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## Predicting the distribution of rubber trees (*Hevea brasiliensis*) through ecological niche modelling with climate, soil, topography and socioeconomic factors

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**Abstract** Identifying the factors that contribute to species distribution will help determine the impact of the changing climate on species' range contraction and expansion. Ecological niche modelling is used to analyze the present and potential future distribution of rubber trees (*Hevea brasiliensis*) in two biogeographically distinct regions of India i.e., the Western Ghats (WG) and Northeast (NE). The rubber tree is an economically important plantation species, and therefore factors other than climate may play a significant role in determining its occurrence. To assist in future planning, we used the maximum entropy model to predict plausible areas for the expansion of rubber tree plantations under a changing climate scenario. Inclusion of elevation, soil and socioeconomic factors into the model did not result in a significant increase in the model accuracy estimates over the bioclimatic model (AUC > 0.92), but their effect was pronounced in the predicted probability scoring of species occurrence. Among various factors, elevation, rooting condition, village population and agricultural labour availability contributed substantially to the model in the NE region, whereas for the WG region, climate was the most important contributing factor for rubber tree distribution. We found that more areas would be suitable for rubber tree plantation in the NE region, whereas further expansion would be limited in the WG region under the projected climate scenario for 2050.

**Keywords** *Hevea brasiliensis* · Future climate · Maxent · Species distribution model · Land suitability

### Introduction

To predict species distribution, the most commonly used approach is ecological niche modelling of the species (Austin 2002). An ecological niche can be defined as the range of tolerance of a species in terms of several environmental factors (Hutchinson 1957). In other words, a species can survive and perpetuate within its ecological niche without external intervention (Austin 2007). When this concept is applied in a human-managed landscape, species' niche distribution can be modelled by determining the relationship between crop presence and various factors contributing to the growth and development of the crop (Heumann et al. 2013). Indeed, the concept of the ecological niche was used to understand and model anthropogenic impacts on species distribution (Peterson 2003). Among various predictive factors, climate is expected to play a dominant role in determining the distribution of any species (Pearson and Dawson 2003). Quantifying the contribution of various factors is assessed from knowledge of the spatial distribution of the species based on field occurrence which is often called a realised niche (Guisan and Thuiller 2005). Assessing the present distribution and predicting future invasion has become possible because of the availability of high spatial and temporal resolution climate data sets (Pradervand et al. 2014).

Ecological niche models (ENMs) are used for predicting species distribution, wherein the basic assumption is that species distributions are always in equilibrium with contemporary climate (Araújo and Pearson 2005). In general, there are two categories of ENMs available that require either: (1) *presence-absence* data for the target species, or (2) *presence-only* data for prediction (Tsoar et al. 2007). Some modelling tech-

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niques use ‘pseudo-absence’ data for calibrating the model initially, but these are classed as presence-only methods because pseudo-absence locations cannot be defined as actual sites where the species cannot occur (Stockwell and Peters 1999; Engler et al. 2004). An evaluation of 16 different methods of modelling based on the distribution data of 226 species from six regions of the world found that presence-only data were effective for modelling species distribution for many species and regions (Elith et al. 2006). Pearce and Ferrier (2000) found that prediction of species distribution based on presence-only data was reasonably accurate for species conservation and other uses. However, in certain cases, the assumption of species-climate equilibrium can be violated by the influence of interactions of the species with related factors other than climate (Brown et al. 1996; Pearson and Dawson 2003). Therefore, including other factors related to species distribution can improve the performance of the model prediction (Hanspach et al. 2010).

The maximum entropy (Maxent) model, one of several ENMs, uses presence-only data for training purposes, in contrast with presence-absence data in the case of the genetic algorithm for rule set prediction (GARP) model (Phillips et al. 2006). Maxent was the method preferred over presence-absence models because of uncertainty over accurate absence data for rubber tree plantations. Accurately modelling the probability of presence of rubber tree species is challenging because as a commercial crop the tree has adapted to wide range of habitats. As rubber trees are often an introduced species, there is a degree of uncertainty in finding the species present in the most climatically suitable land because its cultivation is decided not only by climate but also by favourable local soil and topography. More importantly, the willingness of growers to establish rubber tree plantations also needs to be taken into account (Jeschke and Strayer 2008).

The predictive capability of the model is often evaluated through multiple methods, particularly when the models are trained with presence-only data (Hernandez et al. 2006; Peterson et al. 2008). The area under the curve (AUC) is considered a composite measure of model performance where weights for omission errors (predicted absence in areas of actual presence) and commission errors (predicted presence in areas of actual absence) are equal. However, several authors have criticised the use of AUC as a model accuracy estimator in presence-only ENMs (Lobo et al. 2008; Peterson et al. 2008). Therefore, a modified form of AUC, partial AUC is used for assessing the accuracy of Maxent model (Barve 2008). The true skill statistic (TSS) has been used in ecological studies as an alternative measure of model accuracy (Allouche et al. 2006). The TSS, otherwise known as Hanssen–Kuipers discriminant, compares the number of correct forecasts minus those attributable to random guesses, to that of a hypothetical set of perfect forecasts (Allouche et al. 2006).

The rubber tree (*Hevea brasiliensis*) was chosen as the target species for its economic importance as the only source of natural rubber. According to an industry report from the International Rubber Study Group (IRSG), demand for natural rubber will continue to grow globally (IRSG 2014). To meet market demand, the Indian government has emphasised increasing the production of natural rubber in India by bringing more area under rubber tree plantations (Burger and Smith 2004). Therefore, knowledge about how the species will adapt to changing climate is necessary to quantify new regions suitable for rubber tree plantations. The rubber tree, a native of Amazonia in Brazil, was introduced to tropical Asia in 1876 through Kew Gardens in the UK with the seeds brought from Brazil (Wycherley 1992; Hong 1999). In India, rubber trees have been cultivated in Western Ghats (WG) since the early twentieth century and were introduced to the Northeast (NE) region in the 1960 s.

In predicting the future distribution of rubber trees based on prevailing climate, we assumed that (a) the species would not adapt to a changed climate (IPCC 2007) i.e., the climatic requirement of the species in 2050 remains same as present conditions, and (b) socio-economic factors would remain constant. These assumptions form the basis for assessing how the species will react to changing climate and land suitability. Maxent ecological niche model was used to assess the present distribution pattern of rubber trees in the WG and NE regions of India. The niche modelling approach has been adapted to incorporate various climate and other factors thereby evaluating the results from a habitat suitability point of view (Slater and Michael 2012; Garcia et al. 2013). Here, our focus is also to find out the contribution of other factors in rubber tree distribution in both the WG and NE regions. With this background, the present study has been designed to: (1) identify and quantify bioclimatic and other factors driving rubber tree distribution; (2) simulate the current distribution of rubber trees for future climate scenarios; and (3) assess probable range expansion or contraction of rubber tree plantations under projected climate scenarios by 2050.

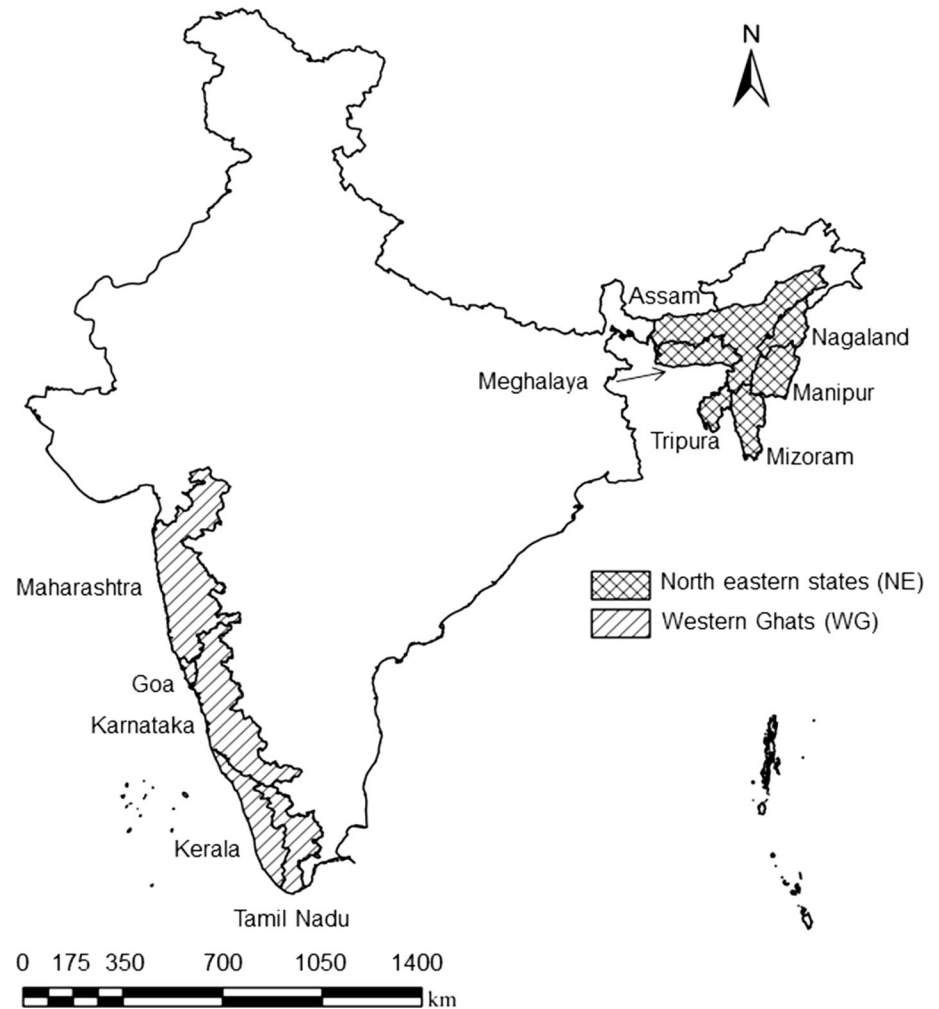
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## Methods

### Study area

The study area includes two rubber tree growing regions in India i.e., the WG and NE (Fig. 1). These two regions fall under three world biodiversity hotspot regions and show distinct biogeographic characteristics. The WG is situated in one biodiversity hotspot region, whereas the NE region is located at the junction of two global biodiversity hotspots in India i.e., Indo-Burma and the Himalayas. The WG ecosystem is disturbed by mining activities, whereas the NE region is affected by shifting cultivation, known as *Jhumming* (INCCA 2010).

**Fig. 1** Study area: Northeast (NE) region and Western Ghats (WG) region of India. The Indian states representing the NE region are Tripura, Assam, Meghalaya, Mizoram, Manipur and Nagaland. The WG region is represented by parts of Kerala, Tamil Nadu, Karnataka Maharashtra states and Goa



Extensive shifting cultivation by communities in the NE has degraded local ecosystems, which in turn has affected agricultural productivity. Rubber tree plantations are seen as a way to provide alternative socioeconomic support for the local community as well as providing ecosystem services in the form of canopy cover over cleared land (Maithani 2005).

In the WG, mean maximum temperatures during the coldest months of December and January vary from 29 °C in parts of the peninsula to 18 °C in the north. Mean minimum temperatures range from 24 °C in the south to below 5 °C in the north. The months from March to May are usually characterised by continuous and rapid rises in temperature. Rainfall ranges from 3000 to 6000 mm across the region. Rubber trees have been cultivated on the coastal slopes of the WG for more than a century. The NE region of India receives an average annual rainfall of 2450 mm. Precipitation in this region occurs during the south-west monsoon from May to October. The temperature varies from 15 to 32 °C during summer and from 2 to 26 °C during winter (Das et al. 2013). These two regions are the major rubber tree growing areas of India with diverse local climatic, soil and socioeconomic conditions.

#### Target species and occurrence data points

The study focuses on rubber trees as an introduced plantation crop. India's first commercial cultivation of rubber trees began in 1902 in Kerala state, and then it expanded rapidly in the WG region. Subsequently, rubber tree cultivation was introduced in the NE region of India particularly in the state of Tripura. The rubber tree is deciduous in nature, reaching a height of 18–39 m, and grows on a wide variety of deep, well-drained soils. The latex produced in the lactiferous vessels in the soft tissue of the bark is extracted from slanted cuts on the bark into containers attached to the trunk (Wycherley 1992).

A total of 218 rubber tree plantation locations in the WG and 127 in the NE regions, respectively, were selected from ground-sampled locations that existed before 2000. The knowledge of field personnel from the Indian Rubber Board was also used to locate rubber tree plantations. While recording occurrence points, a patch of a plantation, covering 1–5 ha with comparable topography was recorded as a single point. However, more points were used on larger estates occupying different topography, which were representative of actual

plantation distribution. The occurrence records of rubber tree plantations were divided into training and test samples: 25 % of total points were selected as test samples using a random data splitting method.

Bioclimatic, topographic, soil and socioeconomic factors

Nineteen bioclimatic factors with 30 s (ca 1 km) spatial resolution were downloaded from the WorldClim dataset ([www.worldclim.org/bioclim](http://www.worldclim.org/bioclim)) and used in the Maxent model (Phillips et al. 2006). Other factors were represented by seven geology and soil grids derived from the Harmonized World Soil Database (HWSD (<http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/SoilQualityData.html?sb=11>)). The raster data layers on seven key soil properties important for crop production, namely nutrient availability, nutrient retention capacity, rooting condition, oxygen availability to roots, excess salts, toxicities, and workability were used as predictor inputs for the model. Rooting condition is the term used in the HWSD to describe soil textures, bulk density, coarse fragments, soil phases affecting root penetration and soil depth and volume, whereas workability indicates soil phases constraining field management such as presence of stones, gravels, concretions and hardpans (Fischer et al. 2008).

Four socioeconomic factors were included as predictive variables i.e., the number of uninhabited villages per district, the number of villages per district having a population < 500, the total number of marginal rural workers per district and the number of agricultural labourers per district. These factors were included in the Maxent model based on the following hypothesised relationships between the factors and the distribution of rubber tree plantations. Uninhabited villages have no permanent structures for human settlement and there may be a seasonal population present during agricultural crop harvesting time. There may be more area under forest or waste land available, which otherwise can be used for rubber tree plantations. Villages with populations < 500 are assumed to have a greater scope for combining rubber tree cultivation with other anthropogenic activities. The number of marginal rural workers (a marginal worker works for < 6 months per year) and agricultural labourers are indicative of the labour availability for plantation activities. District-level data on these factors were obtained from the Indian Government census data portal ([http://www.censusindia.gov.in/2011census/population\\_enumeration.aspx](http://www.censusindia.gov.in/2011census/population_enumeration.aspx)). There are 184 districts in the WG and 65 districts in the NE region with sizes ranging from 174 km<sup>2</sup> (Chennai, Tamil Nadu) to 17,413 km<sup>2</sup> (Ahmednagar, Maharashtra) in the WG region and from 514 km<sup>2</sup> (Thoubal district, Manipur) to 9129 km<sup>2</sup> (Upper Dibang district, Arunachal Pradesh) in the NE region.

Topographical factors such as elevation and slope (%) were obtained from the shuttle radar topography mission dataset. Rubber trees grow below 1100 m in

elevation and on < 20 % slope (Priyadarshan et al. 2005). The source of the land use and land cover (LULC) map was global land cover (GLC) 2000 database, JRC ([http://forobs.jrc.ec.europa.eu/products/glc2000/data\\_access.php](http://forobs.jrc.ec.europa.eu/products/glc2000/data_access.php)). The Human Influence Index is a measure of direct human influence on terrestrial ecosystems, derived from nine other variables including population density, built-up areas, roads, railroads, and navigable rivers (<http://sedac.ciesin.columbia.edu/data/set/wildareas-v2-human-influence-index-geographic>). All predictor factors were resampled to a 1-km resolution in WGS84 projection to match available climate variables and used for both regions, and then converted to a uniform ASCII format using ARC-GIS 9.3 software (<http://www.esri.com/>) (Table 1).

Multi-collinearity in bioclimatic predictive factors

Most of the ENMs work on the basis of relationships between the species occurrence records and climate factors. The actual relationships may not emerge if the input climate factors are spatially auto-correlated and therefore, many combinations of bioclimatic factors can explain the species distribution equally well. Therefore, bioclimatic factors were subjected to multi-collinearity tests using Pearson's correlation coefficient ( $r$ ) to examine relationships among the factors. Bioclimatic factors with a correlation coefficient of  $r > \pm 0.7$  were excluded from final model building (Yang et al. 2013). Out of 19 bioclimatic factors, eight factors i.e., mean diurnal range of temperature, isothermality, temperature seasonality, minimum temperature during coldest month, precipitation during driest month, precipitation seasonality, precipitation during driest quarter and precipitation during coldest quarter were retained and used in the model run.

Ecological niche modelling

To map the potential distribution of rubber trees under the climatic scenarios of both the WG and the NE, the most recently available Maxent 3.3.3 k software was used (Phillips et al. 2006). Maxent is a grid-based machine learning algorithm that follows the principle of maximum entropy. The software takes species presence-only data and chooses the distribution of a species under study that is closest to a uniform distribution. It maximises entropy within distributions that satisfies the constraints derived from species occurrence points. Maxent is capable of incorporating complex dependencies among the predictor factors, leading to better prediction of species distribution compared with models such as GARP and BIOCLIM as measured by higher AUC values (Stockwell and Peters 1999; Elith et al. 2006; Wisz et al. 2008). Here, the choice of a presence-only data model for the study was based on the uncertainty involved in recording absence data for the rubber

**Table 1** Predictor variables used for the ecological niche model

Sl No.	Input variables with respective codes	Scale/resolution	Source
1	Mean diurnal range of temperature (bio2)	Climatic factors 30 arc sec ( $\approx 1$ km)	WorldClim series (Hijmans et al. 2005)
2	Isothermality (bio3)		
3	Temperature seasonality (bio4)		
4	Annual temperature range (bio7)		
5	Precipitation during driest month (bio14)		
6	Precipitation seasonality (bio15)		
7	Precipitation during driest quarter (bio17)		
8	Precipitation during coldest quarter (bio19)		
9	Nutrient availability (Nut_avail)	Soil factors 30 arc sec ( $\approx 1$ km)	Harmonised world soil data base (Fischer et al. 2008)
10	Nutrient retention capacity (Nut_ret_cap)		
11	Rooting conditions (Root_cond)		
12	Oxygen availability to roots (Oxy_avail_roots)		
13	Workability (Wrk)		
14	No. of uninhabited villages per district (TUIV)	District level feature class data converted to similar scale of other raster variables ( $\approx 1$ km) (social)	Census data 2011 of Govt. of India
15	No. of villages less than 500 persons (VPL500)		
16	Total marginal rural workers per district (TMW)		
17	No. of agricultural labourers per district (ALR)		
20	Elevation (ALT)	30 arc sec ( $\approx 1$ km) (Topography)	SRTM
21	Slope (%)	30 arc sec ( $\approx 1$ km)	SRTM
22	Land use and land cover (LULC)	30 arc sec ( $\approx 1$ km)	GLC 2000 data base, JRC.
23	Human influence index (HII)	30 arc sec ( $\approx 1$ km)	SEDAC

tree species. In a previous study, the Maxent model was run for rubber tree distribution using only bioclimatic factors as predictive input in same regions, without incorporating soil and socioeconomic drivers (Ray et al. 2014).

The experimental design aimed to assess the impact on model accuracy of: (1) only climate factors, and (2) climate, soil, elevation and socioeconomic factors. By default, the Maxent model determines the feature types automatically based on the number of samples available for model training (Phillips and Dudik 2008). Ten replications of the model were run, with 75 % of the occurrence points as training sites and 25 % of the points as test sites. The regularization multiplier was retained as the default value of 1. The maximum iterations were fixed at 1000 with a convergence threshold of 0.00001 and a sub-sample replicated run type to allow the program to run up to the sufficient threshold levels.

#### Accuracy assessment

We used two different evaluation procedures for accuracy assessment of the model outputs: (1) the area under the receiver operating curve (AUC), and (2) the true skill statistic (TSS). The AUC was calculated using a number of randomly selected sites equal to the number of test presence sites. The AUC provides a quantitative measure of model performance that ranges between 0 and 1, with 0.5 indicating no better performance than random and values close to 1 indicating a reliable fit

(Fielding and Bell 1997). Models producing AUC values of 0.7–0.9 are considered to be useful models and models with good discrimination ability usually produce AUC values more than 0.9 (Swets 1988). The different modelling techniques use binary data of species presence as the dependent variable and the models produces a continuous probability of presence (P), where 1-P represents the degree to which each case of the model curve fits that of random curve, called the partial AUC.

The TSS is increasingly preferred to the Kappa statistic, which is a statistical measure of the accuracy of presence and absence predicted by the model, because of Kappa's insensitivity to the prevalence of the species. The TSS is measured as:  $TSS = Sensitivity + Specificity - 1$ . The TSS ranges from  $-1$  to  $+1$ , where values of 0 or less indicate a model performance no better than random, and a value of  $+1$  indicates perfect performance (Allouche et al. 2006). Sensitivity is defined as the probability that a model correctly classifies the presence data, whereas specificity denotes the probability of classifying correctly the absence data points. Jackknife is a resampling technique that estimates the change in variance due to the systematic omission of one set of observations from the data sets (Tukey 1958). We used a Jackknife test to identify the percent contribution of various input factors into the model prediction of present as well as future potential rubber tree distribution. The logistic prediction of probability of rubber tree occurrence in both regions was classified into three categories representing different levels of habitat suitability.

Change detection analysis

The probability data of rubber tree distribution was obtained in ASCII format from the model run, and converted to raster using ARC-GIS 9.3. These raster data, corresponding to two time periods, were used in change detection analysis using ERDAS Imagine software (<http://www.hexagongeospatial.com/>). The change probability range varied from -1 to +1 where positive and negative values relate to suitability and non-suitability, respectively. Based on the probability of occurrence, both the study regions were categorised into three suitability classes.

**Results**

Impact of soil, topography and socioeconomic input factors on modelling species distribution

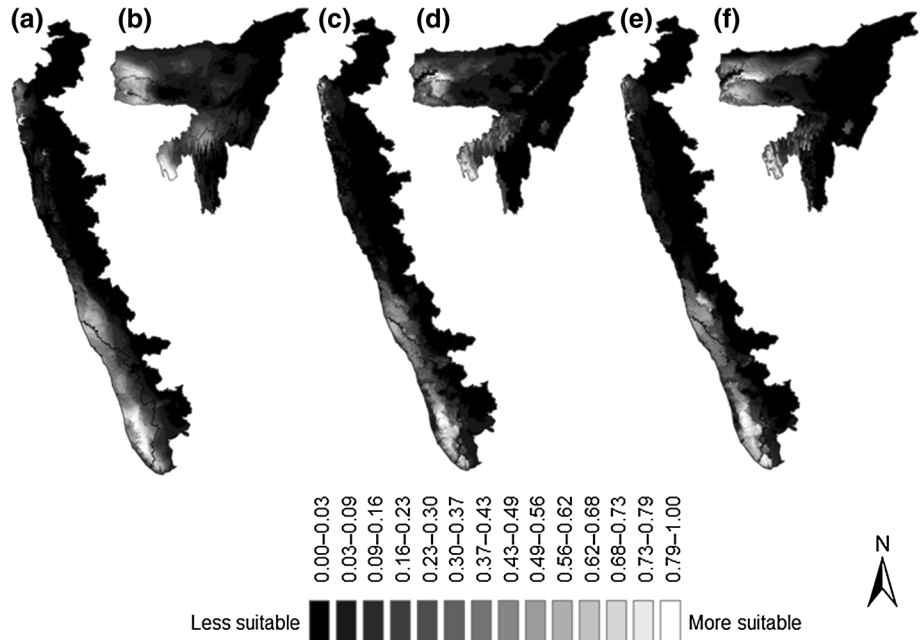
The results of the model predictions for rubber tree distribution for the two districts are shown as follows: (1) niche distribution with 2000 base year climate variables (Fig. 2a, b), (2) 2000 base year climate with soil, topography and socioeconomic factors (Fig. 2c, d), and (3) future climate (2050) with other non-climate factors (Fig. 2e, f). The distribution map for the WG with climate variables showed the most suitable niche of the rubber tree was in the southern WG extending up to northern Kerala. The extent of suitable regions was reduced when other factors (soil, topography and socioeconomic conditions) were incorporated into the model (Fig. 2a). In the NE region, the addition of other factors into the model resulted in an increase in the extent of the most suitable regions in the western parts of Assam, and moderately suitable regions extended with >0.7 suit-

ability value the 2050 scenario. The extent of areas with a >0.7 suitability value for the WG was smaller than in the 2000 base year map especially in the northern Kerala region. The mid-WG region also showed a reduction in suitability. In the NE map of the 2050 scenario, suitable regions expanded towards upper Assam; and certain parts of Mizoram and Manipur became suitable, while parts of southern Assam appeared to be less suitable (Fig. 2f).

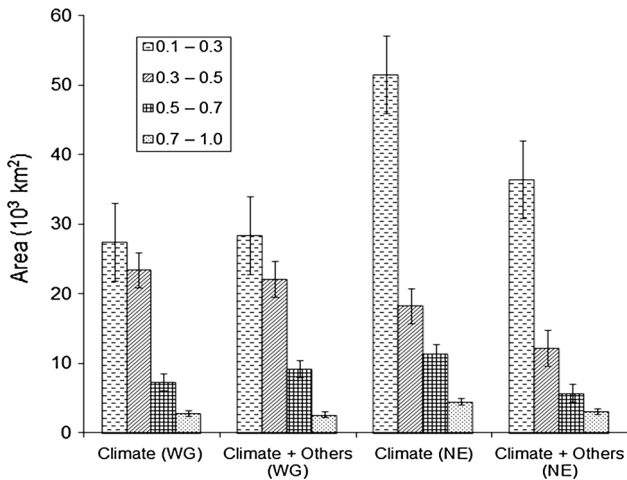
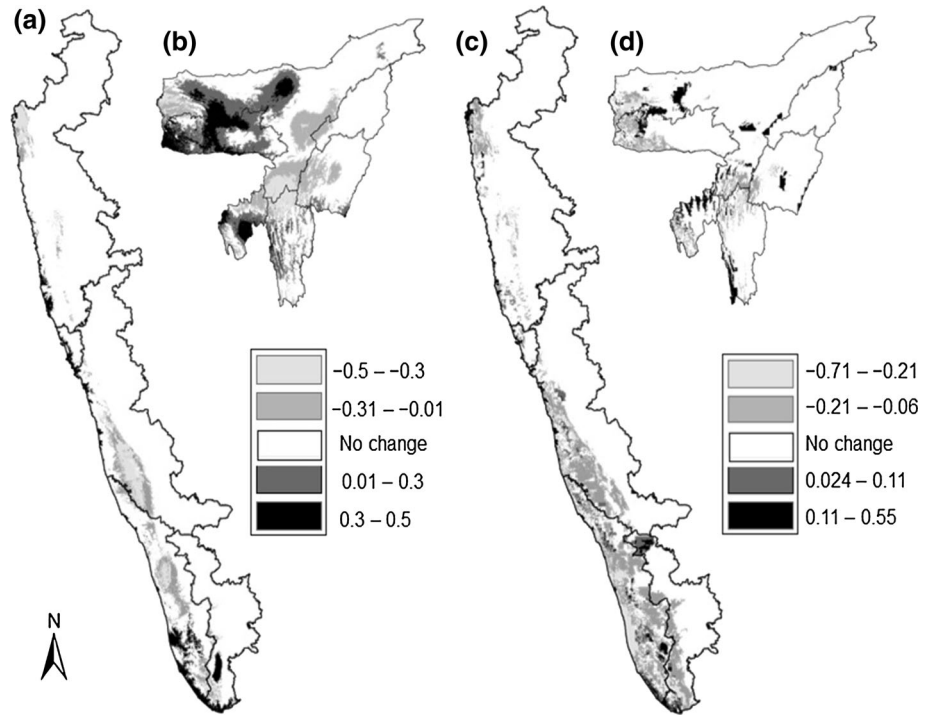
In the change detection map, the change in suitability values obtained by subtracting the 2000 base year map from the 2050 map varied from -1 to +1, where positive values are attributed to more suitable niches for rubber tree plantations and negative values indicate non-suitability (Fig. 3a, b). More negative values were observed in the WG, whereas more positive values were found in the NE region. The change detection map between the rubber tree distribution simulated with climate alone and climate plus other factors indicated that there were areas in parts of WG in Karnataka, some pockets in Maharashtra, Northern Tripura, south of Mizoram, and lower and Western Assam in the NE region where the other factors had a positive impact (>0.5) (Fig. 3c, d).

The addition of other factors (soil, topography and socioeconomic conditions) to the ENM resulted in prominent changes in the distribution map of the WG for the base year 2000. The extent of suitable regions for rubber trees predicted by the model with only climate were 2756 km<sup>2</sup> with a >0.7 suitability value 7295 km<sup>2</sup> with a moderate suitability (0.5–0.7), 23,433 km<sup>2</sup> with a range of suitability of 0.3–0.5, and 27,399 km<sup>2</sup> of the least suitable area (0.1–0.3). Introducing other factors to the model resulted in an increase of the least suitable area and moderately suitable area in the WG to 28,339 and 9191 km<sup>2</sup>, respectively. However, the other

**Fig. 2** Maxent model-derived rubber tree distribution map showing the species distribution predicted **a** with climate factors for the base year 2000 in the WG region; **b** the NE region with climate factors for the base year 2000; **c** with climate, soil and socioeconomic factors for year 2000 in the WG region; **d** the NE region, with climate (base year), soil and socioeconomic factors with projected climate factors of year 2050; **e** with projected climate of year 2050, soil and socioeconomic factors in the WG; and **f** projected climate of year 2050, other soil and socioeconomic factors in the NE region



**Fig. 3** Change detection in ecological niche distribution maps of rubber tree species for **a** the WG, and **b** the NE region between the base year (2000) and the 2050 climate scenario with climate, soil, topography and socioeconomic input factors. Change detection maps between the Maxent model simulated rubber tree distribution with climate, climate plus other factors as input variables in **c** the WG, and **d** the NE, showing the changes due to other factors. *Dark coloured* patches are indicative of positive changes, *light* patches are negative changes and *white* patches indicate no change



**Fig. 4** Changes in area of suitability as influenced by input factors i.e., climate alone, and climate with other factors such as soil, topography and socioeconomic conditions in both the WG and the NE regions. The probability of species occurrence estimated by the model between 0.7 and 1.0 represents most suitable region, 0.5–0.7 represents moderately suitable, 0.3–0.5 represents a suitable region and 0.1–0.3 a less suitable region

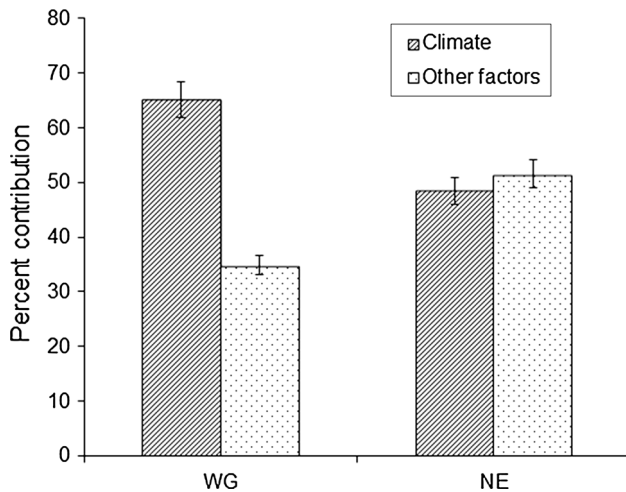
two category of suitable area (0.3–0.5 and >0.7 probability) decreased to 22,089 and 2588 km<sup>2</sup>, respectively (Fig. 4).

Areas with a >0.7 suitability value showed an overall decline compared with the model with only climate in areas such as northern Mizoram, and parts of western and lower Assam. However, some areas in northern Assam became more suitable within the 0.3–0.5 range of suitability values. Numerically, the most suitable area

(with >0.7 suitability value) of 4456 km<sup>2</sup> in the climate-only model was reduced to 3011 km<sup>2</sup> in the climate and other factors model. Similarly, the moderately suitable area with values of 0.5–0.7 decreased from 11,425 km<sup>2</sup> in the climate-only model to 5692 km<sup>2</sup> in model when other factors were included. There was also a decline in the total less suitable area (0.3–0.5) i.e., 18,284 km<sup>2</sup> and least suitable area of 51,459–12,144 and 36,347 km<sup>2</sup>, respectively in the model with climate and other factors (Fig. 4). These results lead to the observation that inclusion of other factors such as soil, topography and socioeconomic conditions into the ENM have an additive impact on the model output. The impact of these factors in the WG was not significantly different compared with the model with only climate factors. In the NE, there was a significant impact of the other factors on the model output compared with the climate-only model.

In the model with climate and other factors, the cumulative contribution of climate variables and other variables were determined separately for the WG and NE regions. In the WG, the climate variables contributed 65.2 % whereas other variables contributed 34.8 %. In the NE the model output with climate and other factors showed a contribution by climate variables of 48.5 % and by other factors of 51.5 % (Fig. 5). This indicated that other factors have a dominant contribution in predicting the distribution of the rubber tree species in the NE region, whereas the distribution of rubber tree species in the WG was dominated by climate variables with a lesser contribution from other factors.

Although use of the AUC alone as an indicator of predictability of the Maxent model was not supported



**Fig. 5** Comparison between the contribution (%) of climate and other factors such as soil, topography and socioeconomic conditions in modelling niche distribution of rubber trees in the WG and the NE regions

by some previous studies (Lobo et al. 2008), AUC was considered here as a measure of confidence for predicting the difference in rubber tree distribution from a random distribution. However, model accuracy was also assessed by TSS. The average AUC value of 10 replications of model runs was found to be 0.923 ( $\pm 0.02$ ) with climate as the sole predictor factors for the NE region in the base year 2000 (Table 2). With the addition of soil and socioeconomic factors in the Maxent model, the average AUC value increased to 0.934 ( $\pm 0.009$ ) (Fig. 6a, b). A higher AUC value is expected in the case of a highly specialised species (Heumann et al. 2011). Although the numerical increase in AUC values was not statistically significant, the effect of including additional factors was visibly prominent in the spatial output for the NE region. The model simulation results from the WG region indicated that there was no improvement of accuracy measures even with soil, elevation and socioeconomic factors. The average AUC value was 0.964 ( $\pm 0.011$ ) with climate factors alone and 0.972 ( $\pm 0.007$ ) with all other factors in 2000 base year scenario (Fig. 6c, d). The traditional AUC and TSS methods of estimation of model accuracy, and the partial AUC (curve AUC and random AUC) values of all the models with different input factors ranged between 1.2 and 1.9, which indicated very good predictability for the models (Fig. 7).

Model validation with satellite image-derived rubber tree species distribution map

The simulated rubber tree distribution from the Maxent model in both the WG and NE region for the base year 2000 was validated with a satellite (IRS-P6 LISS III and LISS IV) image-derived rubber tree distribution map of two sample states, Tripura for the NE region and Kerala for the WG region in a comparable time frame. The model-predicted suitable regions, such as south and west districts of Tripura state and southern part of Kerala state, were found to be occupied by large areas of rubber tree plantations (ISRO 2012; Meti et al. 2014).

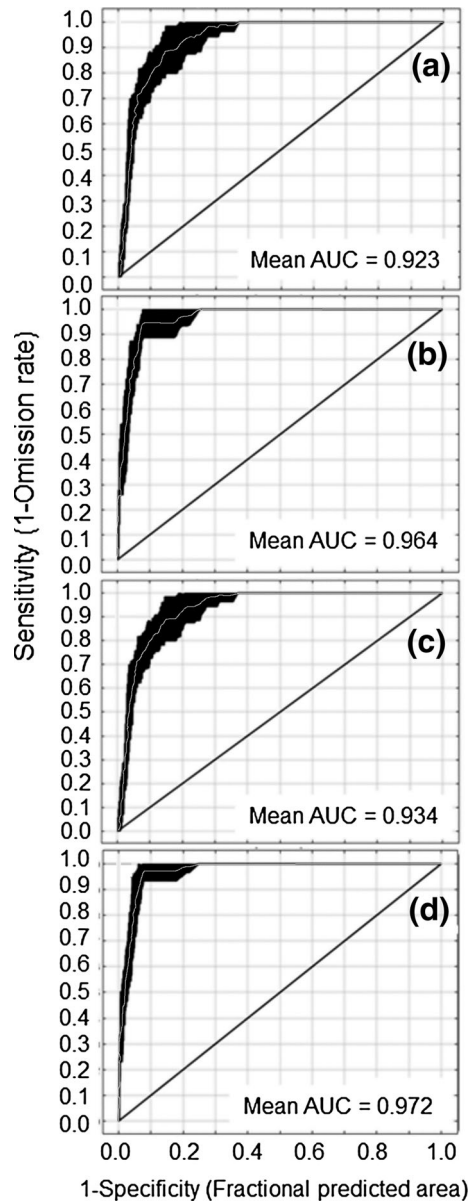
Factors contributing to the geographical distribution of rubber trees

The present results indicated that bioclimatic variables contributed up to 65.2 % to the distribution of rubber trees in the WG and 48.5 % in the NE regions. The contribution of each variable to the model accuracy was estimated using a Jackknife plot (Fig. 8). In the WG region, the climate variables showed the greatest contribution to the model. Precipitation of the coldest quarter (bio19, 34.2 %), mean diurnal range of temperature (bio2, 20.8 %), temperature seasonality (bio4, 6 %), and precipitation of the driest quarter (bio17, 4.2 %), were the major contributing climatic variables in the WG. Among the socioeconomic factors, only the availability of rural agricultural labourers contributed 3.1 % to rubber tree distribution. Precipitation in the driest month (bio14, 28.3 %), temperature seasonality (bio4, 15.7 %), elevation (19.8 %), rooting condition (12.4 %), and village population (3.6 %) were the major contributory variables to the Maxent model in the base year 2000 climate conditions of the NE region. Apart from bioclimatic factors, topographical and soil factors such as rooting condition and socioeconomic factors such as labour availability contributed to rubber tree distribution in the NE region. In the NE region, there was a high contribution of elevation (19.8 %) as a predictor variable. The wide variation in elevation here seems to have limited the expansion of rubber tree plantations. In contrast, in rubber tree growing areas in the WG elevation contributed <9 % to the model (Table 3).

**Table 2** Area under curve (AUC) and true skill statistics (TSS) values generated by the rubber tree distribution model for the Northeast (NE) and Western Ghats (WG) regions

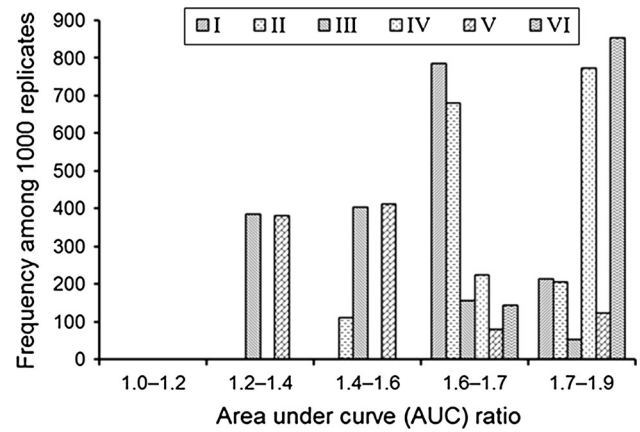
Predictive variables	Northeast (NE)				Western Ghats (WG)			
	Base (2000) climate		Projected (2050) climate		Base (2000) climate		Projected (2050) climate	
	AUC	TSS	AUC	TSS	AUC	TSS	AUC	TSS
Climate alone	0.923	0.671	0.927	0.781	0.964	0.753	0.965	0.789
Climate, soil and socioeconomic factors	0.934	0.677	0.944	0.704	0.972	0.715	0.966	0.725





**Fig. 6** Area under curves (AUCs) for 10 replications of model runs with **a** climate factors in the base year of 2000 in the NE; **b** climate in the base year 2000 and other factors such as soil, topography and socioeconomic conditions of the NE as predictor variables; **c** base year climate of the WG region; and **d** climate of base year 2000 and other factors in the WG. (*white line* indicates the mean AUC. The *dark area* around the *white line* is the  $\pm$  standard deviation (SD) among the replicated runs of the model. The *diagonal line* indicates the random prediction of the model.)

Among the socioeconomic variables, village population and agricultural labour availability contributed around 3.6 and 3.1 % to the species distribution modelling of the NE and WG region respectively. The association of percentage of forest area under each pixel with rubber tree plantations contributed 3.3 % in the NE region and 9.2 % in the WG region. Other factors such as the Human Influence Index showed a contribution of around 1 % in both regions. The findings

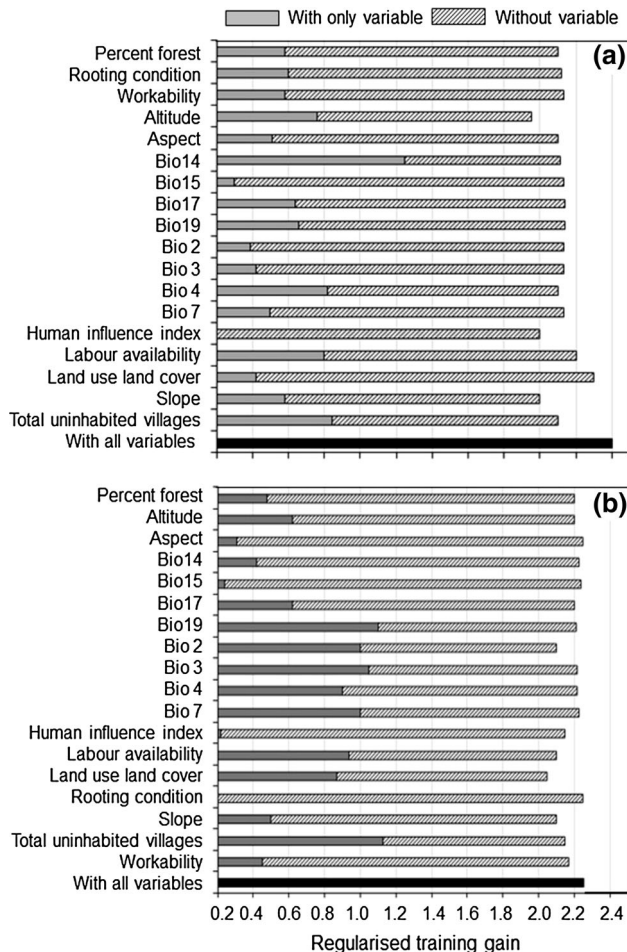


**Fig. 7** Frequency distribution of AUC ratios derived from partial ROC for models generated with different set of input variables of the WG and the NE region. (I) base year (2000) climate of the WG; (II) base year (2000) climate of the NE region; (III) present WG climate along with soil, topography and socioeconomic factors; (IV) present climate of the NE along with soil, topography and socioeconomic factors; (V) future climate (2050) of the WG along with soil, topography and socioeconomic factors; and (VI) future (2050) climate of the NE climate along with soil, topography and socioeconomic factors. Higher AUC ratios of the models with climate and other ancillary factors in the *NE region* indicate higher accuracy compared with only-climate models

regarding the contribution of these socioeconomic factors to the model in both regions matched conditions on the ground. Labour shortages were the main problem in most of the small holdings of rubber tree plantations in Kerala state (Ouseph 1996), but agricultural labour is relatively cheaper in Tripura and other North Eastern states (Sumitha 2012). Village population was considered as a proxy for land occupied by settlement and therefore less populated regions may have more area suitable for plantation activities. This assumes that socioeconomic factors play an important role for species suitability, if bioclimatic and soil factors are suitable (Ureta et al. 2012). In a similar study, it was indicated that the dispersion of species is limited by historic, biotic and sociocultural factors even when temperature and precipitation have a favourable influence on its distribution (Brush and Perales 2007).

The impact assessment of socioeconomic factors as the drivers for rubber tree distribution was the key component of this study. It was observed that city areas and river banks could not be delineated while simulated with only climate factors, whereas the inclusion of elevation, soil and socioeconomic variables resulted in a more detailed prediction of the species' niche. The changes in pixel level probability values in twelve sample sites simulated with climate alone and climate with other factors were compared (Table 4). The results showed that inclusion of socioeconomic variables (CSAS) altered the probability values assigned by other two models where climate (CL), and soil and elevation (CSA) data were added.

The change detection map between the outputs of the model with only climate factors and the model with



**Fig. 8** Average Jackknife analysis results of training gain for 10 replications of model runs for **a** the NE and **b** WG regions in the base year of 2000. The grey bar represents the training gain of the model without the corresponding variable, whereas the dark bar is the gain when only the corresponding variable is used as input variable. The bottom bar is indicative of the gain when all the variables were used

climate and other factors indicated that the impact of other factors was lower in the southern parts of the WG. Only southern parts of coastal Karnataka state and some areas in the northern WG beneath the border of Gujarat state showed a positive impact from other factors on the distribution of the rubber tree species (Fig. 3c). In the NE region, the positive impact of other factors was prominent in northern parts of Tripura, southern parts of Mizoram, lower Assam and parts of western Assam. Some areas in northern Mizoram and western Meghalaya and western Assam were negatively affected by the soil, topography and socioeconomic factors for predicting rubber tree niches in the 2000 base year climate (Fig. 3d).

#### Response curves of predictive factors

The response curves produced by the Maxent model showed how the logistic prediction of rubber tree dis-

tribution varies with changes in the predictive variables, keeping all other variables at the average sample points. In the WG region, the greatest contributing factor for the rubber tree distribution model was precipitation during coldest quarter followed by the mean diurnal range of temperature. According to the response curve, the logistic probability of the species' presence remained high in those areas where mean precipitation during coldest quarter (bio19) ranged from 1000 to 2500 mm (Fig. 9a) and diurnal range of temperature (bio2) was 7–9 °C (Fig. 9b). Percentage forest area had a positive correlation with the rubber tree presence probability values indicating a good association between plantations and forest area (Fig. 9c). A close association was observed between the probability of rubber tree presence and elevation up to 1100 m (Fig. 9d). Higher probabilities of rubber tree presence were noticed with the temperature change of 9–12 % coefficient of variation (CV) over the year (seasonality, bio4) (Fig. 9e). Precipitation during the driest quarter (bio17) showed a positive relationship with the probability of rubber tree presence in the WG region in the range of 20–140 mm, which was explainable in the context of the local climate (Fig. 9f).

A higher probability of rubber tree presence was observed with precipitation during the driest month (bio14) ranging between 5 and 15 mm contributing the most to rubber tree distribution in the NE region (Fig. 10a). An elevation of 500–700 m was associated with a higher probability of rubber tree presence (Fig. 10b). Temperature seasonality of 10–17 % CV in the NE region showed a probability of rubber tree presence greater than 0.5 (Fig. 10c). Rooting condition favoured the probability of species' presence within the range of 1.5–2.5 units (Fig. 10d). Slope showed a negative relationship with the probability of rubber tree presence. The maximum probability was found within a slope range of 5–15 % (Fig. 10e). The initial trend of the response curve of the number of less populated villages per district showed a relationship with the probability of rubber tree presence, however, it decreased with further increases in less populated villages (Fig. 10f). Precipitation during the driest month was the most important input factor for rubber tree distribution in the NE. Monthly precipitation between 10 and 23 mm showed a positive impact on the logistic probability of rubber tree distribution but the response became saturated beyond 23 mm of monthly precipitation. The other important factor in the NE region was elevation, where the response curves clearly showed that the probability of tree presence reduced with an increase in altitude. Elevation up to 1000 m showed a probability of species' presence but model did not respond beyond 2000 m of elevation (Fig. 6f). An important soil characteristic of the NE which appeared to make a strong contribution to the model was rooting condition. According to Fischer et al. (2008) rooting conditions in the HWSO include effective soil depth (cm) and effective soil volume (%) related to the presence of gravel and stoniness. Rooting conditions may be affected by the presence of a soil phase either

**Table 3** Percentage contributions of predictive variables to the rubber tree niche model in base year (2000) and projected changed climate by 2050 in NE and WG regions

NE (base year: 2000)		WG (base year: 2000)	
Variables	Percent	Variables	Percent
Precipitation during driest month (bio14)	28.3	Precipitation during coldest quarter (bio19)	34.2
Altitude	19.8	Mean diurnal range of temperature (bio 2)	20.8
Temperature seasonality (bio4)	15.7	Percent forest	9.2
Rooting condition	12.4	Altitude	9.0
Slope	4.8	Temperature seasonality (bio 4)	6.0
Number of villages less than 500 persons	3.6	Precipitation of driest quarter (bio17)	4.2
Percent forest	3.3	Number of agricultural labourers per district	3.1
Human influence index	1.0	Human influence index	0.9
NE (2050)		WG (2050)	
Altitude	28.1	Precipitation during coldest quarter (bio19)	23.5
Minimum temperature during coldest month (bio 6)	15.5	Mean diurnal range of temperature (bio 2)	22.1
Temperature seasonality (bio 4)	10.8	Temperature seasonality (bio 4)	10.2

**Table 4** Model predicted probability values of occurrence of rubber trees in different models using climate alone (CL), climate, soil and topographic factors (CSA) and climate, soil, topography and socioeconomic factors (CSAS) as predictor variables

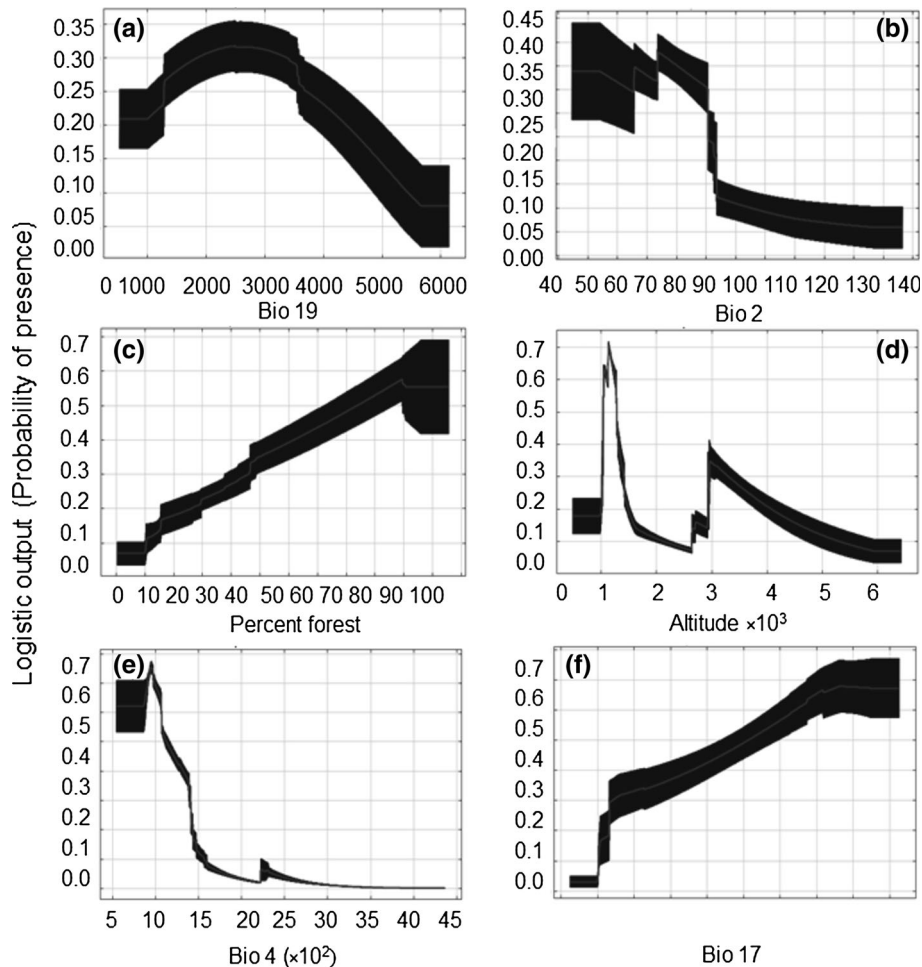
Geographic position	Model predicted probability of <i>Hevea</i> species presence with different variables			Ground observation
	CL	CSA	CSAS	
23.844N, 91.282E	0.44	0.08	0.13	City area
23.805N, 91.556E	0.28	0.14	0.18	High elevation
24.030N, 91.835E	0.19	0.07	0.29	Suitable area
24.114N, 92.019E	0.23	0.15	0.42	<i>Hevea</i> plantation
24.168N, 92.250E	0.33	0.08	0.21	High elevation
24.281N, 92.150E	0.31	0.15	0.43	<i>Hevea</i> plantation
24.181N, 92.358E	0.41	0.12	0.24	Not suitable
26.130N, 90.188E	0.78	0.00	0.00	River band
24.754N, 92.548E	0.22	0.02	0.56	<i>Hevea</i> Plantation
25.379N, 90.145E	0.40	0.22	0.49	Suitable area
24.833N, 92.932E	0.16	0.01	0.13	Agricultural land
25.444N, 90.111E	0.37	0.20	0.43	Suitable area

limiting the effective rooting depth or decreasing the effective volume accessible for root penetration. Therefore, it showed a negative relationship with the logistic probability of rubber tree presence.

#### Range shifting of rubber trees in future climate

Recent advances in ecological niche modelling have resulted in a greater potential of presence-only models for land suitability studies in agricultural crops (Heumann et al. 2011, 2013). According to the results of the present study, predicted base year distribution and future ranges of rubber tree habitat are likely to be affected by climate. The assumption of biophysical factors such as soil, topographic and socioeconomic factors being

stable across the climate, facilitates analysis of the interaction of climate and rubber tree species presence. Based on the probability of species presence, the total area predicted as moderately suitable was 5987 km<sup>2</sup> in the NE and 5752 km<sup>2</sup> in the WG in 2000. The most suitable regions were those niches with 70–100 % probability of occurrence of rubber tree. The most suitable area at present for rubber tree plantations was 2634 km<sup>2</sup> in the NE and 2583 km<sup>2</sup> in the WG. Highly suitable plantation area will increase by 7.3 % in the NE and 1.8 % in the WG by 2050. It appears that the rubber tree plantations will benefit from future climate more prominently in the NE region where suitable area will increase by 1785 km<sup>2</sup>, compared with only 357 km<sup>2</sup> in the WG region by 2050 (Table 5). As per the official records of the Indian Rubber Board, the area under



**Fig. 9** Response curve of **a** precipitation during coldest quarter (bio19); **b** mean diurnal range of temperature (bio2); **c** percent forest cover; **d** elevation; **e** temperature seasonality (bio4); and **f** precipitation during driest quarter (bio17) in the WG showing

their impact on model predictions. The grey line is the mean values for 10 model replications whereas the *darker area* in all plots indicates the standard deviation (SD) among the replicated runs

rubber tree cultivation in the NE region is currently 1284 and 5594 km<sup>2</sup> in the WG region (as of 2011–2012) (Rubber Growers Companion 2014).

## Discussion

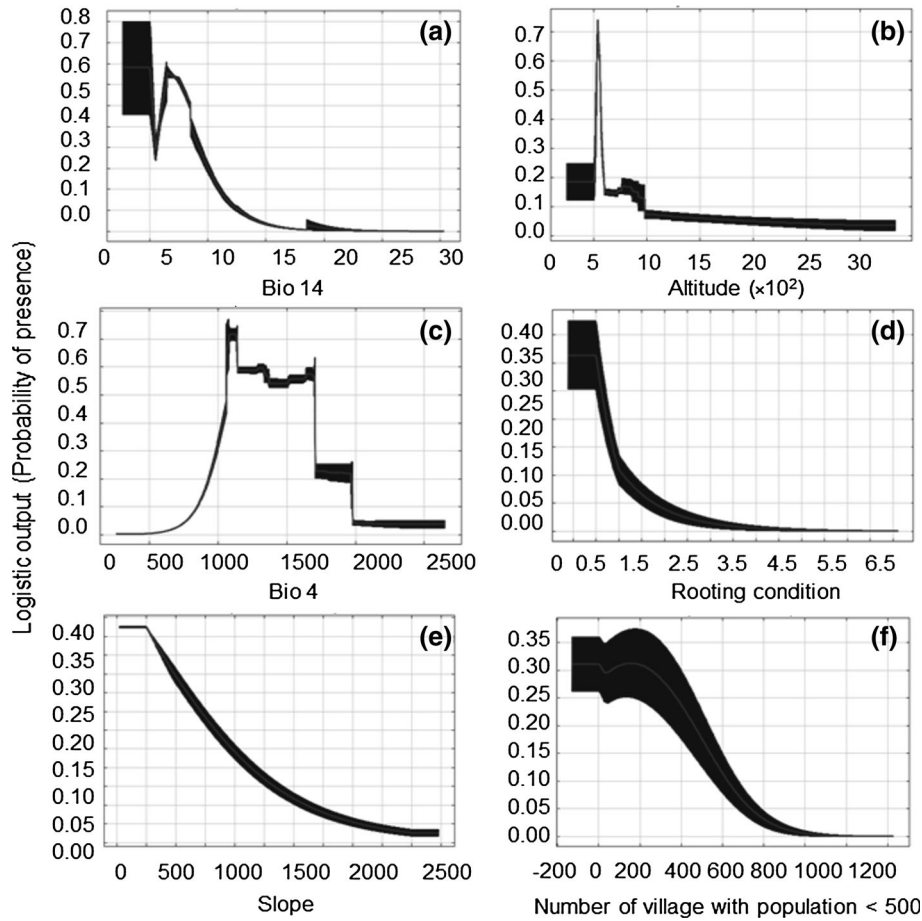
Probable future expansion of rubber tree distribution in India

At present, the WG has more than 5594 km<sup>2</sup> of plantations, whereas only 1284 km<sup>2</sup> are located in NE region (Rubber Statistics 2014). According to the model prediction, more land area will become suitable for rubber tree plantations in the NE compared with the WG by 2050. The present rubber tree plantation extension activities of the Indian government indicate similar findings. Emphasis has been given to the NE region, particularly in the states of Assam, Tripura and Meghalaya, to extend rubber tree cultivation. The Maxent model simulation also generated similar infor-

mation regarding the scope of future expansion of rubber tree plantations. Similar ecological niche studies with Sal (*Shorea rubusta*) suggest a shift from central to northeast India due to projected changes in climate by 2020 (Chitale and Behera 2012). Because the Maxent model is being used for a wide range of species such as agricultural crop species (Evans et al. 2010), invasive species (Gallardo and David 2013) and pathogens (Mischler et al. 2012), some additional factors such as soil topography and socioeconomic factors have been included in the model to make it more appropriate for a plantation species like the rubber tree.

## Bioclimatic factors in the rubber tree Maxent model

The Maxent model is most commonly used as a bioclimatic model with inputs of biologically important climatic factors which are derived from temperature and precipitation measurements (19 bioclimatic factors of Hijmans et al. 2005). Based on our present results, we



**Fig. 10** Response curves of **a** precipitation during driest month (bio14); **b** elevation; **c** temperature seasonality (bio4); **d** rooting conditions; **e** slope (%); and **f** number of villages per district with population less than 500 (VPL500) in the NE showing their impact

on model predictions. The *grey line* is the mean values whereas the *darker area* in all plots indicates the standard deviation (SD) among the replicated runs

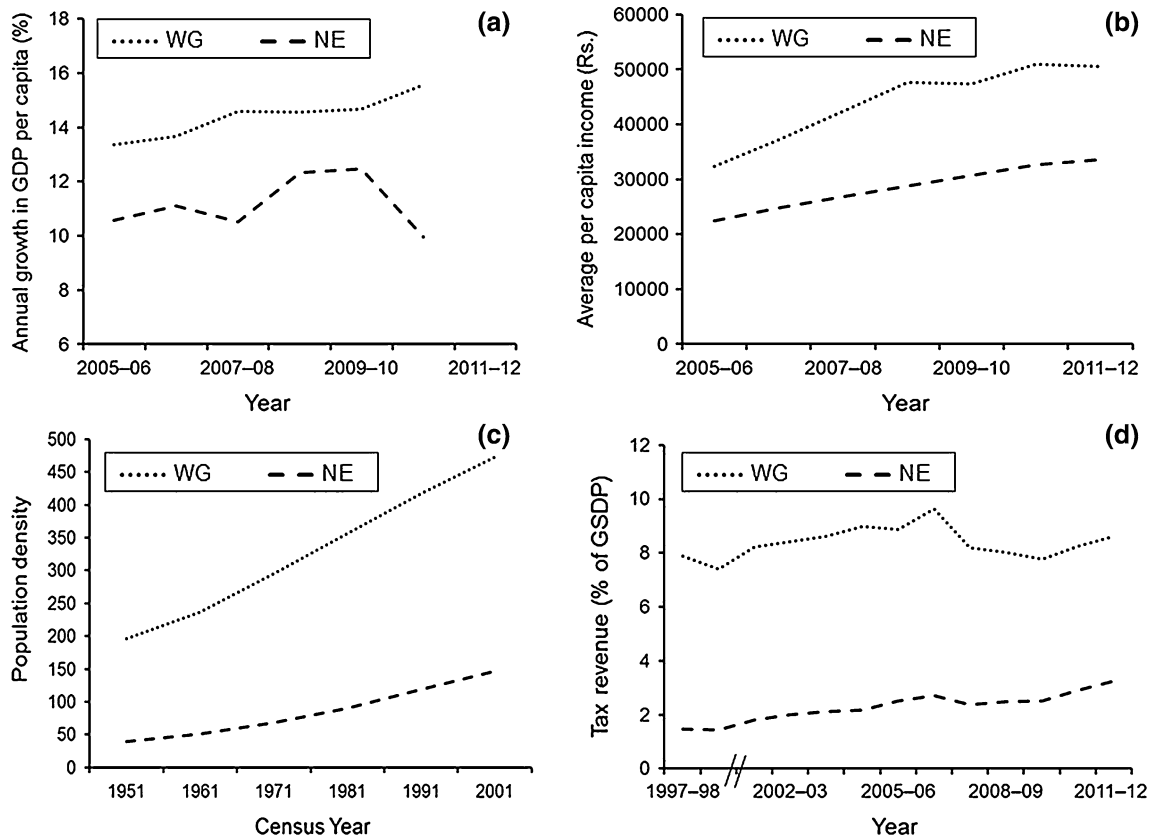
**Table 5** Changes in area of suitability for *Hevea* trees in NE and WG regions with respect to base year (2000) climate and projected climate (2050) scenarios

Classes of probability of species presence	Habitat description	Area (km <sup>2</sup> )				Area change (km <sup>2</sup> )	
		NE		WG		NE	WG
		Base (2000)	Projection (2050)	Base (2000)	Projection (2050)		
0–50	Unsuitable	321,284	319,499	807,959	807,602	–1785	–357
50–70	Moderately suitable	5987	7578	5752	6061	1591	309
70–100	Most suitable	2634	2828	2583	2631	194	48
Area under rubber cultivation as per official records of the Rubber Board, India (as per 2011–2012)		1284		5594			
Net increase in overall suitable area (50–100 % probability of presence)						1785	357

cautiously infer that climate exerts a major influence on rubber tree distribution in both regions. However, the contribution of input factors to model output in the case of a plantation species such as the rubber tree may result from either correlation or causation. In the case of an agricultural crop, the climate dependency of a successfully cultivated species may be influenced by human

intervention. Therefore, there is an on-going debate on the applicability of ecological niche modelling in the context of determining the niche of domesticated crop species (Pearson and Dawson 2003; Dormann 2007; Huntley et al. 2010 Araújo and Peterson 2012).

However, previous field studies on the climatic requirements of rubber trees indicated that minimum



**Fig. 11** Socioeconomic conditions of two regions, the WG and the NE: **a** annual growth (%) in gross domestic product (GDP); **b** average per capita income (Rs.); **c** population; and **d** states' own tax revenue over various time scales (based on available data. (//

indicates the missing data on 2000–2001). Data collected from the Data Book of the Planning Commission of India, Government of India

temperatures of  $< 10^{\circ}\text{C}$  during peak winter season and maximum temperature of  $> 36^{\circ}\text{C}$  during peak summer season limit annual growth and yield (Raj et al. 2005). It was also observed that a temperature range of  $17\text{--}35^{\circ}\text{C}$  and  $1500\text{--}2500$  mm of annual rainfall are the optimum climatic characteristics of areas with higher rubber tree productivity (Rao and Vijayakumar 1992). In general, Tripura and other parts of the NE region of India experience humid climate conditions due to monsoon-driven rainfall patterns (Sehgal et al. 1992). Soil water deficits, experienced during winter in parts of the NE, are comparable with those of South Kerala and appear to affect rubber tree growth in both the regions (Raj et al. 2005). The Maxent model simulation for rubber tree distribution produced similar inferences based on the Jackknife plots.

#### Role of soil factors

Modelling species shifts due to climate change usually involves species distribution modelling with base year climate factors and projections for future climate scenarios. Species distribution depends not only on climate but also on land use, soil types, physiological traits and cultural practices (Coudun et al. 2006). Changes in soil

type take place over a geological time frame and therefore any changes due to climate change are likely to be minimal. In studies assessing the suitability of range expansion for any plant species, evaluating soil constraints is important (Ehrenfeld et al. 2005). Interestingly, only rooting condition was found to contribute to the rubber tree distribution model. Many tree species require a deep soil to accommodate genetic rooting potential and this factor is likely to affect the distribution model of rubber trees (Moraes 1977).

#### Impact of socioeconomic factors on the rubber tree Maxent model

The accuracy of species distribution modelling may be affected by the functional limitations of ENMs due to the contribution of many factors other than climate to the distribution of the species (Garcia et al. 2013; Gallardo and David 2013). Socioeconomic factors were combined with climate factors in the Maxent model, keeping the species' background in mind (Mischler et al. 2012; Gallardo and David 2013). In our study, socioeconomic factors were included in the Maxent model because of the dependency of rubber tree distribution on acceptance by the growers as a profitable cash species.

For example, rubber trees were introduced to the NE region as a means of rehabilitating land following shifting cultivation in Tripura and subsequently the species was adopted by native growers (Jacob et al. 1999; Sinha 2010). As adoption progressed, other socioeconomic factors such as the availability of a work force and settlement pressure on barren land arose as constraints for bringing new areas under rubber tree plantations in both traditional and non-traditional regions.

It was evident from our study that the inclusion of socioeconomic drivers into the Maxent model can alter the probability scores of a particular location for growing a species. Therefore, the disparity in socioeconomic conditions between two study regions as depicted in terms of certain socioeconomic indicators will contribute to the species distribution pattern (Fig. 11). Recent advances in ecological modelling have resulted in greater potential for presence-only models for land suitability studies in agricultural species (Heumann et al. 2011, 2013). As the Maxent model is basically a species' niche-based distribution model, the outputs of this model show the distribution of rubber trees as a function of their requirements of climate, soil conditions and socioeconomic aspects. We created probability classes of species' presence, which are indicative of habitat suitability for the rubber tree. For example, an interpretation of the species suitability scores indicates that in areas with moderate suitability, farmers tend to cultivate a particular species not due to environmental conditions, but due to socioeconomic factors (Heumann et al. 2011). Labour and land availability has not yet been a major limiting factor in the NE yet unlike in the WG region. Socioeconomic factors contributed 10–12 % to model calibration in the WG in compared with 5–7 % in the NE, which supports this hypothesis.

With this background, it was felt that socioeconomic factors were important in combination with climatic factors. However, inclusion of these factors did not affect the high accuracy scores of the Maxent model as also observed by Gallardo and David (2013). Inclusion of these factors did, however, amplify the spatial prediction of suitability for rubber tree distribution. Out of several surrogate factors for socioeconomic factors, the number of agricultural labourers per district taken from Indian census (2011) report was found to contribute as labour availability to the model. As the results in the present study indicated, the influence of these non-climate factors varied across space and time. This could be explained by the cultivation of the species in the WG region for a long period of time as a result of which it has reached a saturation point in species expansion. In our opinion, there is scope for further research to investigate other socioeconomic factors that may play a role in determining rubber tree distribution. We also anticipate that better utility of socioeconomic data may improve model outputs.

## Conclusions

In this study, we concluded that climate plays a major role in rubber tree distribution. Topographic, soil and socioeconomic factors made a significant contribution as well, though this varied between regions. Among all the bioclimatic factors, precipitation during the driest month and temperature seasonality contributed the most to explaining rubber tree distributions in the NE region. Elevation, rooting conditions, labour availability and village population factors also contributed to the distribution of the species in the NE. Rubber trees in the WG were mainly influenced by bioclimatic factors such as mean diurnal range of temperature, temperature seasonality, and precipitation during the coldest and the driest quarter. This study clearly indicated that further scope for expansion of rubber tree distribution will be greater in the NE and limited in the WG region by 2050. However, identification of more surrogate socioeconomic drivers, which can simulate the constraints or facilitators of rubber tree plantation development, can help to improve the spatial predictability of the model. This gives a new direction of future research and attention may be focused on integrating process-based models for natural rubber yield estimation with ecological niche modelling. This will indicate site-specific strategies applicable to rubber tree plantations in India.

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