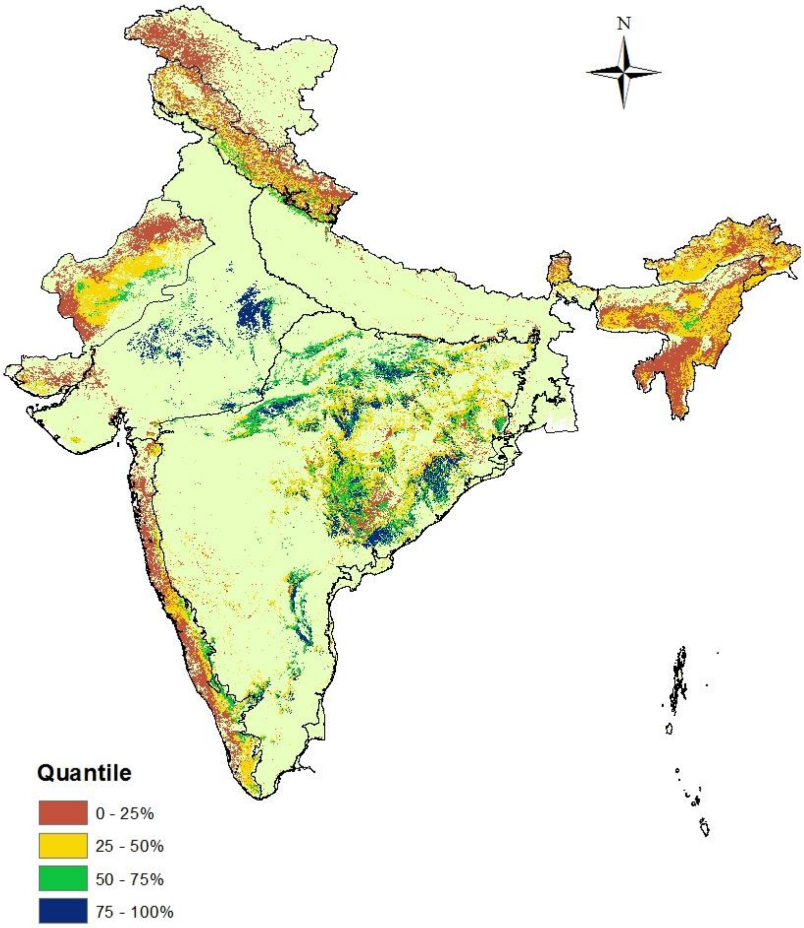
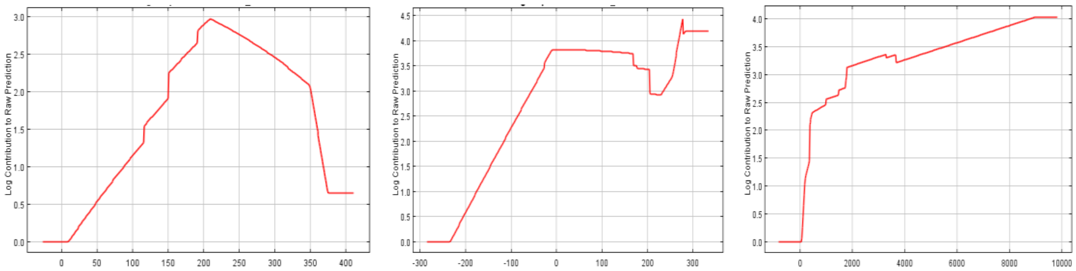


Figure 7: Hotspot map of FIS

5.2.1 Climatic Envelope of Potential Hotspots of FIS

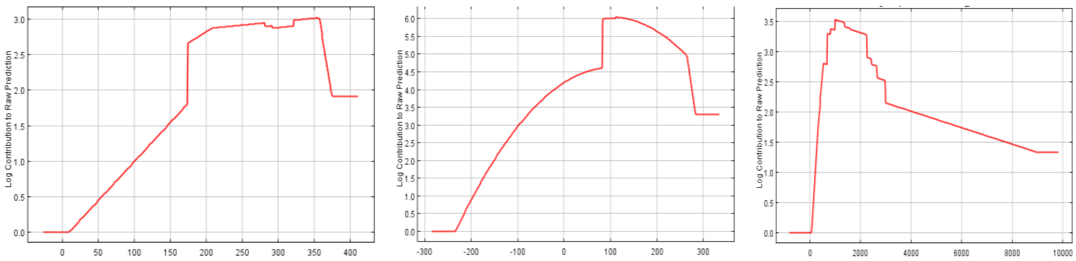
The climatic envelope of potential hotspots FIS has been defined in terms of average maximum temperature, average minimum temperature and average annual precipitation prevailing in such areas. Fig. 8 depicts the climatic conditions of areas identified with various levels of invasion risks.

Response curves for hotspot (<25 %)



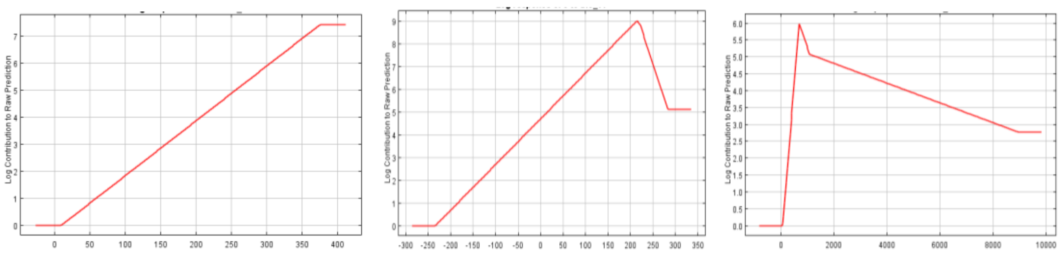
Mean maximum temp. (°C/10) Mean minimum temp. (°C/10) Mean annual precipitation (mm/10)

Response curves for hotspot (25 - 50%)



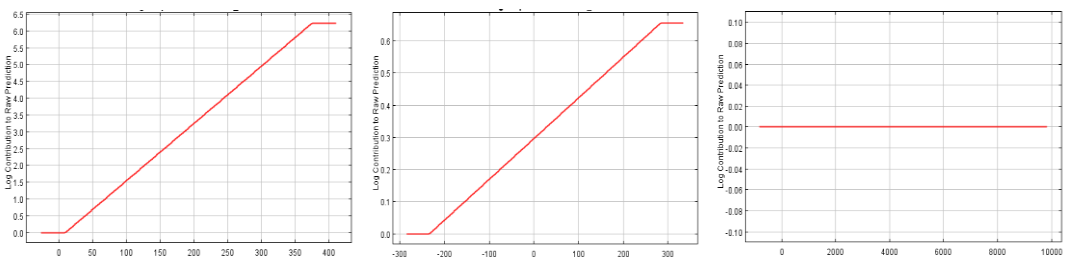
Mean maximum temp. (°C/10) Mean minimum temp. (°C/10) Mean annual precipitation (mm/10)

Response curves for hotspot (50 - 75%)



Mean maximum temp. (°C/10) Mean minimum temp. (°C/10) Mean annual precipitation (mm/10)

Response curves for hotspot (75 - 100%)



Mean maximum temp. (°C/10) Mean minimum temp. (°C/10) Mean annual precipitation (mm/10)

Figure 8: Climatic envelope of potential hotspots FIS

The values on the Y-axis shows the predicted of suitable conditions whereas X-axis shows the variable under consideration. For hotspot zone (<25%) it is observed that predicted habitat suitability increase with increasing temperature up to 20°C above which the conditions becomes unfavourable. While the predicted suitability increases with increase in the annual precipitation. For hotspot zone (25-50%) the habitat suitability is predicted to increase within mean annual temperature < 20 °C above which the unsuitable conditions prevails. 200mm of annual precipitation is predicted to favour suitable habitat for the FIS to spread above which the unfavourable conditions prevails. For hotspots (50-75%) the suitable habitat is predicted to increase with increase in temperature, however extreme temperature conditions may discourage the spread. Annual precipitation over 200mm is unfavourable. Hotspots (>75%) show direct relationship with temperature, the predicted suitability increases with increasing temperature. Extreme temperature conditions would also not discourage the spread of invasive in these zones. However the zone remains unaffected with the precipitation.

5.2.2 FIS Invasion hotspots: Forest Ecosystems and Canopy Closure wise

Table1 represents the forest ecosystems type wise FIS invasion hotspots. It can be observed that for majority (> 45) FIS, the potential distributions was predicted in the geographical areas represented by the evergreen broad leaf forest, mixed forest, woody savannahs, grasslands and open shrub lands.

Table 1: Forest ecosystems type wise FIS hotspots.

Forest Classes	**Area (km^2) under parentage quantile categories**			
	0 – 25	**25 - 45**	**45 - 65**	**> 65**
Evergreen broad leaf	8, 05, 527	35, 457	17, 334	37
Deciduous needle leaf	892	25	7	00
Deciduous broad leaf	3, 389	7, 274	5, 536	1, 088
Mixed	86, 344	64, 679	22, 659	37, 701
Close shrubland	1, 636	1, 651	790	69
Open shrubland	74, 906	40, 129	6, 802	1, 382
Woody savannah	1, 26, 264	1, 57, 542	90, 801	11, 466
Savannah	1, 580	626	218	36
Grasslands	67, 229	9, 169	7, 811	1, 399

Table 2 depicts the FIS hotspots as per the status of canopy cover (%) interpreted using Landsat satellite imageries for the year 2000. It can be inferred from the table that the majority of FIS (74) have their potential occurrence in forested area having tree canopy closer between 0-50% while lesser number of FIS potential distribution are represented in higher canopy closure forest areas (>50%). Woody savannahs and deciduous broad leaf forest with a canopy density ranging from 0 to 50 % were majorly modelled under high risk of invasion by FIS.

Table 2: Forest canopy closure (%) wise FIS invasion hotspots

Forest Canopy Closure	Area (km^2) of FIS invasion hotspots percentile quantile categories			
	0 - 25	**25 - 45**	**45 - 65**	**>65**
0 - 25 %	1, 43, 7802	9, 98, 145	3, 55, 108	100
25 - 50%	26, 435	25, 462	49, 750	11, 319
50 - 75%	42, 303	39, 750	46, 268	7, 058
75 - 100%	82, 155	71, 490	7, 733	459

5.2.3 Potential invasion hotspots vis-a-vis Phyto Richness

The relationship between the geographic distribution of hotspots of FIS invasion and forest type was analysed at country level (Fig. 9 and Fig. 10). Phytorichness map (with categories 0-25%, 25-50%, 50-75% and 75-100%) was used to find relationship with different forest types and the hotspot classes, and their aerial coverage.

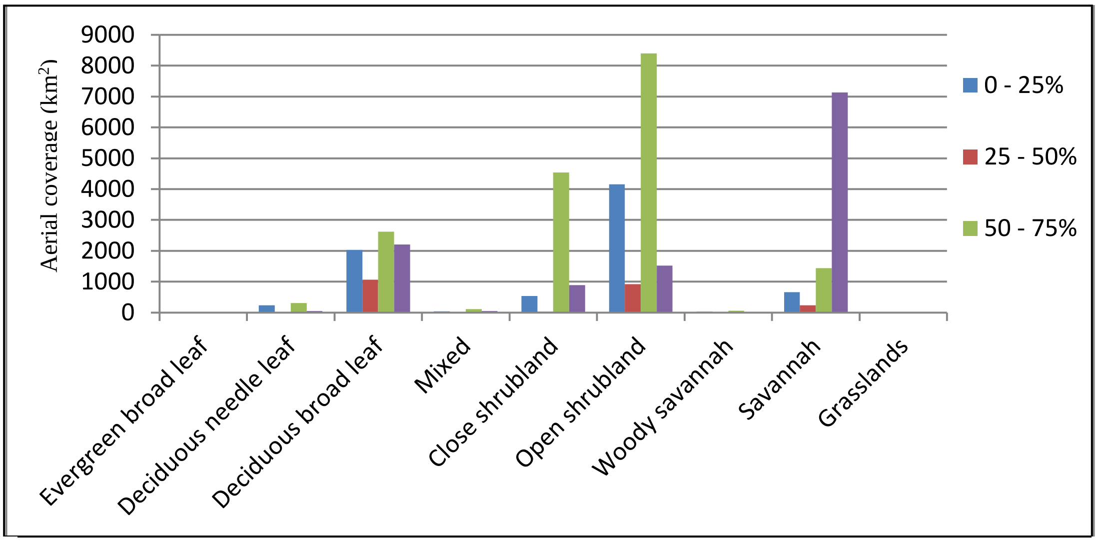


Figure 9: Forest type wise potential invasion risk

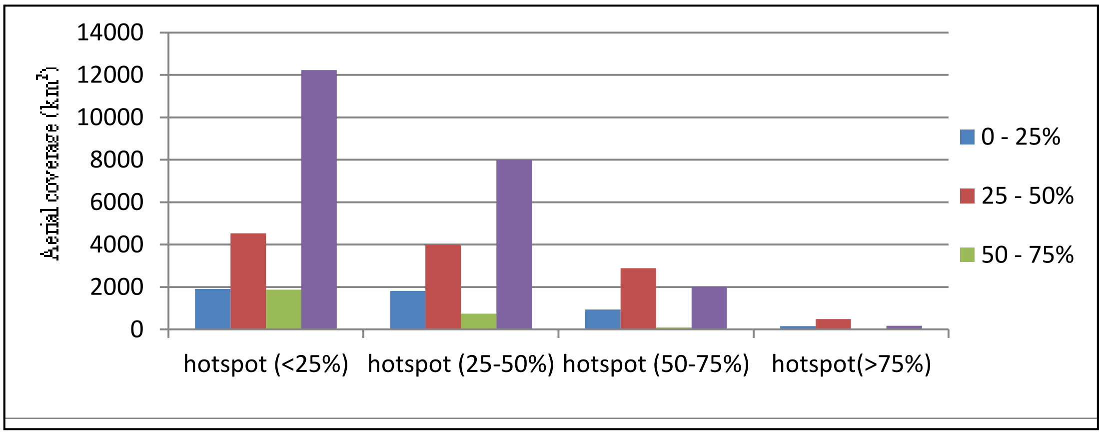


Figure 10: Relationship between potential invasion risk and phytorichness

Phytorichness and invasion were observed to have an inverse relation. The high invasion risk areas falls in the medium (25-50%) to low (<25%) phytorichness regions. However, low invasion risk is encountered in the regions with high phytorichness (>50%).

5.3 Potential Distribution of FIS in Climate Change Scenario

5.3.1 Comparison of Climatic Projections

The three climate models *viz.*, CGCM2, CSIRO-mk2 and HADCM3 considered for under A2a and B2a climate change scenario for 2050 are constructed based conceptually different global general circulation models. Table 3 shows the correlation between mean annual temperature and mean annual precipitation derived by different climate models.

Table 3: Correlation between climate models in terms of mean annual temperature and precipitation

Mean Annual Temperature (ºC)	HADCM3	CGCM2	CSIRO-mk2	Mean Annual Precipitation (mm)	HADCM3	CGCM2	CSIRO-mk2
HADCM3	0.00	0.73	0.72	HADCM3	0.00	0.71	0.70
CGCM2	0.00	0.00	0.99	CGCM2	0.00	0.00	0.99
CSIRO-mk2	0.72	0.00	0.00	CSIRO-mk2	0.70	0.00	0.00

Table 4 and table 5 depict in terms of mean annual temperature and mean annual precipitation HADCM3 differ from CGCM2 and CSIRO-mk2 under A2a and B2a scenario. A similar trend was observed for mean annual precipitation as well.

Table 4: Comparison of climate models based on temperature and precipitation values for A2a scenario

A2 Scenario, Temperature (ºC) & Precipitation (mm)	Present		CGCM2		CSIRO-MK2		HADCM3	
	Temp.	**Prec.**	**Temp.**	**Prec.**	**Temp.**	**Prec.**	**Temp.**	**Prec.**
Lower Western Ghats	18.38	2708	19.8	2742	20	2790	20.0	2861
Vindhyan Plateau	25.44	924	27.2	1071	27.4	1023	27.4	1018
North East India	22.64	1862	24.1	1883	24.7	1852	24.8	2133
Himalayan Foothills	14.87	1882	16.9	1948	17.2	1921	16.7	2054
Eastern Ghats	23.2	1329	24.5	1408	25.1	1419	25.4	1504

Temperature and precipitation projections for the 2050A2a scenario are similar in case of CGCM2 and CSIRO-MK2 but slightly differ from HadCM3 projections. The precipitation projections of HadCM3 are markedly different from CGCM2 and CSIRO-MK2. Overall the HadCM3 projection predicts more quantify of rainfall for all major physiographic zones in the country except for Vindhyan plateau. All the projections show increase in rainfall in the same manner.

Table 5: Comparison of climate models in terms of temperature and precipitation values for B2a Scenario

B2 Scenario, Temperature (°C), Precipitation (mm)	Present		CGCM2		CSIRO-MK2		HADCM3	
	Temp.	Prec.	Temp.	Prec.	Temp.	Prec.	Temp.	Prec.
Lower Western Ghats	18.38	2708	19.5	2716	19.6	2770	19.6	2802
Vindhyan Plateau	25.44	924	27.1	1033	26.7	1049	26.7	994
North East India	22.64	1862	24.1	1836	24.1	1860	24.3	2008
Himalayan Foothills	14.87	1882	16.7	1932	16.4	1966	16.3	2002
Eastern Ghats	23.2	1329	24.2	1516	24.4	1407	24.8	1539

Overall, all three models predict rise in temperature and precipitation levels by the year 2050. The two climate models *viz*., CGCM2, and CSIRO-MK2 are more inter-correlated whereas HadCM3 tends to slightly differ, showing lower correlation with the above two models. A2a projections predict the rise in temperature and precipitation more than that of B2a projection for three climate models.

5.3.2 Effects of Thresholding Techniques on Prediction of Potential Invasion Range

Table 6, table 7 and table 8 show the different thresholding techniques (fractional predicted area, training omission and test omission rate) along with AUC of the model for 15 most noxious species. The thresholding technique was chosen based on results pointing to lower threshold values i.e. greater fractional predicted area, and the omission error nearing 0 values. The fractional predicted area and the AUC values were found higher for the minimum training presence method as well as the omission error was very low as compared to other techniques.

Table 6: FIS associated values using minimum training presence technique

	Minimum Training Presence			
FIS	**Fractional Predicted Area**	**Training Omission Rate**	**Test Omission Rate**	**AUC**
Ageratum conyzoides	0.910	0.000	0.000	0.899
Bidenspilosa	0.472	0.000	0.125	0.944
Cassia occidentalis	0.572	0.000	0.000	0.951
Cassia tora	0.911	0.000	0.000	0.881
Chromolaenaodorata	0.529	0.000	0.000	0.917
Cyprus rotundus	0.837	0.000	0.016	0.918
Ecliptaprostrata	0.670	0.000	0.000	0.909
Eupatorium adenophorum	0.026	0.000	0.000	0.994
Euphorbia hirta	0.698	0.000	0.024	0.896
Hyptissuaveolens	0.702	0.000	0.013	0.918
Lantana camara	0.854	0.000	0.000	0.901
Mikaniacordata	0.230	0.000	0.000	0.981
Mimosa pudica	0.399	0.000	0.022	0.946
Partheniumhysterophorus	0.606	0.000	0.000	0.946
Prosopisjuliflora	0.505	0.000	0.026	0.943

Table 7: FIS associated values using 10 percentile training presence technique

10 Percentile Training Presence				
FIS	**Fractional Predicted Area**	**Training Omission Rate**	**Test Omission Rate**	**AUC**
Ageratum conyzoides	0.280	0.009	0.118	0.890
Bidenspilosa	0.149	0.086	0.321	0.950
Cassia occidentalis	0.198	0.009	0.133	0.945
Cassia tora	0.314	0.100	0.105	0.863
Chromolaenaodorata	0.159	0.100	0.140	0.924
Cyprus rotundus	0.200	0.100	0.159	0.923
Ecliptaprostrata	0.249	0.098	0.250	0.921
Eupatorium adenophorum	0.029	0.053	0.000	0.941
Euphorbia hirta	0.287	0.099	0.145	0.865
Hyptissuaveolens	0.218	0.099	0.103	0.904
Lantana camara	0.354	0.100	0.090	0.847
Mikaniacordata	0.031	0.099	0.296	0.970
Mimosa pudica	0.133	0.097	0.203	0.918
Partheniumhysterophorus	0.200	0.093	0.057	0.943
Prosopisjuliflora	0.117	0.098	0.212	0.920

Table 8: FIS with associated values using Fixed cumulative value 1 technique

Fixed Cumulative Value 1				
FIS	**Fractional Predicted Area**	**Training Omission Rate**	**Test Omission Rate**	**AUC**
Ageratum conyzoides	0.752	0.004	0.007	0.894
Bidenspilosa	0.677	0.000	0.000	0.901
Cassia occidentalis	0.653	0.000	0.000	0.956
Cassia tora	0.291	0.100	0.120	0.870
Chromolaenaodorata	0.464	0.003	0.010	0.914
Cyprus rotundus	0.583	0.002	0.014	0.909
Ecliptaprostrata	0.755	0.000	0.000	0.847
Eupatorium adenophorum	0.403	0.000	0.000	0.961
Euphorbia hirta	0.664	0.002	0.007	0.874
Hyptissuaveolens	0.500	0.006	0.015	0.915
Lantana camara	0.691	0.006	0.013	0.838
Mikaniacordata	0.223	0.000	0.028	0.972
Mimosa pudica	0.549	0.000	0.020	0.911
Partheniumhysterophorus	0.671	0.000	0.000	0.936
Prosopisjuliflora	0.573	0.000	0.000	0.937

5.3.3 Forest-Nonforest Change Scenario

Fig. 11 shows the forest-nonforest map of India for the year 2001, 2006, 2011 and simulated map for 2050. Table 9 shows the forest-nonforest change occurred between year

2001 and year 2006 and between year 2006 and year 2011. Different date forest-nonforest maps are based on MODIS 250 m LULC layers. The forest-nonforest scenario for the year 2050 was simulated using ANN in Land Change Modeller module in IDRISI Taiga software. The model training accuracy for the year 2011 based on forest-nonforest for the year 2001 and year 2006 was found 93% which indicate very good model prediction. The trained ANN model was used to simulate forest-nonforest scenario for the year 2050.

Table 9: Forest-Nonforest area in 2001, 2006 and 2011 and predicted area for 2050

Classes (Area in Km^2)	2001	2006	2011	2050
Forest /Grassland	7, 25,926	11, 45,922	12, 03,626	11,82,675
Non-Forest	19, 95,535	21, 57,840	21, 00,136	21, 21,087
Total area	33, 03,762	33, 03,762	33, 03,762	33, 03,762

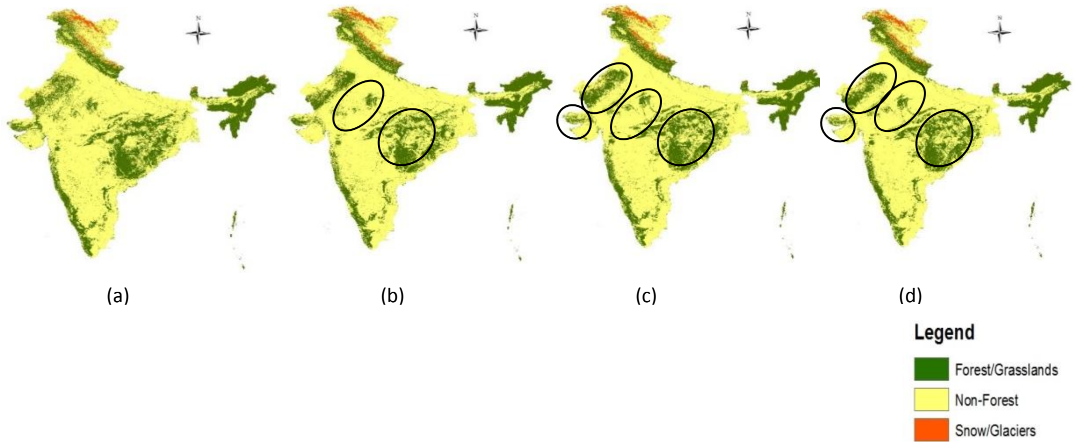


Figure 11: Forest-Nonforest maps of India for year 2001, 2006, 2011(MODIS) and 2050 (simulated)

5.3.4 Potential InvasionRange of FIS in 2050 A2a & B2a Scenarios

This section presents the potential invasion range of 15 most noxious FIS predicted for the year 2050 (A2a and B2a scenarios) using MaxEnT.

5.3.4.1 *Ageratum conyzoides* (Dochunti)

Under A2a and B2a scenarios climate ensemble predicted prominent increase in the suitable area in North-East under A2a scenario and in Himalayas under B2a scenario. The area transforming from non-suitable to suitable under A2a scenario was 1, 09,733 km^2 and from suitable to non-suitable was 1, 38,389km$^{2.}$ Under B2a scenario the area transforming from non-suitable to suitable was 1, 11,999 km^2 and from suitable to non-suitable under B2a scenario was 1, 29, 252km^2. A loss of habitat for the FIS in Deccan Peninsula both for A2a and B2a scenario was observed. Fig. 12 shows the current and future potential distribution of *Ageratum conyzoides.*

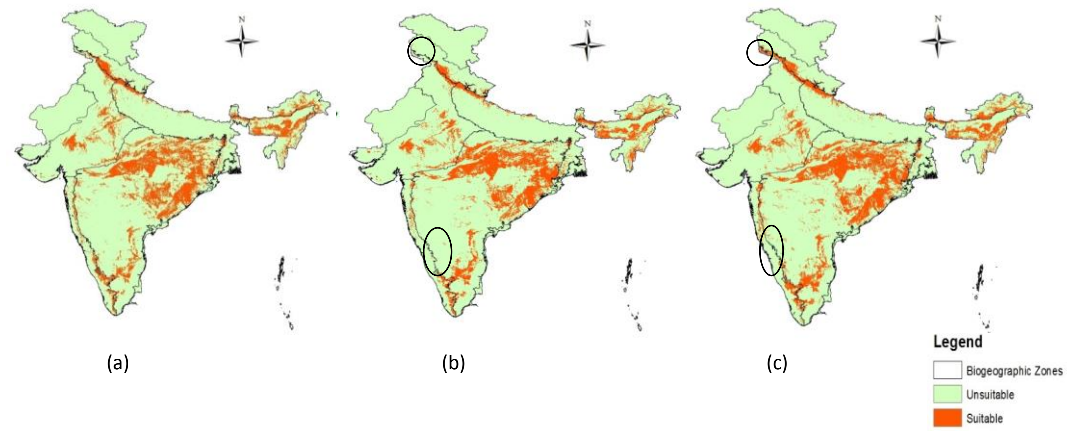


Figure 12: Area predicted suitable for *Ageratum conyzoides* in (a) current & ensemble A2a (b) B2a (c)

5.3.4.2 *Bidenspilosa* (Black jack)

An increase in the suitable habitat in Himalaya and semi-arid regions and loss in habitat in north-east India was predicted by the climate ensemble under A2a scenario. However, under B2a scenario ensemble predicted increase in the suitable habitat in Himalaya and semi-arid regions. The area transformed from non-suitable to suitable under A2a scenario was 1, 80, 941km^2 from suitable to non-suitable was 96, 046 km^2. Under B2a scenario the predicted area transformed from non-suitable to suitable was 1, 69,737 km^2 and from suitable to non-suitable was 97, 840 km^2. Fig. 13 shows the current and future potential distribution of *Bidens pilosa.*

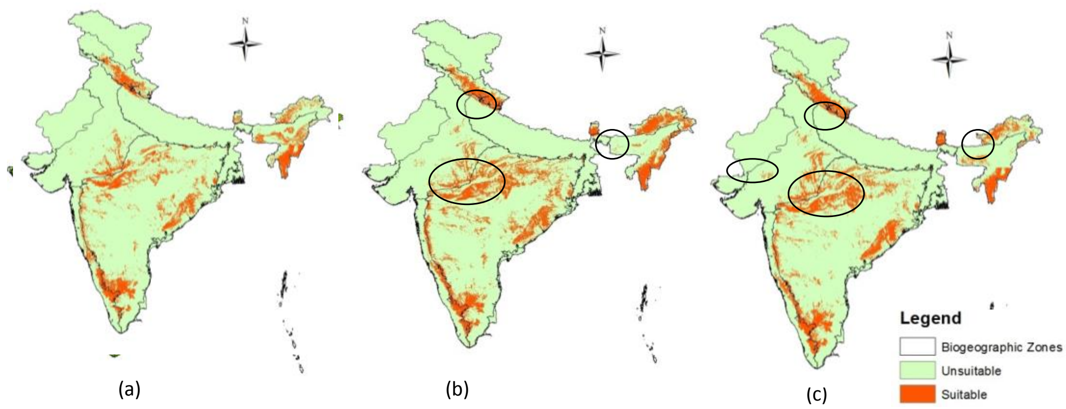


Figure 13: Area predicted suitable for *Bidenspilosa* in (a)current, ensemble A2a (b) B2a (c)

5.3.4.3 *Cassia occidentalis*(Coffee weed)

Under both the scenarios climate ensemble predicted an increase in the suitable area in Indo-Gangetic Plains, Deserts and Deccan Peninsula. The shift from suitable to non-suitable habitat was predicted in North-East, Western Himalayas, Eastern Himalayas, Central, Eastern and Southern Highlands of Deccan Peninsula under A2a scenario and Western Himalayas, Eastern Himalayas, Semi-Arid and North-East and Central, Eastern and Southern Highlands of Deccan Plateau under B2a scenario. Fig. 14 shows the current and future potential distribution of *Cassia occidentalis.*

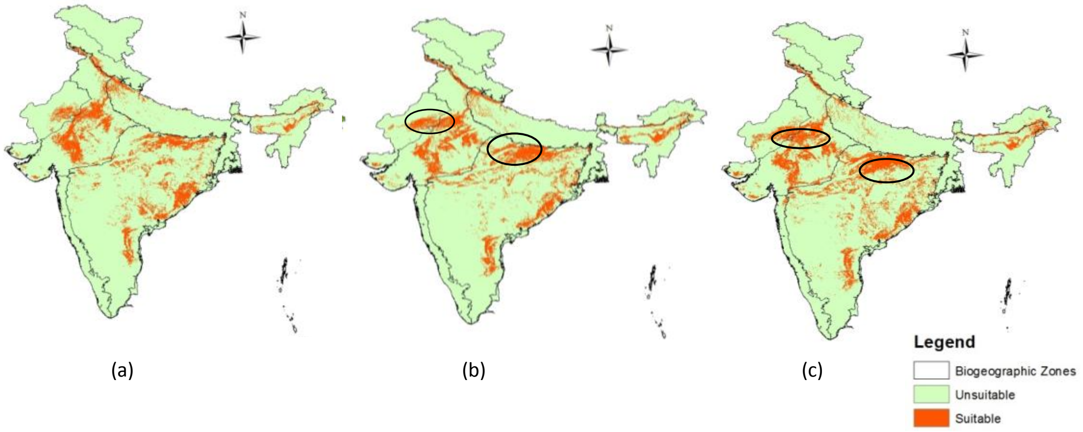


Figure 14: Area predicted suitable for *Cassia occidentalis* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.4 *Cassia tora*(Coffee pod)

Indo-Gangetic Plains, North-East, and Deserts were predicted with a decrease in the habitat area while Deccan Peninsula with increase in habitat under A2a scenario. Deserts, Indo-Gangetic Plains and Central Deccan peninsula on the other hand showed a predicted increase in habitat under B2ascenario. The area transformed from non-suitable to suitable under A2a scenario was 3, 74, 137km^2 and from suitable to non-suitable was 1, 99,965 km^2. Under B2a scenario the area transformed from non-suitable to suitable was 1, 00,115 km^2 and from suitable to non-suitable was 1, 20,855 km^2 respectively. Fig.15 shows the current and future potential distribution of *Cassia tora.*

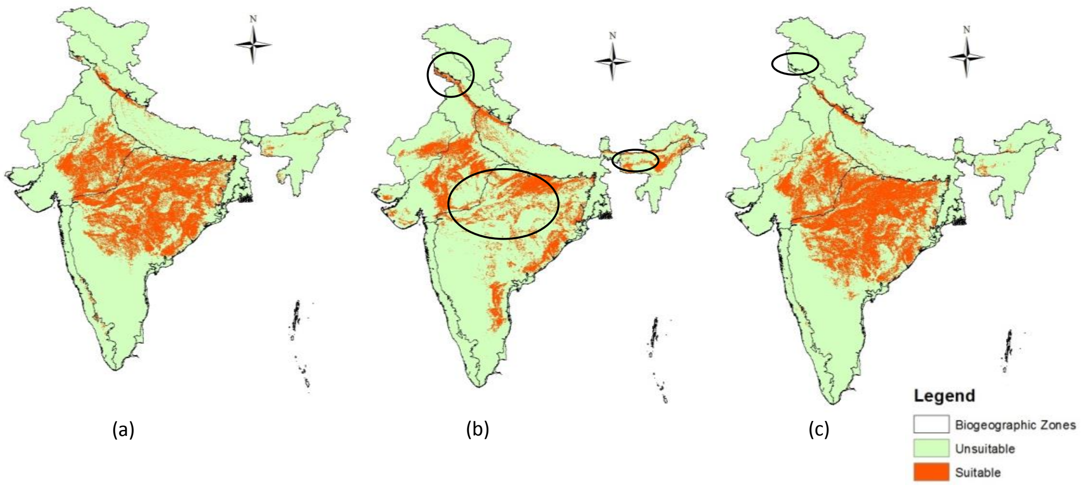


Figure 15: Area predicted suitable for *Cassia tora* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.5 *Chromolaenaodorata*(Siam weed)

Decrease in the suitable area under both the scenarios was only predicted in Semi-Arid regions. The area transformed from non-suitable to suitable under A2a scenario was 65, 312 km^2 and from suitable to non-suitable was 1, 02,074 km^2. Under B2a scenario the area transformed from non-suitable to suitable was 74, 441 km^2. Similarly the area transformed from suitable to non-suitable was 1, 03,722 km^2. Fig. 16 shows the current and future potential distribution of *Chromolaenaodorata*

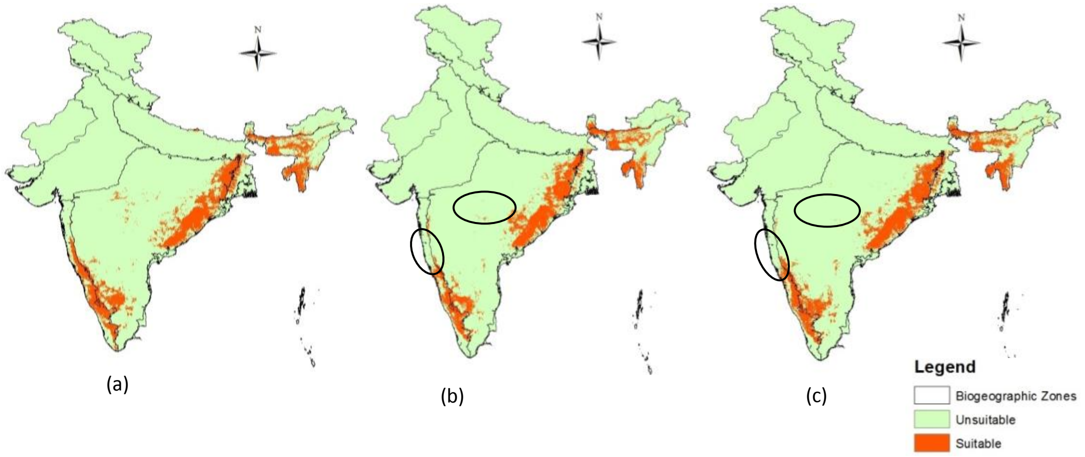


Figure 16: Area predicted suitable for *Chromolaenaodorata* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.6 *Cyperusrotundus*(Nut grass)

Under A2a and B2ascenario climate ensemble predicted shift from non-suitable to suitable habitats in Deccan Peninsula including Eastern Highland and Chota Nagpur Plateau and the Southern Highlands of Deccan Peninsula, East Himalayas and North-East regions. Habitat reduction is noticed in Deccan Peninsula, North-East and some parts of Himalayas. Fig. 17 shows the current and future potential distribution of *Cyperusrotundus.*

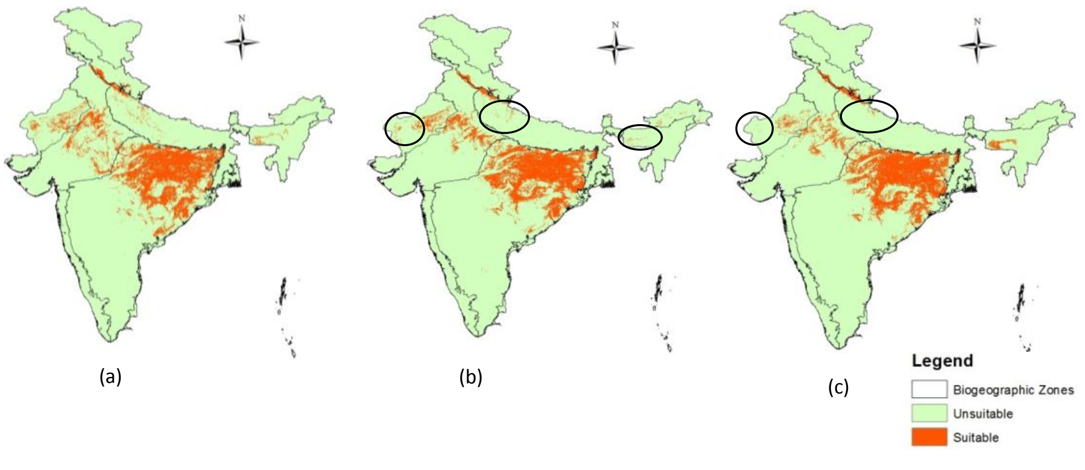


Figure 17: Area predicted suitable for *Cyperusrotundus* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.7 *Eclipta prostrate* (Bhringraj)

Under A2a scenario climate ensemble predicted a decrease in habitat area in Indo-Gangetic and North-East regions of the country. Under B2a scenario it predicted a decrease in habitat area in Semi-Arid and Deccan Peninsula regions of the country. The area transformed from non-suitable to suitable under A2a scenario was 1, 22,321 km^2. Similarly the area transformed from suitable to non-suitable was 2, 70,752 km^2. Under B2a scenario the area transformed from non-suitable to suitable was 1, 65,447 km^2 and from suitable to non-suitable was 2, 17,000 km^2. Fig. 18 shows the current and future potential distribution.

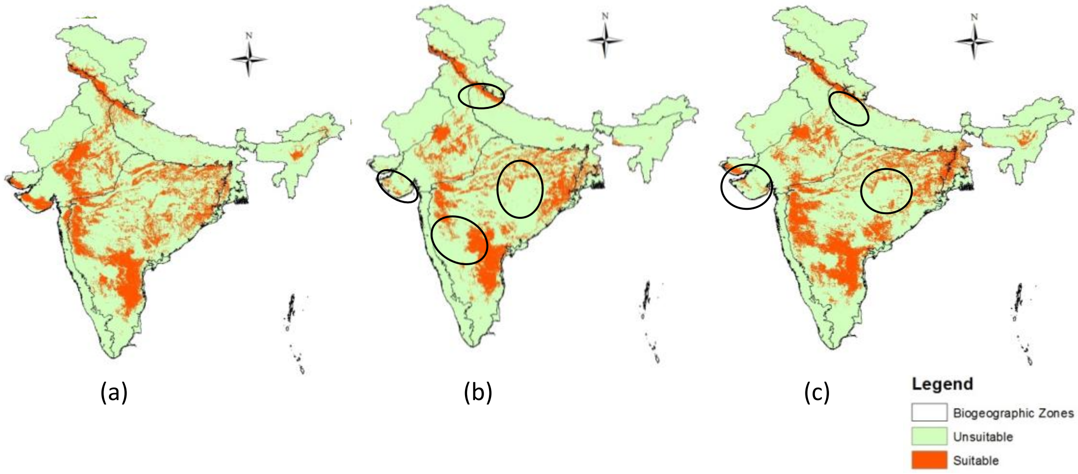


Figure 18: Area predicted suitable for *Ecliptaprostrata* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.8 *Eupatorium adenophorum*(Crofton weed)

A shift from non-suitable to suitable habitat in North West, West and East Himalayas along with North East with an area change of 14, 732 km^2 was predicted under A2a scenario. Change from suitable to non-suitable habitat was predicted in North West Himalayas and North East with an area change of 9018 km^2. Under B2a scenario shift from non-suitable to suitable habitat in Deccan Peninsula, Deserts, Himalayas, Western Ghats, Deserts and Semi-Arid with an area change of 1, 11,552 km^2 is observed. Change from suitable to non-suitable habitat was predicted in Deserts, Semi-Arid regions, Deccan Peninsula, Gangetic Plains North-West Himalayas. Area changed is 1, 75, 457 km^2. Fig. 19 shows the current and future potential distribution of *Eupatorium adenophorum.*

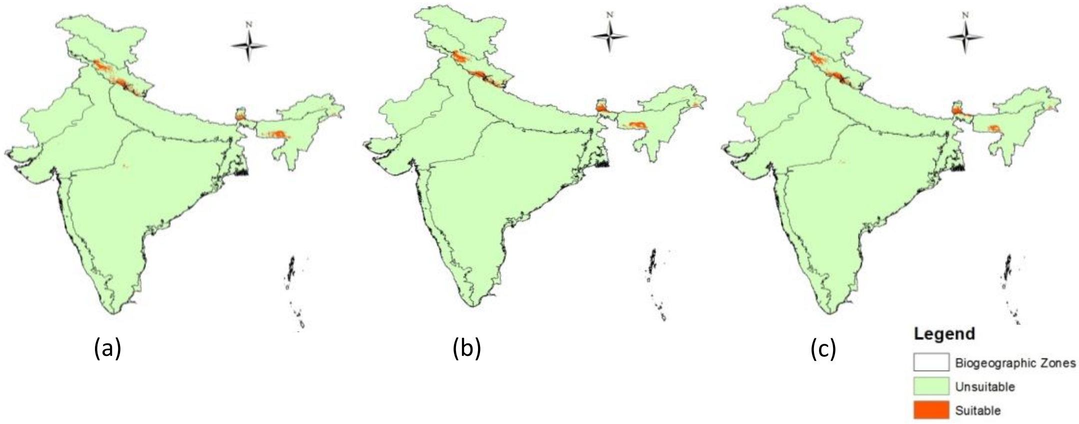


Figure 19: Area predicted suitable for *Eupatorium adenophorum* (a) current, ensemble A2a (b) B2a (c)

5.3.4.9 *Euphorbia hirta*(Asthma weed)

Under A2a scenario climate ensemble predicted decrease in the suitable area in Indo-Gangetic-regions and Himalayas and an increase in North-East and Deserts. Under B2a scenario it predicted a decrease in the suitable area in Indo-Gangetic-regions. The area transformed from non-suitable to suitable under A2a scenario was 1, 19, 069 km^2 and from suitable to non-suitable was 1, 72, 250 km^2 while under B2a as 1, 11,552 km^2 and 1, 75, 457 km^2 respectively. Fig. 20 shows the current and future potential distribution of *Euphorbia hirta.*

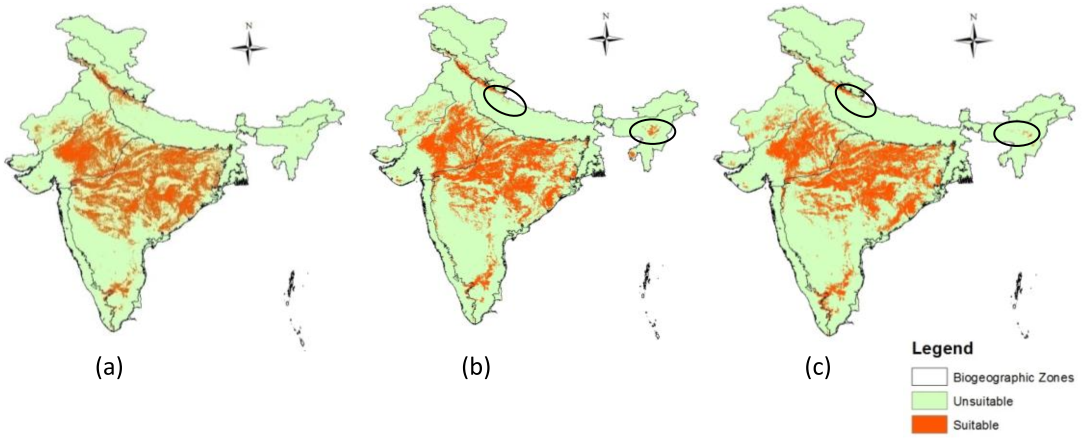


Figure 20: Area predicted suitable for *Euphorbia hirta*in (a) current, ensemble A2a (b) B2a (c)

5.3.4.10 *Hyptissuaveolens*(Vilayatitulsi)

A prominent decrease in the suitable area in Indo-Gangetic regions and Deccan Peninsula was predicted under both the climate change scenarios. The predicted area of transformation from non-suitable to suitable under A2a scenario was 57,433 km^2. Similarly the area transformed from suitable to non-suitable was predicted as1, 72, 250 km^2. Under B2a scenario the area transformed from non-suitable to suitable was 64, 434 km^2 and from suitable to non-suitable was 1, 62,188 km^2. Fig. 21 shows the current and future potential distribution of *Hyptissuaveolens.*

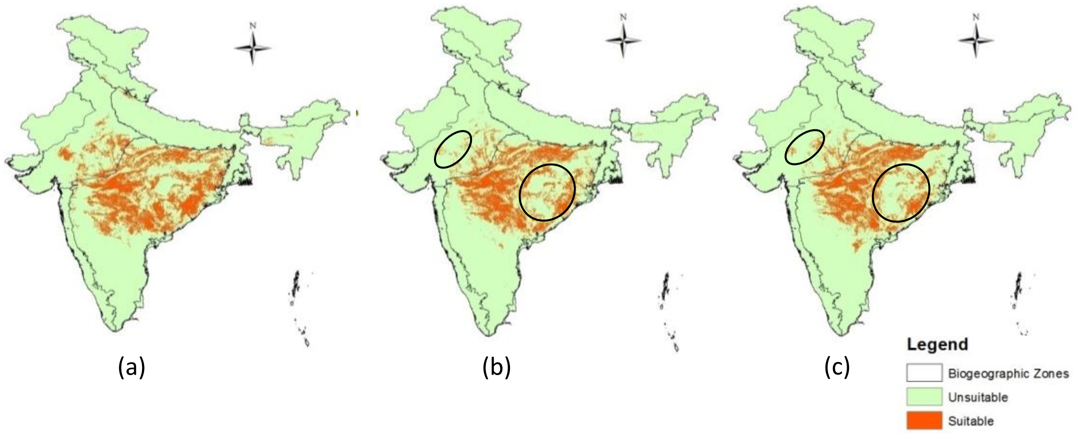


Figure 21: Area predicted suitable for *Hyptissuaveolens* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.11 *Lantana camara*(Wild sage)

Under A2a scenario climate ensemble predicted a shift from non-suitable to suitable habitat in Deccan Peninsula, Semi- Arid and Himalaya. Area changed was predicted as 72, 437 km^2. Change from suitable to non-suitable was predicted in Deccan Peninsula, Semi-Arid, Himalaya, and Western Ghats. Predicted area changed was 1, 69,156 km^2. Under B2a scenario it predicted a shift from non-suitable to suitable habitat in Deccan Peninsula, Semi-Arid, North-East, Himalaya along with North-East. Area changed was 1, 11,399 km^2.

Change from suitable to non-suitable habitat is shown in Deccan Peninsula, Semi-Arid, North-East, Himalaya, and Western Ghats with an area change of 1, 64, 750 km^2 Fig. 22 shows the current and future potential distribution of *Lantana camara.*

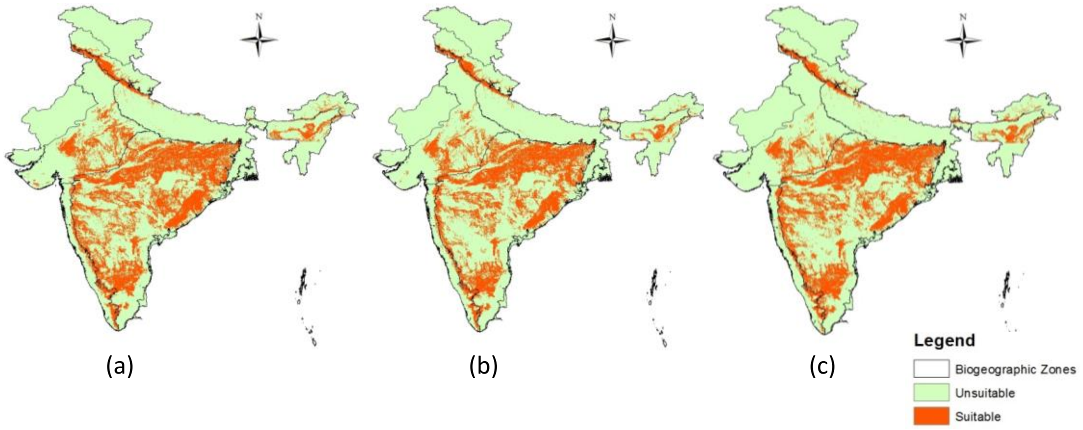


Figure 22: Area predicted suitable for *Lantana camara* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.12 *Mikaniacordata*(Heartleaf hempvine)

Under A2a and B2a scenario the climate ensemble predicted a prominent increase in the suitable area in Himalayas and some parts of North-East. The area transformed from non-suitable to suitable under A2a scenario is 23, 332 km^2 and from suitable to non-suitable is 19, 253 km^2. Similarly, under B2a scenario as 26, 233 km^2 and 22, 365 km^2 respectively. Fig. 23 shows the current and future potential distribution of *Mikaniacordata.*

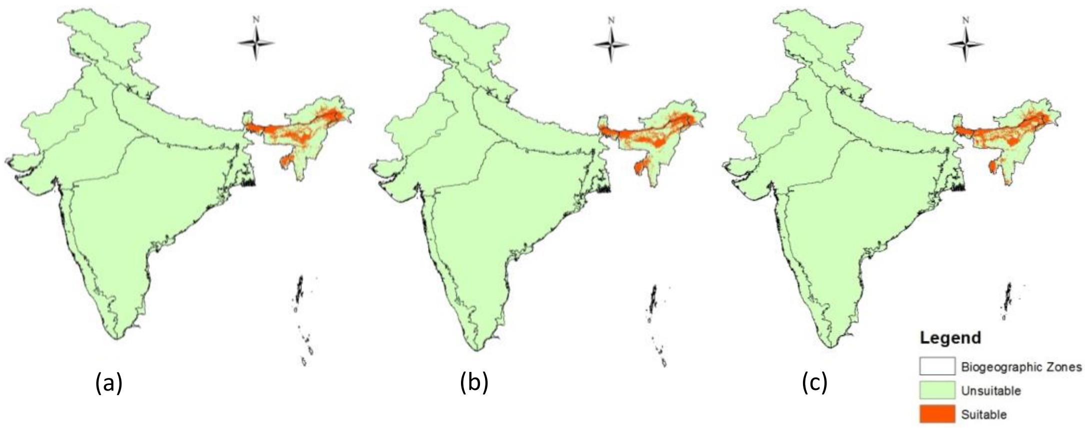


Figure 23: Area predicted suitable for *Mikaniacordata* in (a) current, ensemble A2a (b) B2a (c)

5.3.4.13 *Mimosa pudica*(Touch me not)

A decrease in suitable habitat was predicted in semi-Arid regions, Deccan Peninsula and Indo-Gangetic Plains under A2a scenario by the climate ensemble. Whereas, under B2a scenario it predicted a decrease in Indo-Gangetic plains and Deccan Peninsula. The area transformed from non-suitable to suitable under A2a scenario was predicted to be 1, 07,047 km^2 and from suitable to non-suitable as 1, 11,709 km^2 and under B2a as 1, 08, 757 km^2 and 1, 32, 729 km^{2}respectively. Fig. 24 shows the current and future potential distribution.

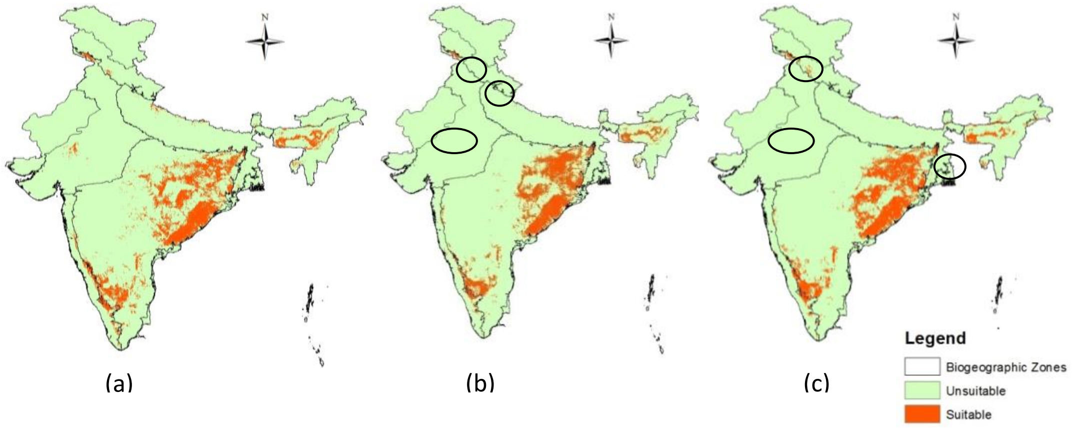


Figure 24: Area predicted suitable for Mimosa pudica in (a) current, ensemble A2a (b) B2a (c)

5.3.4.14 *Partheniumhysterophorus*(Congress grass)

Under A2a scenario climate ensemble predicted a decrease in the suitable habitat in Semi-Arid and Deccan Peninsula, while increase in Central Deccan Peninsula. Under B2a it predicted decrease in the suitable area in Semi-Arid regions and Deccan Peninsula. The area transformed from non-suitable to suitable under A2a scenario was 97, 799 km^2 and from suitable to non-suitable was 91, 251 km^2. Similarly under B2a scenario the area transformed was 1, 22, 092 km^2 and 1, 32, 729 km^2 respectively. Fig. 25 shows the current and future potential distribution of *Partheniumhysterophorus.*

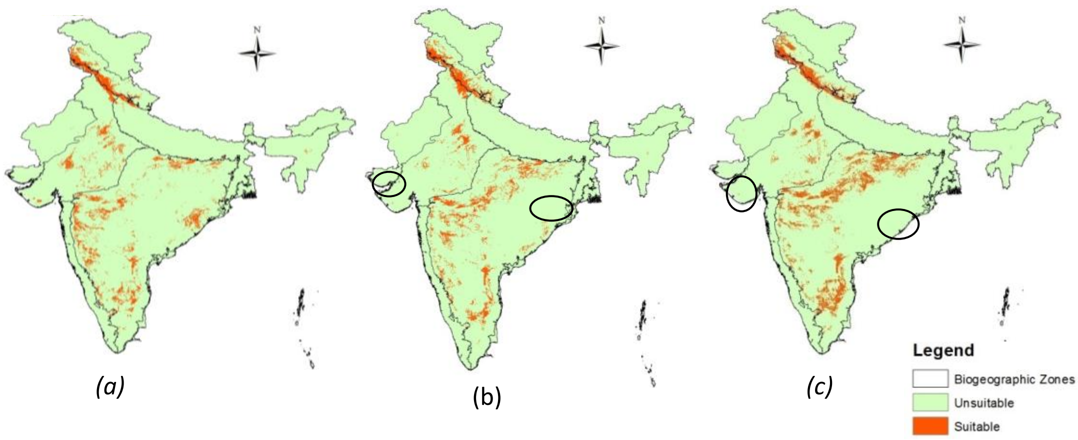


Figure 25: Area predicted suitable *Partheniumhysterophorus* (a) current, ensemble A2a(b) B2a(c)

5.3.4.15 *Prosopisjuliflora*(Vilayati babul)

The climate ensemble predicted a decrease in the suitable area in Semi-Arid regions and some parts of Deccan Peninsula under A2a scenario. Under B2a scenario it predicted a decrease in the suitable area in Semi-Arid regions. The area transformed from non-suitable to suitable under A2a scenario was predicted as 60, 867 km^2 and from suitable to non-suitable as 64, 435 km^2. Similarly under B2a scenario the area transformed was predicted as 63, 232 km^2 and 76, 687 km^2. Fig. 26 shows the current and future potential distribution.

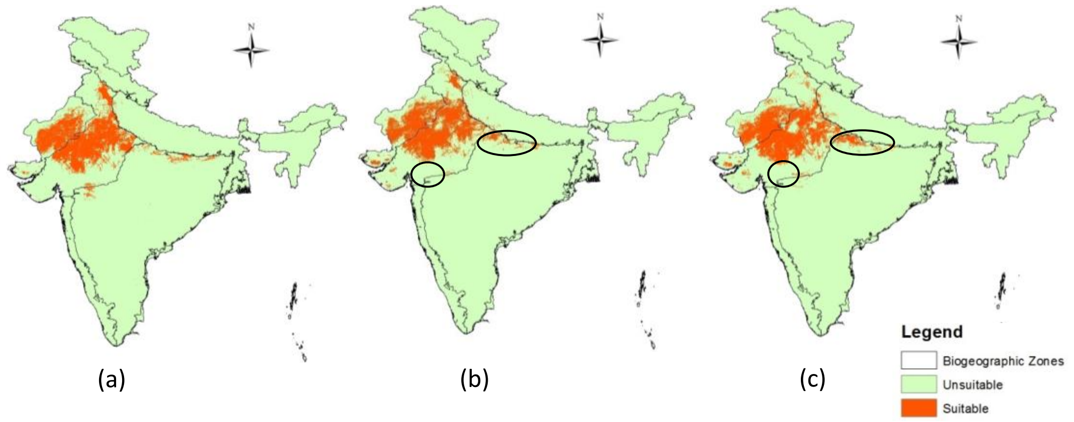


Figure 26: Area predicted suitable for *Prosopisjuliflora* in (a) current, ensemble A2a (b) B2a (c)

The area suitable for the occurrence of selected FIS is shown in table for 2050 A2a and B2a scenarios is represented in table 10 and table 11.

Table 10: Area predicted suitable for FIS 2050 A2a scenario

FIS	Present	CGCM2	CSIRO-mk2	HADCM3	Ensemble
Ageratum conyzoides	5, 83,877	5,92,778	6,10,366	5, 92, 133	5,90,134
Bidenspilosa	3, 83,442	4,52,506	4,40,203	5, 10, 987	5,06,950
Cassia occidentalis	4, 22,865	4,94,294	4,89,137	4, 25, 887	4,59,445
Cassia tora	7, 05,124	7,21,814	7,52,508	8, 22, 767	8,02,282
Chromolaenaodorata	3, 76,690	3,69,805	4,48,542	3, 20, 223	3,50,331
Cyprus rotundus	4, 59, 064	4,24,192	4,04,948	4, 30, 224	4,12,900
Ecliptaprostrata	6, 96,822	6,39,425	4,27,766	5, 20, 667	5,48,551
Eupatorium adenophorum	30, 431	36,665	34,353	48, 567	42,765
Euphorbia hirta	7, 46,851	6,74,669	7,19,510	6, 75, 778	6,95,185
Hyptissuaveolens	5, 46,851	4,07,891	4,28,233	3, 90, 678	3,96,204
Lantana camara	9, 03,341	9,10,110	9,37,191	9, 05, 346	9,06,784
Mikaniacordata	85,210	90,164	95,884	87, 327	88,845
Mimosa pudica	3, 41,484	3,34,446	3,30,545	3, 10, 674	3,22,671
Partheniumhysterophorus	2, 03,749	2,00,753	2,27,040	2, 00, 000	2,00,083
Prosopisjuliflora	3, 36,045	3,37576	3,31,908	3, 30, 234	3,32,556

Table 11: Area predicted suitable for FIS 2050 B2a scenario

FIS	Present	CGCM2	CSIRO-mk2	HADCM3	Ensemble
Ageratum conyzoides	5, 83,877	5,97,071	6,33,482	6, 22, 567	6,05,408
Bidenspilosa	3, 83,442	4,02,084	4,72,405	4, 56, 234	4,55,611
Cassia occidentalis	4, 22,865	4,27,325	4,90,767	5, 09, 213	4,95,977
Cassia tora	7, 05,124	7,37,423	7,58,567	7, 78, 998	7,73,970
Chromolaenaodorata	3, 76,690	3,77,916	3,82,671	3, 42, 231	3,52,943
Cyprus rotundus	4, 59, 064	4,11,895	4,38,059	4, 06, 657	4,07,112
Ecliptaprostrata	6, 96,822	5,83,979	4,66,667	6, 66, 547	6,45,447

Eupatorium adenophorum	30, 431	48,893	41,023	38, 756	34,681
Euphorbia hirta	7, 46,851	6,52,566	7,55,766	7, 39, 354	6,84,955
Hyptissuaveolens	5, 46,851	4,00,440	4,17,573	3, 67, 254	3,85,944
Lantana camara	9, 03,341	9,10,980	9,23,429	9, 56, 398	9,48,032
Mikaniacordata	85,210	92,985	89,602	89, 992	88,713
Mimosa pudica	3, 41,484	3,17,324	3,30,178	3, 40, 876	3,34,905
Partheniumhysterophorus	2, 03,749	1,88,241	2,15,915	2, 70, 765	2,50,794
Prosopisjuliflora	3, 36,045	3,24,085	3,36,321	3, 20, 097	3,22,653

5.4 Model Validation for A2a and B2a climate change scenarios

For the purpose of evaluation/validation of the model results, the AUC and TSS values for each of the models were considered (table 12, table 13). The AUC and TSS values for majority of the species were considerably high, therefore it means that MaxENT model shows perfect fit and provides unbiased predictions.

Table 12: AUC/TSS scores for CGCM2, CSIRO-mk2, HADCM3 climate models for A2a scenario

		A2a					
		CGCM2		**CSIRO-mk2**		**HADCM3**	
S.No.	**FIS**	AUC	TSS	AUC	TSS	AUC	TSS
1	*Ageratum conyzoides*	0.899	0.675	0.903	0.661	0.905	0.651
2	*Bidenspilosa*	0.942	0.719	0.946	0.691	0.940	0.720
3	*Cassia occidentalis*	0.952	0.727	0.949	0.720	0.945	0.708
4	*Cassia tora*	0.875	0.677	0.871	0.672	0.874	0.685
5	*Chromolaenaodorata*	0.932	0.789	0.928	0.786	0.931	0.795
6	*Cyprus rotundus*	0.927	0.714	0.932	0.735	0.931	0.732
7	*Ecliptaprostrata*	0.906	0.591	0.910	0.567	0.922	0.588
8	*Eupatorium adenophorum*	0.986	0.751	0.994	0.784	0.996	0.786
9	*Euphorbia hirta*	0.899	0.678	0.920	0.657	0.897	0.691
10	*Hyptissuaveolens*	0.926	0.742	0.923	0.725	0.926	0.758
11	*Lantana camara*	0.878	0.699	0.863	0.635	0.855	0.654
12	*Mikaniacordata*	0.983	0.817	0.985	0.852	0.988	0.859
13	*Mimosa pudica*	0.951	0.780	0.950	0.689	0.948	0.691
14	*Partheniumhysterophorus*	0.953	0.705	0.962	0.684	0.963	0.692
15	*Prosopisjuliflora*	0.948	0.785	0.946	0.726	0.948	0.765

Table 13: AUC/TSS scores for CGCM2, CSIRO-mk2, HADCM3 climate models for B2a scenario

		B2a					
		CGCM2		**CSIRO-mk2**		**HADCM3**	
S.No.	**FIS**	AUC	TSS	AUC	TSS	AUC	TSS
1	*Ageratum conyzoides*	0.903	0.715	0.899	0.691	0.895	0.682
2	*Bidenspilosa*	0.951	0.681	0.943	0.713	0.944	0.689
3	*Cassia occidentalis*	0.946	0.762	0.950	0.7351	0.949	0.732
4	*Cassia tora*	0.875	0.684	0.870	0.678	0.872	0.673

5	*Chromolaenaodorata*	0.931	0.751	0.918	0.791	0.920	0.795
6	*Cyprus rotundus*	0.931	0.702	0.931	0.713	0.935	0.737
7	*Ecliptaprostrata*	0.907	0.631	0.920	0.642	0.909	0.612
8	*Eupatorium adenophorum*	0.997	0.742	0.996	0.754	0.995	0.821
9	*Euphorbia hirta*	0.899	0.667	0.897	0.668	0.902	0.666
10	*Hyptissuaveolens*	0.929	0.703	0.926	0.743	0.906	0.724
11	*Lantana camara*	0.871	0.654	0.862	0.675	0.864	0.593
12	*Mikaniacordata*	0.985	0.823	0.983	0.812	0.984	0.845
13	*Mimosa pudica*	0.952	0.801	0.947	0.809	0.950	0.821
14	*Partheniumhysterophorus*	0.960	0.712	0.951	0.703	0.958	0.732
15	*Prosopisjuliflora*	0.950	0.723	0.939	0.713	0.944	0.709

5.5 FIS Range Shift

Table 14, 15 and Fig. 25, 26 represents the change (increase or decrease) in the range of FIS in each of the forest type class. Whereas Table 16, 17 and Fig. 27, 28 makes representation for 10 biogeographic zones of the country under A2a and B2a climate change scenarios respectively.

It is observed that under A2a scenario majority of the FIS showed increase in potential distribution ranges than reported under B2a scenario. As A2a scenario considers an unrestricted rise in CO2 emissions, high population growth, increase in energy levels and slow technological changes leading to more harsh conditions for the native species to survive and compete. This would give opportunities for the invasive species to invade into newer ecosystems and show increase in the distribution ranges. On the contrary B2a scenario reflects moderate increase in CO2 emissions and growing trend towards environmental protection and social equity giving fewer opportunities for the invasive species to increase in their potential distribution range as compared to A2a scenario.

Table 14: Range shift of 15 FIS with in different forest types in A2a scenario

FIS	Area (km2)								
	evergreen broad leaf forest	deciduous needle leaf forest	deciduous broad leaf forest	Mixed forest	close shrubland	open shrubland	woody grassland	savannah	grasslands
Ageratum conyzoides	2281	0	1736	4953	172	-202	11903	28	-349
Bidenspilosa	-5347	3	-413	23	-114	-441	-8059	-67	76
Cassia occidentalis	5215	3	1598	8137	234	6459	30558	42	2323
Cassia tora	-12880	4	5660	16658	528	-13365	77357	136	49
Chromolaenaodorata	12691	0	-34	-405	72	292	2908	96	107
Cyperusrotundus	1197	1	853	5132	108	4531	15834	12	1451
Ecliptaprostrata	5054	0	2134	2746	283	5360	22271	270	1198
Eupatorium adenophorum	70	2	-2	-2827	7	10	-626	-4	334
Euphorbia hirta	-2135	-1	1030	611	103	-827	9406	-4	571
Hyptissuaveolens	610	1	711	4402	222	1079	21711	77	1212
Lantana camara	4709	4	1603	4188	145	2591	22690	116	1670
Mikaniacordata	-378	0	22	220	5	-32	-1486	7	-75
Mimosa pudica	3921	0	791	2915	72	311	6771	125	56
Partheniumhysterophorus	254	0	-325	-2448	11	523	-823	1	-403
Prosopisjuliflora	3	2	105	34	10	1410	-402	-31	477

Table 15: Range shift of 15 FIS with in different forest types in B2a scenario

FIS	Area (km^2)								
	evergreen broad leaf forest	**deciduous needle leaf forest**	**deciduous broad leaf forest**	**Mixed forest**	**close shrubland**	**open shrubland**	**woody grassland**	**savannah**	**grasslands**
Ageratum conyzoides	2474	-1	1263	-1848	36	-518	1629	-39	-704
Bidenspilosa	7896	-4	-700	-12644	-132	-1206	-11327	-22	-2139
Cassia occidentalis	5084	2	2073	9218	325	10615	39036	145	2914
Cassia tora	433	-4	-126	-58	-22	-1645	4727	43	-63
Chromolaenaodorata	9580	0	13	-782	27	99	5045	79	22
Cyperusrotundus	1735	0	1193	6673	95	3849	18567	13	1536
Ecliptaprostrata	1002	4	1848	2637	260	131	9003	103	1005
Eupatorium adenophorum	1091	1	5	-63	18	13	793	-2	371
Euphorbia hirta	-265	0	626	1409	57	37	6303	-2	613
Hyptissuaveolens	623	-1	516	4138	150	1187	22376	76	1021
Lantana camara	591	3	1343	9	101	2469	17438	77	1871
Mikaniacordata	780	0	21	393	-8	-111	-160	-1	-230
Mimosa pudica	4098	-3	-417	1063	4	347	1907	62	-36
Partheniumhysterophorus	185	-1	-1368	-9431	-103	739	-9737	-22	-1052
Prosopisjuliflora	2	0	105	261	7	5423	-523	-21	558

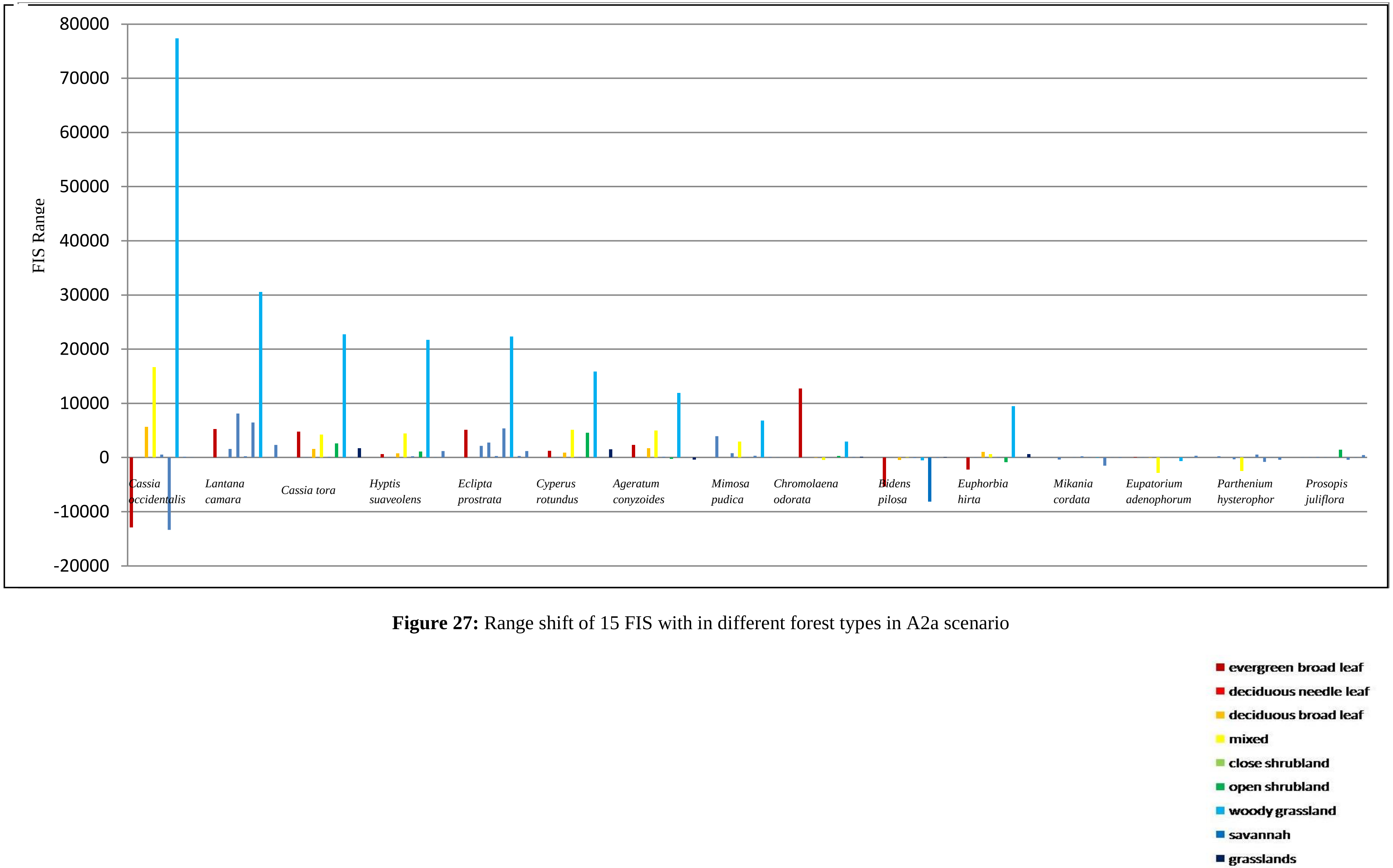


Figure 27: Range shift of 15 FIS with in different forest types in A2a scenario

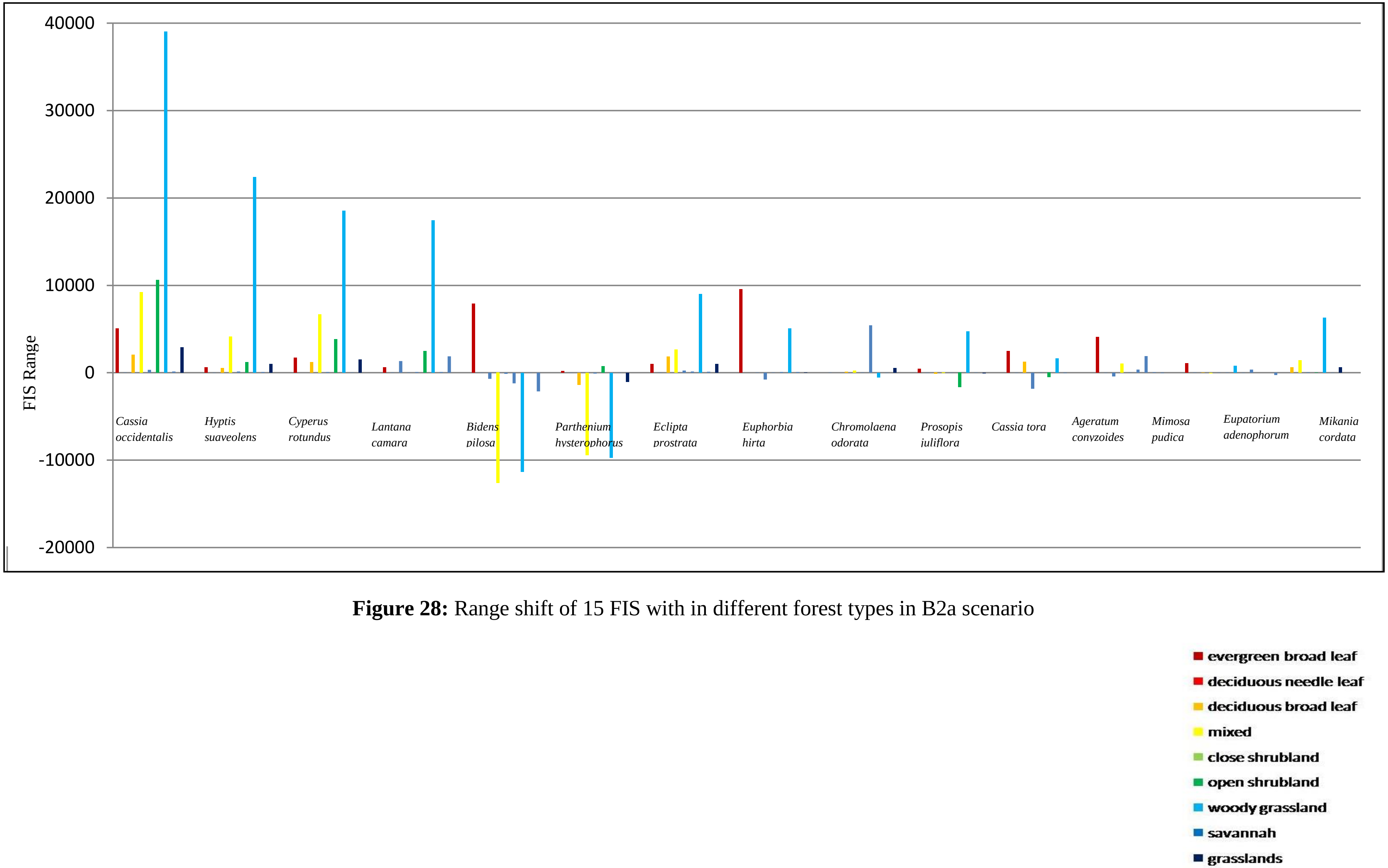


Figure 28: Range shift of 15 FIS with in different forest types in B2a scenario

Table 16: Range shift of 15 FIS with in different Bio-geographic zones in A2a scenario

FIS	Area (km^2)									
	Trans-Himalayas	Himalaya	Semi-Arid	Gangetic Plains	Desert	North-East	Deccan Peninsula	Coasts	Islands	Western Ghats
Ageratum conyzoides	0	4666	4969	-369	-1257	2086	12678	-53	-586	5100
Bidenspilosa	8	2229	4755	-230	0	-160	36712	0	1	3011
Cassia occidentalis	90	3229	3755	-130	0	160	38712	0	0	7011
Cassia tora	66	1456	-22442	15649	30559	31810	-79434	189	93	-3505
Chromolaenaodorata	0	1343	0	-4687	0	-10059	-6477	26	-239	-16977
Cyperusrotundus	0	2617	14578	2129	4901	312	42818	0	12	5
Ecliptaprostrata	293	-5263	-60773	-4571	-6917	-7940	-54444	-502	3849	-7476
Eupatorium adenophorum	0	6281	439	3139	0	1321	0	0	0	0
Euphorbia hirta	0	-978	3992	5323	-1049	-6841	50362	-15	-10	-493
Hyptissuaveolens	0	-840	-21456	-2715	-1	-1725	-57000	0	4	-108
Lantana camara	0	3546	10503	-86	-160	4431	40534	0	4	2765
Mikaniacordata	0	882	0	-242	0	2620	-29	0	0	0
Mimosa pudica	0	190	-3373	-2668	-3	-3556	-2111	-65	-86	-7227
Partheniumhysterophorus	175	4630	-8270	-1251	169	-307	-1334	4	0	-456
Prosopisjuliflora	0	-121	-6475	1923	5465	-87	-4230	0	0	-38

Table 17: Range shift of 15 FIS with in different Bio-geographic zones in B2a scenario

FIS	Area (km^2)									
	Trans-Himalayas	Himalaya	Semi-Arid	Gangetic Plains	Desert	North-East	Deccan Peninsula	Coasts	Islands	Western Ghats
Ageratum conyzoides	0	2728	188	427	-3	-1156	17338	60	230	-2827
Bidenspilosa	221	21105	16887	713	0	-19426	48920	0	13	-348
Cassia occidentalis	430	4736	38741	5309	15865	9992	96136	165	54	2513
Cassia tora	0	-3983	-16491	-703	2731	-971	193	0	69	-1821
Chromolaenaodorata	0	863	0	-4370	0	-7709	2251	0	-128	-15103
Cyperusrotundus	0	2448	12574	3330	3703	4838	42761	1	10	0
Ecliptaprostrata	681	-8363	-63981	10885	998	1404	15118	-367	1319	-5944
Eupatorium adenophorum	0	-126	-27	1963	0	-3515	-173	0	0	-5
Euphorbia hirta	0	-690	-19742	-5563	2068	955	-40925	15	10	1977
Hyptissuaveolens	0	-844	-25661	-2165	-1	-934	-65055	0	0	-193
Lantana camara	0	8796	39461	1584	17	7353	88504	0	7	10406
Mikaniacordata	0	483	0	62	0	2547	-29	0	0	0
Mimosa pudica	0	3898	-3550	-1395	-3	-6934	7663	117	-33	-7144
Partheniumhysterophorus	156	6666	-7136	458	-70	-414	44735	0	0	36
Prosopisjuliflora	0	-539	-13049	2564	-698	-87	-375	0	0	117

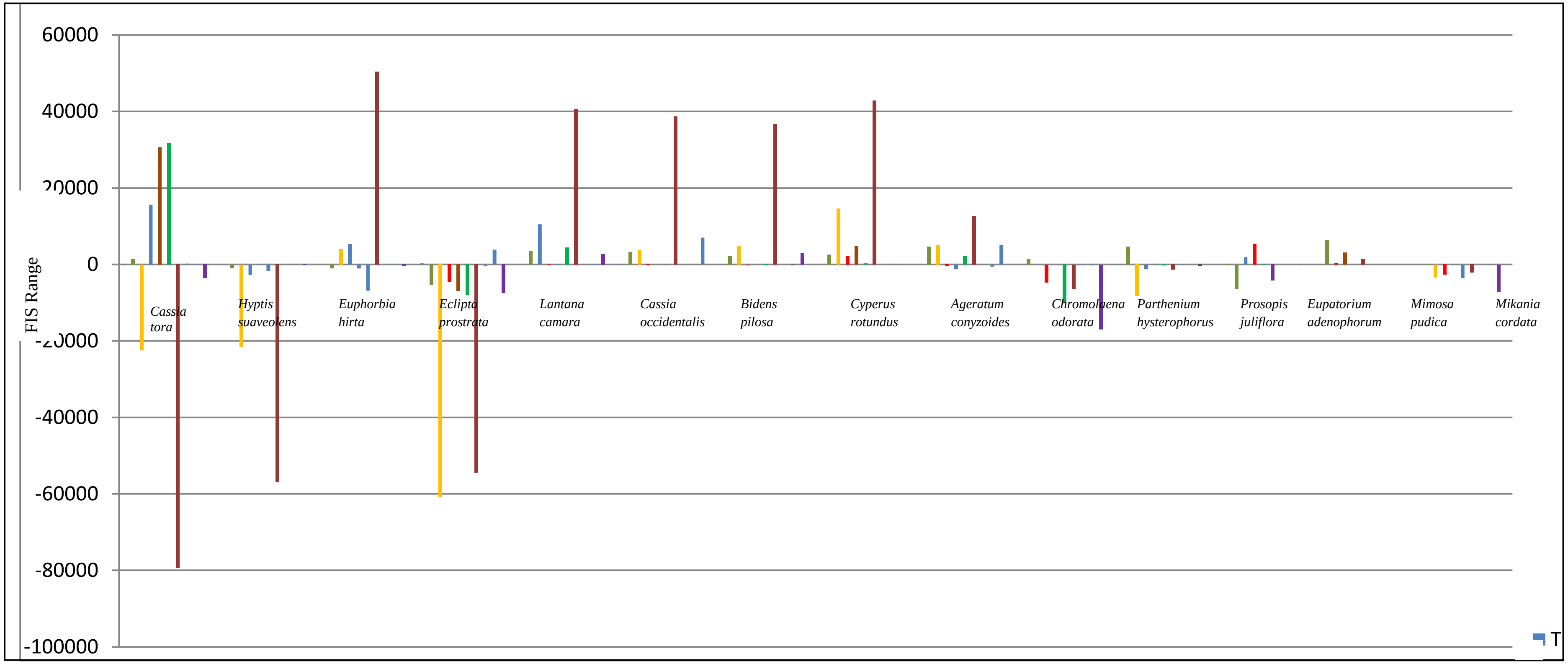


Figure 29: Range shift of 15 FIS with in different Bio-geographic zones in A2a scenario

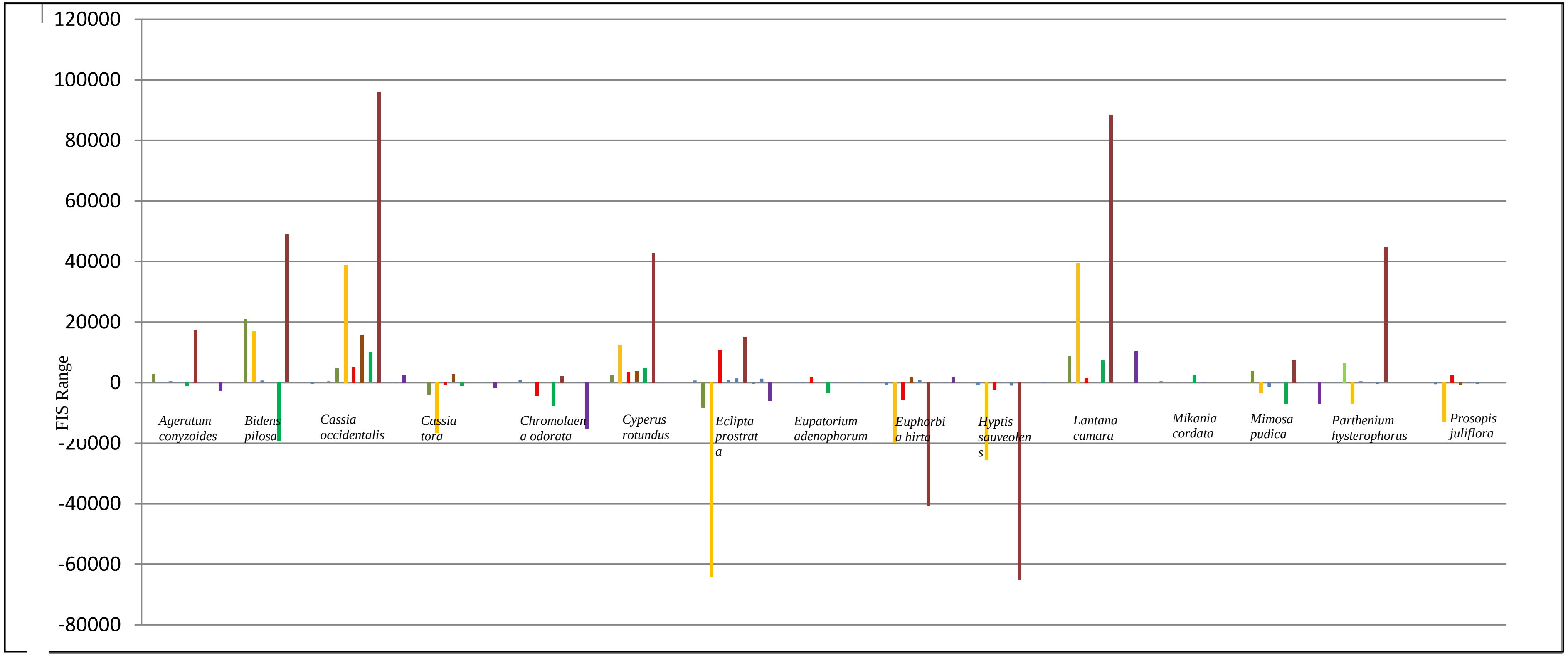


Figure 30: Range shift of 15 FIS with in different Bio-geographic zones in B2a scenario

5.6 Discussion

Over last few decades, the rapid spread of invasive has drawn the attention of researchers and resource managers. The knowledge about the geographical areas which could be infested by the large number of potential invasive species is critically required. Therefore, it becomes essential to model and identify the hotspots of plant invasion to carry out pre-emptive management of the regions that are under severe threat of invasion or susceptible to establishment in future under projected climate change. The invasion hotspots are not often not easy to identify due to the lack of occurrence data on invasive species across the country.

The results demonstrated the hotspots with more than 75 species found together are located in semi-arid regions and northern eastern part of Deccan Peninsula biogeographic zones. The species in the region are resistant to high temperature and precipitation and are predicted to show increase in their potential suitable habitat.

It is evident that change in the climatic conditions might change the distribution patterns of existing invasives. This study has tried to predict possible shift in the geographical range of selected most noxious FIS using projected climate change scenarios. Various available atmosphere-ocean global circulation models (AOGCMs) have varying impact on the projected species range. The three widely used AOGCMS namely: CGCM2, CSIRO-mk2 and HADCM3 averaged from 2040 to 2069 ('2050') were used. These global models however showed differences in their climatic parameters such temperature and precipitation for Indian regions. It was observed that out of the three models the predictions were similar in case of CGCM2 and CSIRO-mk2 than HADCM3 under climate change scenarios. To overcome the contradictions in predictions of species range using different climate models, ensemble method was used. It integrated multiple climate models highlighting the regions of agreement based on AUC weights to provide more realistic predictions. It was observed that FIS such as *Eclipta prostrate*, *Euphorbia hirta*, *Cyperusrotundus* and *Hyptis suaveolens* were predicted with reduction in their potential habitat while the other FIS were predicted to increase in their potential habitat under climate change scenarios. The study revealed that along with climate change, the landscape heterogeneity including forest-nonforest change helped in refining the future potential range shift of FIS. The percentage contribution of forest-nonforest change in the model predictions for future varied from 10 % to 35%.

Not all FIS were considered for range shift analysis, 15 most noxious and aggressive species were considered based on literature survey and consultation. The range shift information generated for these FIS under future climate scenarios using ensemble forecast projections would be useful for the forest managers and policy makers in selecting the sites for urgent monitoring and designing local, regional and national level integrated management strategies for biodiversity conservation. The study also identified FIS species that can show significant reduction in their potential geographic distribution creating opportunities for ecosystem restoration. Under A2a scenario the species that were predicted to show maximum change in their habitat (increase or decrease) included *Hyptissuaveolens*, *Bidenspilosa*, *Lantana camara*, *Euphorbia hirta*, *Cassia tora and Cassia occidentalis*, *Ecliptaprostrata and Chromolaena odorata.* However under B2a scenario the species predicted with maximum change in their habitat included *Bidenspilosa, Hyptissuaveolens, Cassia occidentalis, Cassia tora, Ageratum conyzoides, Euphorbia hirta and Ecliptaprostrata.*

While dealing at national level, it becomes essential to target the ecosystems and regions that have varying ecoclimatic structure and that would be most affected by the invasion process. The future range shift was therefore studied for the forested ecosystems and the biogeographic zones across the country. It was observed that the maximum range shift for the species under A2a and B2a scenario took place in evergreen broad leaf, deciduous broad leaf, mixed forest, woody grasslands and open shrublands with a canopy closure ranging between 0 and 50%. On the other hand the biogeographic zones that encountered maximum range shift of the species included Deccan Peninsula, Western Ghats, Himalaya, semi-arid and the regions of North-East India. The information generated emphasises to adopt more strict conservation practices in the vulnerable forest types and biogeographic zones for protecting and restoring the native diversity.

Apart from the merits of the study there are few limitations of the study too. The study considered climate, landscape heterogeneity and topography i.e. the abiotic factors as the variables for the prediction of potential distribution of invasives. The SDMs does not take into consideration, the biotic interactions and the dispersal mechanism (Gaston and Fuller, 2009). It was assumed the species to be in dynamic equilibrium with the environment which might not be true for the recently introduced invasive species into newer ecosystems (Bellard *et al.,* 2013). The presence of suitable potential environment does not lead to immediate establishment of any new invader, although the SDMs fail to incorporate it and might lead to over predictions.

The present thesis has addressed the following research questions:

1. *What is the levels of uncertainty associated climatic data models, and thresholding techniques used for predicting invasion?*

   Most of the global climate models differ from each other due to difference in their assumptions and the interpolation techniques. It was observed that in Indian context, CGCM2 and CSIRO-mk2 climate models are highly correlated while show less correlation with HADCM3. The predictions of HADCM3 model therefore slightly differs from the other two models. Apart from the uncertainties in the climate models yet another uncertainty arises about appropriate inference based on a suitable thresholding technique for MaxEnT model. Taking into consideration relative commission and omission errors, the technique was adopted for the methods that resulted in lower threshold values i.e. wide distribution of habitat and close to zero omission error. Comparatively the fractional predicted area and the AUC values for “minimum training presence” was higher as well as omission error was very low as compared to the results obtained from the other techniques. Therefore, this technique was considered more relevant to incorporate least uncertainty in the prediction.

2. *Does an ensemble overcome the predictive uncertainties of future climate change projections?*

    To overcome the contradictions between the predictions of different climate models, a consensus method was used. It integrated the results of multiple individual climate models highlighting the regions of agreement based on weights. Therefore, while the ensemble model combined different model predictions they provided a more realistic species distribution simulation. However, it was noticed that ensemble maps did not significantly outperformed any single model predictions. The extent to which an ensemble model might outperform a single model is still under debate (Marmion *et al.* 2009).It is clear that the ensembling helps in overcoming the predictive accuracy of individual model. Although, the use of extremely less correlated model should be avoided to prevent over prediction.

3. *Does inclusion of landscape heterogeneity and soil characteristics help SDM in improving prediction of potential spread of invasive?*

    It was observed that variation in soil type at order level plays less to moderate role in improving the predictive accuracy of the model. Forest-nonforest change and forest density on the other hand showed high contribution in predicting the potential spread of the selected invasive species marked with high AUC values. The species included *Ageratum conyzoides, Bidenspilosa, Chromolaenaodorata, Eupatorium adenophorum, Hyptissauveolens, Lantana camara, Mikaniacordata*and *Partheniumhysterophorus.*While for the remaining species it showed moderate contribution. These results were drawn using the jack-knife method. Therefore, it is analysed that landscape heterogeneity plays an important role while soil characteristics play less role in improving the prediction of potential spread of invasives.

Chapter 6 - CONCLUSION& RECOMMENDATIONS

6.1 Conclusion

Species distribution modelling is becoming an increasingly important tool in the field of conservation biology. Species distribution models provide a much better approximation of the invasive species distribution over currently largely unknown geographic limits. In this thesis, the hotspot of potential invasion derived through MaxEnT model is effective in considering the bias resulting due to false absence as a result of under sampling. Further, MaxEnT was used to obtain potential distribution of the selected noxious species invading various parts of the country under current and future climate projections. The outcomes of the study comprise the knowledge on the current potential distribution of hotspots of species and as well as ensemble potential invasion maps for the future climatic projections. The shift in the geographic range of the noxious invasive species in each of the biogeographic zones and forest type gives valuable information to prioritize pre-response and surveillance strategies.

We found out that change in climate regimes have profound impact on the ecosystems, creating suitable environment for the invasive species to establish and spread. The species range shift in future therefore is closely associated with the climate change and is adequately significant. The projected climate change can alter the potential habitats of the species forcing them to acquire new areas or shrink in their existing habitats. Through this study we provide a new picture of present and future invasion highlighting the response of the invasive species in different forest types and biogeographic regions. The information can be used by the policy makers and the land managers for preparation of appropriate eradication and management strategies to check future loss of biodiversity.

6.2 Recommendations:

The following recommendations are proposed from the present study:

- The current and future potential distribution maps of the most noxious FIS in India, produced in the following study can be used at regional or local level by the forest departments and resource managers for devising conservation strategies.
- The results from the study gives useful inputs to the Ministry of Environment, Forest and Climate Change (MoEF) to take up the eradication of few invasive species more seriously based on their future potential spread and consider them seriously while formulating the management plans.
- The potential distribution of various FIS should be validated with the actual distribution on ground; this would be helpful for the forest officers to arrest the loss of biodiversity and therefore take necessary eradication measures.
- The species occurrence database should be made rich with more number of species occurrence points since the SDM’s highly depends upon the sample size and their spatial occurrence.

References

Allouche, O., Tsoar A., Kadmon, R., (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). Journal of Applied Ecology, 46, 1223–1232.

Araújo, M. B., and New, M.,(2007). Ensemble forecasting of species distributions. Trends in ecology & evolution, 22(1), 42-47.

Araújo, M.B., Pearson, R.G., Thuiller, W. & Erhard, M., (2005). Validation of species-climate impact models under climate change. Global Change Biology, 11, 1504–1513.

Babar, Shilpa.,Giriraj, Amarnath., Reddy, C.S., anke, Jentsh., and Sudhakar, S., (2012). Species Distribution Models: Ecological Explanation and Prediction of a Endemic and Endangered Plant species (PterocarpusSantalinus L.F.). Current Science (Bangalore) 102 (1): 99-102. Scholars.

Bazzaz, F. A., (1986). Life history of colonizing plants: Some demographic, genetic, and physiological features. In: H. A. Mooney and J. A. Drake, eds. Ecology of Biological invasions of North America and Hawaii. Ecological Studies 58, pp. 96-110. Springer Verlag, New York.

Bellard, C., Thuiller, W., Leroy, B., Genovesi, P., Bakkenes, M., Courchamp, F., (2013). Will climate change promote future invasions? Global Change Biology, 19, 3740–3748. doi:10.1111/gcb.12344.

Benton, T.G., Vickery, J.A., Wilson, J.D., (2003). Farmland biodiversity: is habitat heterogeneity the key? Trends EcolEvol 18: 182–188. doi: 10.1016/s0169-5347(03)00011-9.

Brown, D.G., Walker, R., Manson, S., Seto, K.C., (2004). Modeling Land Use and Land Cover Change. In Land Change Science: Observing, Monitoring and Understanding Trajectories of Change on the Earth's Surface. Kluwer Academic Publishers. pp. 395-409.

Buckley, L., Urban, M., and Angilletta, M., (2010). Can mechanism inform species distribution models? Ecology Letters 13, 1041–1054.

Busby, J.R., (1991). BIOCLIM — A BioCLIMate Analysis and Prediction System. Nature Conservation: Cost effective biological surveys and data analysis. Nature conservation (ed. By Margules, C.R., and Austin, M.P.,) pp. 64–68. CSIRO, Melbourne.

Catford, J.A., Vesk, P.A., White, M.D., Wintle, B.A., (2011). Hotspots of plant invasion predicted by propagule pressure and ecosystem characteristics. Drivers. Distrib. 17, 1099-1110.

Carpenter, G., Gillison, A.N., Winter, J., (1993). DOMAIN — A flexible modelling procedure for mapping potential distributions of plants and animals. Biodiversity and Conservation, 2, 667–680.

Cheong, M., Brown, D., Kok, K., Lopez, D., (2012). Mixed Methods in Land Change Research: Towards integration. Trans.Inst.Br.Geogr. 37: 8-12.

Dukes, J.S., and Mooney, H.A., (1999). Does global change increase the success of biological invaders? Trends in Ecology& Evolution, 14, 135-139.

Duursma, E.D., Gallagher, R.V., Roger, E., Hughes, L., Downey, P.O., Leishman, M.R., (2013). Next-Generation Invaders? Hotspots for Naturalised Sleeper Weeds in Australia under Future Climates. PLOS ONE 8(12): e84222.

Echavarria, F., (1996). Remote Sensing of Forest Fragmentation in the Tropics. IEEE Geoscience and Remote Sensing Society Newsletter, June 1996, [accessed 10 April 2015].

Elith, J., Graham, C.H., Anderson, R.P., Dudik, M., Ferrier, S., Guisan, A., (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29(2):129– 151.

Elton, C. S., (1958). The ecology of invasions by plants and animals. Meuthuen and Company, London.

Flase-brome Working Group., (2003). Invasive Plant Alert: False-brome (Brachypodiumsylvaticum). Corvallis (OR): Institute for Applied Ecology. 19 : 34–43.

Ficetola, G.F., Tuiller, W. and C. Miaud., (2007) Prediction and validation of the potential global distribution of a problematic alien invasive species - the American bullfrog, Diversity and Distributions, 13, 476-485, 2007.

Foley, J.A., Defries, R., Asner, G.P., (2005). Global consequences of land use. Science, 309, 570–574.

Gregory, A.W., Smith, G.W. and Yetman, J., (2001). Testing for forecast consensus. Journal of Business and Economic Statistics, 19, 34–43.

Guisan, A., Thuiller, W., (2005).Predicting species distribution: Offering more than simple habitat models. Ecology Letters, 8(9):993–1009.

Guisan, A., Zimmerman, N.E., (2000). Predictive habitat distribution models in ecology. Ecological Modelling, 135, 147–186.

Hastie, T., Tibshirani, R., (1986). Generalized additive models. Stat. Sci. 1: 297-318.

Hernandez, P.A., Graham, C.H., Master, L.L., & Albert, D.L., (2006). The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography, 29, 773–785.

Hijmans, R.J., and C.H. Graham., (2006). Testing the ability of climate envelope models to predict the effect of climate change on species distributions. Global change biology, 12: 2272-2281.

IPCC (2007b) Climate change 2007: impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of Intergovernmental Panel on Climate Change, pp. 1-976. Cambridge University Press, Cambridge

Johnson, J.B., and Omland, K.S., (2004). Model selection in ecology and evolution. Trends in Ecology and Evolution, 19, 101–108.

Kumar, S., and Stohlgren, T.J., (2014). Maxent modelling for predicting suitable habitat for threatened and endangered tree Canacomyricamonticola in New Caledonia. Journal of Ecology and natural Environment.

Kolar, C. S., and D. M. Lodge., (2001). Progress in invasion biology: Predicting invaders. Trends in Ecology and Evolution, 16:199-204.

Liu, C., White, M. and Newell, G., (2013). Selecting thresholds for the prediction of species occurrence with presence-only data. Journal of Biogeography 40: 778-789.

Liang, L., Clark, J.T., Nicole, K., Lynne, K.R., Songlin, F., (2013). Spatial analysis facilities invasive species risk assessment. Forest Ecology and Management 315 (2014) 22-29.

Miller, T.K., Allen, C.R., Landis, W.G., Merchant, J.W., (2010). Risk assessment: Simultaneously prioritizing the control of invasive plant species and the conservation of rare plant species. Biology of Conservation. Vol. 143: 2070-2079.

Mooney, H.A., and Hofgaard, A., (1999). Biological Invasions and global change. In O.T. Sandlund, P.J., and Schei, A., eds. Invasive species and biodiversity management. Population and Community Biology Series. 24: 139-148.

Ortega-Huerta, M. A., & Peterson, A. T., (2008). Modelling ecological niches and predicting geographic distributions: a test of six presence-only methods.Revista Mexicana de Biodiversidad, 79(1), 205-216.

Parmesan, C., Yohe, G., (2003). A globally coherent figure print of climate change impacts across natural ecosystems. Nature 421:37-42.

Parry, Martin, Lewis., (2007). Climate Change 2007: Impacts, Adaptation and vulnerability: Working Group I Contribution to the Fourth Assessment Report of IPCC. Vol. 4. Cambridge University Press.

Pearce, J., Ferrier, S., and Scotts, D., (2001). An evaluation of the predictive performance distributional models for flora and fauna in north-east New South Wales. Journal of Environmental Management, 62, 171–184.

Pearson, R.G., Raxworthy, C.J., Nakamura, M. & Peterson, T., (2006). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. Journal of Biogeography, 34, 102–117.

Peterson, A., Townsend, Monika. Papecs., and Muir, Eaton., (2007). Transferability and Model Evaluation in Ecological Niche Modelling: a Comparison of GARP and MaxEnT. Ecography 30 (4): 550-60.

Peterson, A., Stewart, A., Mohamed, K.I., and Araujo, M.B., (2008). Shifting global invasive potential of European plants with climate change. PLoS One, 3(6),e2441, doi:10.1371/journal.pone.0002441.

Phillips, S. J., Anderson, R. P., Schapire, R. E., (2006). Maximum entropy modelling of species geographic distributions. Ecological Modelling, 190(3-4): 231–259.

Phillips, S. J. and Dudík, M., (2008). Modeling of species distributions with MaxEnT: new extensions and a comprehensive evaluation. Ecography31: 161-175.

Reddy, C.S., (2008). Catalogue of invasive alien flora of India. Life Science Journal 5, 84–89.

Richardson, D.M., Pysek, P., Rejmanek, M., Barbour, M.G., Panetta, F.D., and West, C.J., (2000). Naturalization and invasion of alien plant: concepts and definitions, Diversity and Disturbutions 693-107.

Richardson, D.M., & Blanchard, R., (2011) Learning from our mistakes: minimizing problems with invasive biofuel plants. Current Opinion in Environmental Sustainability, 36–42.

Richardson, D.M., Pysek, P., Rejmanek, M., Barbour, M.G., Panetta, F.D., and West, C.J., (2000). Naturalization and invasion of alien plant: concepts and definitions, Diversity and Disturbutions 693-107.

Robertson, M.P., Villet, M.H., and Palmer, A.R., (2004). A fuzzy classification technique for predicting species distribution: Applications using invasive alien plants and indigenous insects. Drivers. Distrib., 10, 461-474.

Rodgers, W.A., Panwar, H.S., and Mathur, V.B., (2002). Wildlife Protected Area Network in India: A review (Executive summary). Wildlife Institute of India, Dehradun.

Roura-Pascula, N., Saurez, A.V., Gomes, C., *et al.*, (2004). Geographical potential of Argentine in the face of global climate change. Proceedings of Royal Societyof London, 271, 2527-2534.

Solomon, Susan, Gian-Kasper Plattner, RetoKnutti, and Pierre Friedlingstein. (2009). "Irreversible Climate Change Due to Carbon Dioxide emissions." Proceedings of National Academy of Sciences106(6): 1704-9.

Sutherst, R.W., Maywald, H.F., Russel, B.L., (2000). Estimating vulnerability under global change: modular modelling of pests. AgricEcosyst Environ 82:303-319.

Stockwell, D. R. B., and D. P. Peters., (1999). The GARP modelling system: Problems and solutions to automated spatial prediction. International Journal of Geographic Information Systems, 13,143-158

Stohlgren, T. J., Ma, P., Kumar, S., Rocca, M., Morisette, J. T., Jarnevich, C. S., & Benson, N., (2010). Ensemble habitat mapping of invasive plant species. Risk Analysis, 30(2), 224-235.

Taylor, K.E., Stouffer, R.J., and Meehl, G.A., (2012). An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc., 93(4), 485-498, doi:10.1175/BAMS-D-11-00094.1.

Tewolde, M.G., Cabral, P., (2011). Urban sprawl analysis and modeling in Asmara, Eritrea. Remote Sens. 3: 2148-2165.

Tews, J.U., Grimm, B.V., Tielbörger, K., Wichmann, M,C,, Schwager, M., et al. (2004). Animal species diversity driven by habitat heterogeneity/diversity: the importance of keystone structures. J Biogeogr 31: 79–92. doi: 10.1046/j.0305-0270.2003.00994.x

Walther, G.R., Roques, A., Hulme, P.E., Sykes, M.T., Pysek, P., (2009). Alien species in a warmer world: risks and opportunities. Trends in ecology & evolution, 24: 686–693.

Wiens, John. A., Diana, Stralberg., Dennis, Jongsomjit., Christine, A. Howell., and Mark, A. Snyder., (2009). Niches, Models, and Climate Change: Accessing the Assumptions and Uncertainities. Proceedings of the National Academy of Science 106: 19729-36.

With, K.A., and King, A.W., (1997). The use and misuse of neutral landscape models in ecology. Okios 79: 219-229.

Wulff. A.S., Hollingsworth, P.M., Ahrends, A., Jaffrey, T., Vellion, J., Hullier, L., Fogliani, B., (2013). Conservation Priorities in a Biodiversity Hotspot: Analysis of Narrow Endemic Plant Species in New Caledonia. DOI: 10.1371/journal.pone.0073371.

Yang, X., Kushwaha, S.P.S., Saran, S., Xu, J., and Roy, P.S. (2013). Maxent modelling for predicting the potential distribution of medicinal plant, justiciaadhatoda L. In Lesser Himalayan foothills. Ecological Engineering 51:83-87.

Zhang, M.-G., Zhou, Z.-K., Chen, W.-Y., Cannon, C.H., Raes, N., Slik, J.W.F., (2014). Major declines of woody plant species ranges under climate change in Yunnan, China. Diversity and Distributions 20, 405–415. doi:10.1111/ddi.12165.

Appendix-1

Selected species description

Sno	Species	Family	Habit	Nativity
1	*Acacia farnesiana*	Mimosacceae	Tree	Trop. South America
2	*Acanthospermumhispidum*	Asteraceae	Herb	Brazil
3	*Achyranthesaspera*	Asteraceae	Herb	Brazil
4	*Ageratum conyzoides*	Asteraceae	Herb	Trop. America
5	*Ageratum houstonianum*	Asteraceae	Herb	Trop. America
6	*AlternantherapungensKunth*	Amaranthaceae	Herb	Trop. America
7	*Argemonemexicana*	Papaveraceae	Herb	Trop. Central & South America
8	*Asclepiascurassavica*	Asclepiadaceae	Herb	Trop. America
9	*Asphodelustenuifolius*	Liliaceae	Herb	Trop. America
10	*Bidenspilosa*	Asteraceae	Herb	Trop. America
11	*Blainvilleaacmella*	Asteraceae	Herb	Trop. America
12	*Blumeaeriantha*	Asteraceae	Herb	Trop. America
13	*Blumeaobliqua*	Asteraceae	Herb	Trop. America
14	*Borassusflabellifer*	Asteraceae	Herb	Trop. Africa
15	*Cardaminehirsuta*	Brassicaceae	Herb	Trop. America
16	*Cardaminetrichocarpa*	Brassicaceae	Herb	Trop. America
17	*Cassia absus*	Caesalpiniaceae	Herb	Trop. America
18	*Cassia alata*	Caesalpiniaceae	Shrub	West Indies
19	*Cassia obtusifolia*	Caesalpiniaceae	Herb	Trop. America
20	*Cassia pumila*	Caesalpiniaceae	Herb	Trop. South America
21	*Cassia tora*	Caesalpiniaceae	Herb	Trop. South America
22	*Cassia uniflora*	Caesalpiniaceae	Herb	Trop. South America
23	*Catharanthuspusillus*	Apocynaceae	Herb	Trop. America
24	*Celosia argentea*	Amaranthaceae	Herb	Trop. Africa
25	*Chamaesycehirta*	Euphorbiaceae	Herb	Trop. America
26	*Chloris barbata*	Poaceae	Herb	Trop. America
27	*Chromolaenaodorata*	Asteraceae	Herb	Trop. America
28	*Cleome monophylla*	Cleomaceae	Herb	Trop. Africa
29	*Cleome rutidosperma*	Cleomaceae	Herb	Trop. America
30	*Cleome viscosa*	Cleomaceae	Herb	Trop. America
31	*Corchorusaestuans*	Tiliaceae	Herb	Trop. America
32	*Corchorustridens*	Tiliaceae	Herb	Trop. Africa
33	*Corchorustrilocularis*	Tiliaceae	Herb	Trop. Africa
34	*Crotalaria retusa*	Papilionaceae	Herb	Trop. America
35	*Croton bonplandianum*	Euphorbiaceae	Herb	Temperate South America
36	*Cuscutachinensis*	Cuscutaceae	Herb	Mediterranean
37	*Cyperusdifformis*	Cyperaceae	Herb	Trop. America
38	*Cyperusiria*	Cyperaceae	Herb	Trop. America
39	*Cyperusrotundus*	Cyperaceae	Herb	Trop. America
40	*Cytisusscoparius*	Papilionaceae	Herb	Europe
41	*Daturainnoxia*	Solanaceae	Shrub	Trop. America
42	*Dicomatomentosa*	Asteraceae	Herb	Trop. Africa
43	*Digeramuricata*	Amaranthaceae	Herb	SW Asia
44	*Echinochloacrusgalli*	Poaceae	Herb	Trop. South America
45	*Echinopsechinatus*	Asteraceae	Herb	Afghanistan
46	*Ecliptaprostrata*	Asteraceae	Herb	Trop. America

47	*Eupatorium adenophorum*	Asteraceae	Herb	Trop. America
48	*Euphorbia cyathophora*	Euphorbiaceae	Herb	Trop. America
49	*Galinosogaparviflora*	Asteraceae	Herb	Trop. America
50	*Hyptissuaveolens*	Lamiaceae	Herb	Trop. America
51	*Impatiens balsamina*	Balsaminaceae	Herb	Trop. America
52	*Indigoferaastragalina*	Papilionaceae	Herb	Trop. America
53	*Indigoferaglandulosa*	Papilionaceae	Herb	Trop. America
54	*Indigoferalinnaei*	Papilionaceae	Herb	Trop. Africa
55	*Ipomoea carnea*	Convolvulaceae	Shrub	Trop. America
56	*Ipomoea hederifolia*	Convolvulaceae	Herb	Trop. America
57	*Ipomoea pes-tigridis*	Convolvulaceae	Herb	Trop. East Africa
58	*Lagasceamollis*	Asteraceae	Herb	Trop. Central America
59	*Lantana camara*	Verbenaceae	Herb	Trop. America
60	*Leucaenaleucocephala*	Mimosacceae	Herb	Trop. America
61	*Ludwigiaadscendens*	Onagraceae	Herb	Trop. America
62	*Ludwigiaperennis*	Onagraceae	Herb	Trop. Africa
63	*Malvastrumcoromandelianum*	Malvaceae	Herb	Trop. America
64	*Martyniaannua*	Pedaliaceae	Herb	Trop. America
65	*Mecardoniaprocumbens*	Scrophulariaceae	Herb	Trop. North America
66	*Melilotus alba*	Papilionaceae	Herb	Europe
67	*Melochiacorchorifolia*	Sterculiaceae	Herb	Trop. America
68	*Merremiaaegyptia*	Convolvulaceae	Herb	Trop. America
69	*Mikaniamicrantha*	Asteraceae	Climber	Trop. America
70	*Mimosa pudica*	Mimosacceae	Herb	Brazil
71	*Mirabilis jalapa*	Nyctaginaceae	Herb	Peru
72	*Ocimumamericanum*	Lamiaceae	Herb	Trop. America
73	*Opuntiastricta*	Cactaceae	Herb	Trop. America
74	*Oxalis corniculata*	Oxalidaceae	Herb	Europe
75	*Partheniumhysterophorus*	Asteraceae	Herb	Trop. North America
76	*Passiflorafoetida*	Passifloraceae	Herb	Trop. South America
77	*Pedalium murex*	Pedaliaceae	Herb	Trop. America
78	*Peristrophepaniculata*	Acanthaceae	Herb	Trop. America
79	*Phyllanthustenellus*	Euphorbiaceae	Herb	Mascarene Islands
80	*Physalisangulata*	Solanaceae	Herb	Trop. America
81	*Portulacaoleracea*	Portulacaceae	Herb	Trop. South America
82	*Portulacaquadrifida*	Portulacaceae	Herb	Trop. America
83	*Prosopisjuliflora*	Mimosacceae	Shrub	Mexico
84	*Ruelliatuberosa*	Acanthaceae	Herb	Trop. America
85	*Saccharumspontaneum*	Poaceae	Herb	Trop. West Asia
86	*Salviniamolesta*	Salviniaceae	Herb	Brazil
87	*Scopariadulcis*	Scrophulariaceae	Herb	Trop. America
88	*Sesbaniabispinosa*	Papilionaceae	Shrub	Trop. America
89	*Solanumamericanum*	Solanaceae	Herb	Trop. America
90	*Solanumseaforthianum*	Solanaceae	Climber	Brazil
91	*Solanumtorvum*	Solanaceae	Shrub	West Indies
92	*Solanumviarum*	Solanaceae	Herb	Trop. America
93	*Sonchus asper*	Asteraceae	Herb	Mediterranean
94	*Sonchusoleraceus*	Asteraceae	Herb	Mediterranean
95	*Spermacocehispida*	Rubiaceae	Herb	Trop. America
96	*Stachytarphetajamaicensis*	Verbenaceae	Herb	Trop. America
97	*Synadeniumgrantii*	Euphorbiaceae	Shrub	Trop. America
98	*Tribulusterrestris*	Zygophyllaceae	Herb	Trop. America
99	*Tridaxprocumbens*	Asteraceae	Herb	Trop. Central America
100	*Triumfettarhomboidea*	Tiliaceae	Herb	Trop. America

101	*Turneraulmifolia*	Turneraceae	Herb	Trop. America
102	*Urenalobata*	Malvaceae	Shrub	Trop. Africa
103	*Waltheriaindica*	Sterculiaceae	Herb	Trop. America
104	*Xanthium strumarium*	Asteraceae	Herb	Trop. America
105	*Youngia japonica*	Asteraceae	Herb	Trop. South America

Appendix-2

Ecological specifications of the selected 15 most noxious invasive plant species for modelling under future scenario

S.no.	Species	Habit	Family	Nativity	Habitat Effected	Climate
1.	*Lantana camara* (2706)	Shrub	Verbenaceae	Trop. America	Open unshaded situations- Wetlands, rain forest edges, forest recovering from fire, margins of the intact rain forests	Tropical and Sub Tropical, less encountered in the temperate regions
2.	*Chromolaenaodorata* (1437)	Herb	Asteraceae	Trop. America	forests (annual rainfall 1500mm), grassland and arid bush veld (annual rainfall less than 500mm)	Tropical and Sub tropical, not suitable for Semi Arid and temperate climate
3.	*Ageratum conyzoides* (982)	Herb	Asteraceae	Trop. America	natural forests agricultural areas, , planted forests, range/grasslands, riparian zones, ruderal/disturbed, scrub/shrublands, water courses, wetlands	Suitable in Tropical and Sub Tropical climate
4.	*Hyptissauveolens* (840)	Herb	Lamiaceae	Trop. America	Scrubland, non marine, plain, wasteland, woodland	Tropical and sub tropical
5.	*Prosopisjuliflora* (624)	Shrub	Mimosacceae	Mexico	saline and alkaline lands, eroded hills and ravines, along river beds, and dry and degraded wastelands, often where rainfall is low and variable	Arid and Semi Arid climatic conditions
6.	*Partheniumhysterophorous (186)*	Herb	Asteraceae	Trop. North America	agricultural areas, range/grasslands, ruderal/disturbed, scrub/shrublands, urban areas, seasonal floodplains	Semi-arid, subtropical, tropical and warmer temperate regions
7.	*Eupatorium adenophorum*	Shrub	Asteraceae	Trop. America	Degraded slopes, disturbed areas, near	Temeprate regions

	(88)				urban regions.	
8.	*Cassiatora* (1787)	Herb	Caesalpinaceae	Trop. South America	wasteland , degraded forest rainy season weed	Tropical and Sub tropical climate
9.	*Cassia occidentalis* (146)	Herb	Caesalpinaceae	Trop. South America	Roadsides, waste areas, disturbed sites, pastures, grasslands, open woodlands	Tropical, Sub tropical and Semi arid
10.	*Bidenspilosa* (106)	Herb	Asteraceae	Trop. America	natural forests, planted forests, range/grasslands, riparian zones, agricultural areas, ruderal/disturbed, scrub/shrublands, urban areas, wetlands Herb Trop. America	Tropical, Sub tropical and Temperate climatic conditions
11.	*Mimosa pudica* (528)	Shrub	Mimosacceae	Trop. North America	Wetlands and around dams and waterways, moist situations such as flood plains and river banks	Mostly tropical, also sometimes found in moist situations such as floodplains and river banks
12.	*Mikaniacordata* *(72)*	Vine, climber	Asteraceae	Trop. America	natural forests, planted forests, agricultural areas, coastland, riparian zones, ruderal/disturbed, scrub/shrublands, urban areas, wetlands	Tropical and sub tropical climatic conditions
13.	*Cyperusrotundus* (761)	Herb	Cyperaceae	Trop. America	open, disturbed habitats to an elevation of about 1800 m.	Tropical, Sub tropical and temperate climatic conditions
14.	*Ecliptaprostrate* (66)	Herb	Asteraceae	Trop. America	Poorly drained wet areas, saline conditions, along streams, in drains and canals of irrigated lowland rice paddies, in waste areas, and in upland fields.	Moisttemperate, warm temperate and tropical areas
15.	*Euphorbia hirta* *(920)*	Herb	Euphorbiaceae	Trop. America	Margins of rainforest, Eucalypt forest, vine forest, various types of woodland and in wooded grassland.	Tropical and Sub Tropical climatic conditions

Appendix-3

List of Bioclimatic variables with their associated codes

Bioclimatic Codes	**Bioclimatic Variables**
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Temperature
BIO3	Isothermality
BIO4	Temperature Seasonality
BIO5	Maximum Temperature of Warmest Quarter
BIO6	Minimum Temperature of Coldest Month
BIO7	Temperature Annual Range
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Quarter
BIO14	Precipitation of Driest Quarter
BIO15	Precipitation Seasonality
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

Appendix-4

Pearson's correlation coefficient for different bio-climatic variables

	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
bio_1	-	-0.01	0.39	-0.60	0.91	0.95	-0.36	0.94	0.88	0.96	0.88	0.20	0.27	-0.34	0.28	0.65	-0.36	-0.01	-0.08
bio_2	-	-	-0.20	0.51	0.28	-0.26	0.73	0.10	-0.01	0.15	-0.15	-0.59	-0.45	-0.26	-0.48	0.33	-0.28	-0.38	-0.26
bio_3	-	-	-	-0.82	0.05	0.56	-0.79	0.35	0.31	0.17	0.53	0.28	0.21	-0.06	0.19	-0.11	-0.11	0.15	0.22
bio_4	-	-	-	-	- 0.25	-0.80	0.92	-0.51	-0.49	-0.38	-0.76	-0.50	-0.44	0.14	-0.44	-0.11	0.17	-0.21	-0.10
bio_5	-	-	-	-	-	0.75	0.06	0.85	0.84	0.98	0.81	-0.05	0.10	-0.43	0.10	0.79	-0.43	-0.25	-0.17
bio_6	-	-	-	-	-	-	-0.61	0.86	0.84	0.85	0.99	0.34	0.37	-0.27	0.37	0.49	-0.30	0.05	0.01
bio_7	-	-	-	-	-	-	-	-0.28	-0.26	-0.11	-0.53	-0.58	-0.44	-0.10	-0.45	0.20	-0.07	-0.38	-0.23
bio_8	-	-	-	-	-	-	-	-	0.77	0.91	0.90	0.20	0.25	-0.26	0.26	0.62	-0.27	0.09	-0.10
bio_9	-	-	-	-	-	-	-	-	-	0.88	0.86	0.11	0.23	-0.34	0.21	0.63	-0.35	-0.13	-0.03
bio_10	-	-	-	-	-	-	-	-	-	-	0.89	0.07	0.17	-0.37	0.18	0.74	-0.39	-0.12	-0.13
bio_11	-	-	-	-	-	-	-	-	-	-	-	0.29	0.34	-0.32	0.35	0.57	-0.35	0.03	-0.04
bio_12	-	-	-	-	-	-	-	-	-	-	-	-	0.92	0.19	0.95	-0.01	0.22	0.91	0.17
bio_13	-	-	-	-	-	-	-	-	-	-	-	-	-	0.01	0.98	0.25	0.03	0.50	0.07
bio_14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.03	-0.53	0.94	0.38	0.38
bio_15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.23	-0.54	-0.23	-0.30
bio_16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.06	0.57	0.07
bio_17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.40	0.43
bio_18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.10
bio_19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-