Period wise future distribution and range-shift estimation using shared socioeconomic pathways on Taxus wallichiana medicinal plant

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Research Article

Keywords: Himalayan medicinal plant, Climate change, Shared socio-economic pathways, Range-shift.

Posted Date: March 29th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2742770/v1

Abstract

The threats of extinction and loss of diversity of Himalayan medicinal plants have been accelerated since decades due to global climate change associated with anthropogenic pressure. Such a flora, Taxus wallichina is facing regional extinction due to over-exploitation for its superb utility in various medicinal and non-medicinal trading purposes. The assessment of the impact of climate change on the suitability of ecological habitats of this climate-sensitive species is of utmost importance. The new generation climate model, CMIP6, provides us with different plausible future climatic scenarios driven by shared socio-economic pathways for different future periods. Through the implementation of ensemble species' distribution modelling, we assess the probabilistic niche distribution of Taxus wallichina under current and different future climatic scenarios. A precise wide-range spatial-temporal assessment of suitable niche distribution leads us to the identification of potential regions for conservation of the species to facilitate their sustainability. A detailed time frame estimation in the niche distribution assists the identification of any retrieval or consistent declination in habitat suitability of a particular zone. The target species featuring its potential distribution in the zones of ample precipitation and cooler monsoon is observed to show drastically different range-shifts under different projection pathways. The present study reveals that the habitat suitability assessment should be carried out time to time under all possible socio-economic projection pathways to update the conservation policies in future.

1. Introduction

At present, biodiversity is subjected to a massive threat and unsustainable exploitation through extinction of species. The loss of biodiversity is majorly driven by habitat degradation, fragmentation and destruction; introduction and expansion of invasive species; over-exploitation of species through human activities; climate change and other anthropogenic environmental affects; and last but not least, the increase in population with indiscriminate exploitation (Butchart et al. 2010). High rate of plant extinction has been observed during the second half of the last century, loss of 137 species per day (Mora et al. 2011; Mehta et al. 2020). In mountain regions like Himalaya, bioclimatic envelops assumed, as pockets of occurrences of species, are primarily specific to elevation zones (Pearson and Dawson 2003). Correspondingly, global climate change has imposed a profound effect on the elevational distribution of mountain species over a few decades (Rana et al. 2020). Regional temperature is likely to exceed 2.0°C by the end of 2100 whereas global surface temperature may change up to 1.5°C (Field et al. 2014). This climatic change may induce range shift of many species for sustaining their populations resulting in the change in species richness (Telwala et al. 2013), functional behavior (KHARUK et al. 2007) and ecology. However, such species may undergo threats of extinction due to unavailability of suitable habitat to forward reproduction (You et al. 2018). This concern is particularly alarming for highly traded medicinal plants due to uncontrolled over-exploitation to mitigate increasing demand (Rana et al. 2017).

Taxus wallichiana, commonly known as Himalayan yew, is such an important species regarding its usefulness in medicinal and non-medicinal purposes (Phillips et al. 1998). The over-exploitation due to its high demand has resulted in a declination of the population of near about 90% in Nepal and India and more than 50% in China for the last two-three decades (Molur and Walker 1998; Thomas and Farjon 2011). However, restoration or cultivation of the species face challenges because of its poor 'seed regeneration' and 'long pre-reproductive phase' resulting in weak ecological adjustability (Uniyal 2013). Moreover, previous study (Poudel et al. 2014) suggests that the distribution of the species is range-restricted and fragmented to climatic pockets. Thus, the assessment of the impact of climate change on the distribution of the endangered species is of utmost importance regarding its conservation and selection of priority areas.

The prediction of suitable niche distribution of species is evaluated through the combination of species occurrence and ecological estimates of the occurrence points using species distribution models (Pearson 2010). These models are widely used in recent years to assess future distribution of the species (Gritti et al. 2006), estimate the possibility of extinction (Thomas et al. 2004), examine adequacy of the existing reserve system (Araújo et al. 2004) and mitigate biodiversity conservation planning (Mehta et al. 2020). To avoid the uncertainty in prediction due to model variability, ensemble approaches are widely used in recent days for this purpose (Jones-Farrand et al. 2011). These ensemble approaches combine different model algorithms to project optimized consensus maps (Rana et al. 2020). The future habitat prediction of the species needs to be based on some pre-determined future climatic scenarios derived from climate projection models. The General Circulation Model (GCM) projections provided by the World Climate Research Programme (WCRP) are adopted in the present study to serve the purpose. The WCRP is based on the Intergovernmental Panel on Climate Change (IPCC)'s sixth Assessment Report, AR6 (Eyring et al. 2016). This new generation future climate-projection model comes up with monthly average of climatic data for four Shared Socioeconomic Pathways (SSPs) *viz.* ssp126, ssp345, ssp370 and ssp585. These SSPs span a wide range of uncertainty in future forcing pathways. They designate different levels of emission scenarios guided by socio-economic global changes mainly driven by anthropogenic drivers like greenhouse gases, chemically radiative gases, aerosols and land-use (O'Neill et al. 2016). The model projects the future climate for different SSPs over 20 year periods (2021–2040, 2041–2060, 2061–2080, 2081–2100).

Notable studies (Rathore et al. 2019; Rana et al. 2020) regarding climate driven range shift of the endangered medicinal plants are primarily based on the previous climate generation model (Tayler et al. 2012) yielding the future habitat distribution for 2050 and 2070. However, the period-to-period variability is not extensively studied. The new generation climate-projection model facilitates us with the opportunity to deal with four different future spans. Against this backdrop, the present study investigates the period-to-period change in the future habitat distribution of the species. The incorporation of SSPs-guided climate projections in the prediction of the future distribution of the endangered and important species under consideration through ensemble modelling approach is the first attempt to the author's best knowledge. In brief, the present study aims to

1. Assess the impact of climate change on the distribution of T. wallichina, an endangered medicinal plant of high trade value.

2. Predict period-wise, i.e. 2021–2040 (2030), 2041–2060 (2050), 2061–2080 (2070) and 2081–2100 (2090), future distribution of the species in the aspect of shared socio-economic pathways of global climate change.
3. Identify period-to-period range-shift of the species to develop suitable conservation mechanisms.

The details of the methods and the outcomes of the proposed work are furnished in the subsequent sections. Section 2 summarises the details of collected data required for the evaluation and the corresponding methods used for the purpose. Extensive results are presented in Section 3 and the corresponding analysis and discussion have been given in section 4. We conclude this paper with final remarks drawn from our study in section 5.

2. Materials And Methods

The assessment of the impact of climate change on the distribution of the target species should be evaluated through a predictive model. To accomplish this, data collection and data processing are executed at this stage. This section outlines the geographic extent of our study, record of species occurrence within that area, data of selective explanatory variables, the process of combination of the species presence data with the explanatory variables and the corresponding model performance.

2.1 Study area

T. wallichiana Zuccarini (Himalayan Yew) is among the most prominent species under the genus Taxus L., one of the most economically valuable evergreen gymnosperm tree species of the family Taxaceae (Paul et al. 2013). The species mostlyn occupies the temperate zone of the Northern Hemisphere, extending into the tropics and south of the Equator into Malaysia. In the Indian Himalayan Region, the occurrence of the species has been reported from the states of Arunachal Pradesh, Himachal Pradesh, Jammu and Kashmir, Manipur, Meghalaya, Nagaland, Sikkim, Uttarakhand, and West Bengal

(Sahni 1990). In this study, we have considered the species occurrences extending over China, Chinese Taipei, India, Indonesia, Myanmar, Nepal, Pakistan, Afghanistan, Bhutan, the Philippines, and Vietnam. The study area extends from 58.20° to 130.27° east and 10.55° south to 47.86° north.

2.2 Species Data

For the current study, the species occurrence data was collected from the online portal, Global Biodiversity Information Facility (GBIF 2018). The presence-only data was further processed in *R* (RStudio and others 2020) to remove multiple or duplicate occurrence points and data unavailability. After filtering, a total 645 occurrence points within the study area of interest were kept for further analyses. The coordinates of the occurrence points in the global map for the study area under consideration is shown in Fig. 1. The species majorly occupies the elevation range of ca. 1000 m to ca. 3000 m within the north-facing slopes of the Himalayan mountain regions. However a scattered distribution can also be found in the plains (< ca.1000m), especially in the territories of the Philippines and Vietnam.

2.3 Environmental explanatory variables

Table 1 presents 19 bioclimatic features (Bio1 through Bio19) along with the elevation as topological feature which are chosen as the explanatory variables for ensemble modelling (discussed in section 2.4). Grid-based current data (monthly average for the period of 1970 to 2000) for these 19 bioclimatic variables, derived from monthly temperature and precipitation data, were obtained from WorldClim version 2 (Fick and Hijmans 2017). The elevation data generated from Shuttle Radar Topography Mission (SRTM) (Jarvis et al. 2008) was downloaded from WorldClim site. All data were collected for the spatial resolution of 10 minutes (~ 340 km2). The high collinearity among the explanatory variables makes difficult to perceive the effects of predictors in the ensemble modelling approach (Ranjitkar et al. 2014). Collinearity matrix describing the correlation coefficient between each

Table 1
List of all explanatory variables for species distribution modelling

Category	Features	Features' names	Unit
Bioclimatic variable	Bio1	Annual Mean Temperature	˚C
	Bio2	Mean Diurnal Range	˚C
	Bio3	Isothermality (Bo2/Bio7) (×100)	Dimensionless
	Bio4	Temperature Seasonality (Standard Deviation × 100)	Percent
	Bio5	Max Temperature of Warmest Month	˚C
	Bio6	Min Temperature of Coldest Month	˚C
	Bio7	Temperature Annual Range	˚C
	Bio8	Mean Temperature of Wettest Quarter	˚C
	Bio9	Mean Temperature of Driest Quarter	˚C
	Bio10	Mean Temperature of Warmest Quarter	˚C
	Bio11	Mean Temperature of Coldest Quarter	˚C
	Bio12	Annual Precipitation	Mm
	Bio13	Precipitation of Wettest Month	Mm
	Bio14	Precipitation of Driest Month	Mm
	Bio15	Precipitation Seasonality (Coefficient of Variation)	Dimensionless
	Bio16	Precipitation of Wettest Quarter	Mm
	Bio17	Precipitation of Driest Quarter	Mm
	Bio18	Precipitation of Warmest Quarter	Mm
	Bio19	Precipitation of Coldest Quarter	Mm
Topographic variable	Elevation		Km

explanatory variable with other is depicted in Fig. 2. To test the multi-collinearity and remove the highly correlated redundant variables we incorporated the calculation of Variance Inflation Factor (VIF) (Fox and Weisberg 2011) using 'usdm' package (Naimi et al. 2014) in R. In this procedure, VIF for all variables are calculated and that with the highest value (greater than specified threshold of 10) is excluded. The same procedure is repeated until the final subset of explanatory variables with VIF values < 10 is achieved, keeping in mind that a VIF value greater than 10 is evidence of the collinearity problem within a model

(Dormann et al. 2013). Six species-specific predictor variables thus obtained after exclusion of high collinear variables are Bio2, Bio3, Bio8, Bio14, Bio15 and Bio18.

Future bioclimatic variables were derived from a global circulation model (GCM), BCC-CSM2-MR (Wu et al. 2019) developed by the National Climate Center, China Meteorological Administration. It is the middle-resolution climate system model, fully coupled with four components viz. atmosphere, ocean, land surface and sea-ice, interacting with each other (Xiao-Ge et al. 2019). This model also participates in 10 Model Inter-comparison Projects (MIPs) of CMIP6 (Eyring et al. 2016) organised by World Climate Research Project (WCRP). The choice of a single model lies in the evidence of less inter-model variability of CMIP6 and its outperformance over CMIP5 in terms of accuracy, particularly for precipitation (Ba\ugçaci et al. 2021). Shared socio-economic pathways (SSPs) that depict plausible alternative future states of environment (O'Neill et al. 2017) drive the latest IPCC-guided climate change researches at global and regional level. These socio-economic development trends are made up of five contrasting development pathways, (SSP1- a sustainable path; SSP2- a middle of the road with uneven development; SSP3- 'regional rivalry' with high inequality in developing countries; SSP4- a road divided with inequalities both between and within countries; and SSP5- a fossil-fuelled development with high competitiveness and exploitation of abundant fossil fuel resources but optimistic human development). Studies have revealed the integration of SSPs with climate change and their links with future greenhouse gas-concentrations (Marangoni et al. 2017). These SSPs incorporated with different radiative forcing pathways are included in 'Tier 1' of ScenarioMIP experimental design based on priority level to span a wide range of uncertainty (O'Neill et al. 2016). Three of these scenarios, as the update of previous versions of RCPs in CMIP5 (Tayler et al. 2012), correspond to the stabilization of radiative forcing level at 2.6 (SSP 1-2.6), 4.5 (SSP 2-4.5) and 8.5 (SSP 5- 8.5) W/m2 by the end of 2100. An additional unmitigated 'gap' scenario (SSP3-7.0) with particularly high aerosol emissions and land use change is also included (O'Neill et al. 2016). Thus future climate data of bioclimatic variables (consisting of 19 layers for Bio1 through 19) for the aforementioned 4 SSPs downscaled to 10 minutes spatial resolution for the years 2021–2040, 2041–2060, 2061–2080 and 2081–2100 are downloaded for further simulations.

2.4 Species distribution modelling

We adapted ensemble species distribution predictive modelling using "*sdm*" package (Naimi and Araújo 2016) in R programming language (RStudio and others 2020). The package "*sdm*" provides with a single platform to combine different ecological niche modelling and allow them to perform with same presence-only and pseudo-absence data (Naimi and Araújo 2016). We gathered 645 species occurrence points within the range of our study area as 'presence-only' data. In lieu of the real absence-data, 1000 random points were selected as pseudo-absence data points in accordance with Barbet-Massin et al. (2012), using the "*sdmdata*" function inherent in "*sdm*" package. The sample size is sufficient in the aspect of prediction accuracy, though keeping in mind that the species is widespread (van Proosdij et al. 2016). In this study, we have incorporated seven modelling techniques i.e. GLM, GAM, CART, RF, FDA, MARS and MaxEnt.

Generalized linear model (GLM) uses a linear regression approach and incorporated in R (Friedman et al. 2010) to efficiently deal with big-data problems and sporadic features. In flexible and easy-to-interpret generalized additive models (GAM) (Hastie and Tibshirani 1990), the expected value of the response variable through a ‘link’ function is related to the unknown ‘smooth’ functions of the predictor variables. This modelling approach is mid-way between the simple linear regression and complex machine learning approaches. Classification and regression trees (CART) are basically binary partitioning trees which use a sequence of binary partitions or “splits” on individual variables and the process of splitting continues recursively until ‘terminal nodes’ with final predictor space (Cutler et al. 2012). The non-linear classification algorithm Random Forest (RF) builds and combines these decision trees (CART) to achieve more accurate prediction through averaging or voting among multiple grown forest of trees (Bangira et al. 2019). Flexible discriminant analysis (FDA) is nonparametric regression on ‘optimal’ discriminant coordinate functions, especially useful for large number of predictors (Hastie et al. 1994). Multi-variate Adaptive Regression Splines (MARS) efficiently capture the non-linearity aspect of polynomial regression (Gu and Wahba 1991). MaxEnt (Phillips et al. 2006) uses the maximum entropy method to model species’ geographic distribution with presence-only data through the estimation of a target probability distribution by finding the probability distribution of maximum entropy (‘most spread-out or closest to uniform’).

The combination of the performances of individual models at this stage may be evaluated through true skill statistics (TSS) weighted average in order to achieve better predictive ability with high reliability (Thuiller et al. 2019). TSS is more effective to improve model’s predictive ability compared to the intuitive median or mean based approach (Naimi and Araújo 2016). This is perhaps, attributed to the independence of TSS on the ‘prevalence’ i.e. the ratio of presence to pseudo-absence data (Fielding and Bell 1997). However, each modelling approach should be validated against threshold value of TSS (adopted as TSS $\geq$ 0.70 in this study) before inclusion in the ‘sdm’ (Hao et al. 2019). Each model was calibrated on 70% data for training purpose and the remaining 30% was used to evaluate the predictive power. The sampling procedure for each model was replicated 3 times employing ‘sub-sampling’ and ‘bootstrapping’ method, in order to achieve model stability against small perturbations in the data on which it has been fitted in multivariate regression models (De Bin et al. 2016). After calibration, the consensus model projects future climate scenarios for adopted periods.

2.5 Parameters for performance and accuracy assessment

Standard evaluation parameters for the assessment of a model’s performance are obtained from a confusion matrix describing ‘sensitivity’ i.e. correctly predicted presences and ‘specificity’ i.e. correctly predicted absences (Fielding and Bell 1997). A novel way to represent the performance, graphically, is through the receiver operating curve (ROC) plotting true positive rate (TPR) or sensitivity against false positive rate (FPR). Area under the ROC curve (AUC) accounts for the measure of distinguishing ability between the presence and absence class. The values of AUC range between 0 and 1 with 0 indicating 100% inaccurate and 1 indicating the perfect prediction. An AUC value greater than or equal to 0.70 indicates a fair predictive performance of the model (Mohammadi et al. 2019). Another measure of model performance is True Skill Statistics (TSS) which combines the specificity and sensitivity with its values ranging from − 1 (no agreement) to + 1 (perfect agreement) and a value les than or equal to 0 indicting most of the predictions produced by chance(Fielding and Bell 1997). TSS value between 0.60 and 0.90 indicates fair to good model performance (van Proosdij et al. 2016). We assessed the AUC and TSS values for all the seven performing models from their respective ROC curves and validated their efficiency in the ensemble approach.

3 Results

The explanatory variables and different predictive models participating in the ensemble approach are discussed in the this foregoing section. The model outputs obtained from ensemble approach outline the distribution of the species under consideration for current as well as four SSPs-guided IPCC future climate scenarios followed by the period-wise possible range shifts. The model outputs obtained from ensemble approach outline the distribution of the species under consideration for current as well as four SSPs-guided IPCC future climate scenarios. The period-wise range shifts along with any possible retrieval or successive declination in the habitat suitability are also assessed for better understanding of the future scenarios. The findings are furnished in the subsequent subsections.

3.1 Predictor variables and their responses

The VIF statistics is used to assess the test of multi-collinearity. It suggests the inclusion of six explanatory variables into SDM from the variables shown in Table 1. Among these six variables, some are temperature dependent (e.g., mean diurnal range (Bio2), isothermality (Bio3) and mean temperature of wettest quarter(Bio8)). Remaining variables are precipitation dependent (e.g., precipitation of driest month (Bio14), precipitation seasonality (Bio15) and precipitation of warmest quarter (Bio16)). The only topographical variable used in the study, elevation, was excluded through VIF statistics as it shows high collinearity with Bio8 (Fig. 2). We recall the participation of the precipitation of driest month and temperature of wettest quarter as the distribution of the species in southeast Asia is profound in the regions of cooler summer and heavy precipitation (Rathore et al. 2019).

The predictor-probability relationships for seven participating models are depicted in Fig. 3. More or less each participating model reveals a positive distribution scenario with abundance of precipitation especially for the warmest quarter. However, the distribution comes out to be profound in the regions with less temperature in the wettest quarter (Bio8) suggesting the occurrences of the species in cooler summer or monsoon. Distribution probability is reaching near 80 to 90% beyond certain limit of Bio18 near 1000 cm of precipitation for almost all models. Other precipitation dependent variables, not so much determining as of Bio18, generally shows an increase in distribution with increase in magnitude. However, precipitation seasonality (Bio15) suits the increase in probability of distribution up to a value around 100–150 for most of the models. Isothermality (Bio3) shows a mixed effect for different models. MaxEnt, RF, GAM and MARS suggest the distribution to be maximized for around 50% isothermality whereas GLM indicates the increase in distribution with increase in isothermality though the effect of is not very significant indicating less than 50% distribution at maximum in most of the cases.

The importance of predictor variables on the habitat distribution of the target species is assessed through relative variable importance of each individual variable for the ensemble model and presented in Fig. 4. Certainly, the more the value of variable importance, the more influence the variable has on the model. Precipitation of the warmest quarter (Bio18) imparts the highest influence (relative importance of around 0.50) on the ensemble model followed by isothermality (Bio3) and temperature in the wettest quarter (Bio8). Contributions of the variables in each individual participating model were assessed and it was found that Bio18 imposes the highest relative importance under CART, GLM, RF and FDA, whereas Bio3 has the highest influence on the rest three models GAM, MARS and MaxEnt. Under RF, Bio18, Bio3 and Bio8 impart comparable influence with relative importance values of 0.27, 0.24 and 0.20 respectively with other three variables not much significant. Under Max- Ent, MARS and GAM, Bio3 and Bio8 have higher importance (Bio3- 0.41, 0.43 and 0.42 respectively, Bio8- 0.28, 0.23 and 0.31 respectively) than other variables. Bio18 majorly guides CART, FDA and GLM with its relative importance of around 0.80, where other variables' contributions lie in the range of 0.2 to 0.3. Our concern goes with the contribution of the variables in the ensemble and that is why their importance in individual models is not shown for brevity.

3.2 Model Assessment

The performances of the participating models are assessed through the smoothed ROC curves depicted in Fig. 5 along with the AUC (training as well as test) values. It is observed that MaxEnt and GLM among the seven models show relatively better consistency between calibration and prediction. For all the models, AUC on calibration as well as evaluation come out to be more than 0.90 indicating their high performances (AUC > 0.90 considered high, 0.70–0.90 considered moderate, 0.50–0.70 considered low and < 0.50 considered no better than random) (Phillips et al. 2006). Among all the models, RF shows the best performance in predicting the distribution in case of subsampling (AUC- **Fig. 3** Predictor-probability relationship for different participating models using smoothed curves for each contributing explanatory variables,

0.97) as well as bootstrapping (AUC- 0.99) procedure of sampling. The mean performance of the models is evaluated through AUC and TSS values and presented through scatter plot in Fig. 6. For all the models, AUC values are greater than 0.90 and TSS values ranging between 0.73 and 0.86. From Fig. 5, it is evident that RF performs the best followed by MaxEnt. CART performs the least in terms of accuracy measures though it showed good agreement (Fig. 5) between training and evaluation under both sampling procedures.

3.3 Projection under baseline climate

The probable climatic niche of the target species obtained from the ensemble model, combining the best performances of all the participating models, under base-line climate scenario (i.e. current, 1970–2000) is shown in Fig. 7. The probability of occurrence is predicted to be high in the regions of northeast India, Nepal and southeast China. The species shows the tendency to occupy medium to high altitude region and is majorly, distributed in the temperate forests of the Himalayan region (Pant and Samant 2008). However, strong occurrences are scattered over Chinese Taipei and some places of Indonesia, Vietnam, the Philippines, Bangladesh and Sri Lanka as well. Interestingly, the distribution is skewed towards northeast of India whereas low to very low presence is observed towards west and north-west in spite of high altitude in those regions.

3.4 Prediction under future scenarios

The probable climatic niches of the target species within the study area of our consideration under four SSPs-driven future scenarios for each of the four future epochs (FE1 denoting 2021–2040, FE2 denoting 2041–2060, FE3 denoting 2061–2080 and FE4 denoting 2081–2100) are presented in Fig. 8 through Fig. 11. On an average, all scenarios for all the future epochs suggest a steady decline in the distribution in north and northeast India, south China and Nepal. However, a clear shift in the climatic niche towards higher elevation range in northeast is prominent. The occupancy is more profound in southeast and east China for most of the future scenarios.

At this stage, it comes out to be difficult to assess properly the potential changes incurred in a particular zone from one epoch to another from the probabilistic habitat suitability distribution depicted in Fig. 8 through Fig. 11. These figures may be considered as overview of the distribution scenarios for different periods. To asses the inspection of potential changes, we present the differences occurred in one period with respect to its immediate preceding period evaluated as the distribution-probability difference between the two periods (Fig. 12 through Fig. 15). As the niche distribution probability ranges from 0 to 1 the presentation of period to period change acquires a scale of -1 to 1 where any negative value signifies a declination and positive value represents a gain in the habitat suitability. It is interesting to observe that even under the most favourable sustainable path (SSP1) there is a notable decline in the distribution of the species in the territories of north and north-east India and in the province of Nepal in the future over all four epochs (Fig. 8). The probability of distribution is prominent in east and southeast China, up to 80 to 90% in some places. A clear range-shift of the niche suitability towards northeast is visible suggesting the plausible habitat of the species in east and southeast China in future.

3.4.1 Prediction under ssp126

It is observed from Fig. 12a that in the near future (FE1) around 10–20% decline in the distribution is prominent in the Himalayan region of northeast India (especially in Arunachal Pradesh, Assam and Nagaland), Bhutan and Nepal. However, a strong increase up to 80% in the distribution is observed in east and southeast China. The declination is also prominent in the Philippines and Chinese Taipei. A close inspection to Fig. 12b reveals that major change in the distribution does not occur between the epochs of FE1 and FE2 except some parts of northern India in the Himalayan valley (Jammu and Kashmir, Uttarakhand and Himachal Pradesh), east China (near Shenyang), south-east China (near Changsha), west Japan (along the shore of the sea of Japan), mid Indonesia (Borneo), south Malaysia and north Singapore where still a declination of 10 to 30% is observed. The change in terms of decrease in the distribution between FE2 and FE3 (Fig. 12c) draw attentions particularly for Malaysia, Indonesia and

Singapore. For Indonesia, the suitability of species' distribution notably shifts to mid of the country from rest of the part in contrast to the previous epoch. Interestingly, the most sustainable pathway of global climate change still show a noticeable decline in the distribution in the far future of FE4 (Fig. 12d) in north India (Punjab and Himachal Pradesh), a small portion of east China and Cambodia.

3.4.2 Prediction under ssp245

In contrast to SSP1, the middle of the way SSP2 suggests an increased declination in the distribution especially in north India (in the states of Himachal Pradesh and Uttarakhand) and Nepal. The strong probability of occurrences in some places of south-east China obtained as around 80% under SSP1 also decreases to 50–60% under SSP2 (Fig. 9). For better scrutiny, the periodwise change in the distribution under SSP2 is presented in Fig. 13. The regions of north-east India and Nepal draw attention suffered by a probable decrease of 20–30% in the species' niche in the nearest future of FE1 (Fig. 13a). This declination continues for the next epoch, FE2, extending into the states of Uttarakhand where around 30–40% decrease with respect to FE1 is noticed (Fig. 13b). However, the distribution probability in east and southeast China increases rapidly up to 90% in FE1 with respect to the base-line scenario followed by a stability and slight further increase in FE2. It should be noted from Fig. 13b that the matter of concern lies with the regions of Uttarakhand and Nepal suffered by consecutive steady declination in two future epochs. The change in the distribution in FE3 with respect to FE2 is not profound though indicating a decrease of around 10% in a vast area and up to 20% decline in the states of Jammu and Kashmir and Himachal Pradesh of north India and Wuhan in east China (Fig. 13c). Interestingly, further declination of around 30% is observed in FE4 in Uttarakhand and Himachal Pradesh and a major part of Myanmar and Thailand (Fig. 13d).

3.4.3 Prediction under ssp370

Under the socio-economic path of regional rivalry (SSP3), the strong possibility of niche is observed to occur in north-east India, east and south-east China and Japan whereas a very poor distribution is observed in the regions of Myanmar, Vietnam, Indonesia and the Philippines for all the future epochs (Fig. 10). From Fig. 14 it is clear that north and north-east India along with Nepal possess a strong declination extending up to 20–30% in the habitat distribution in near future of FE1 with respect to the current scenario (Fig. 14a). This decrease is also visible for some places of Vietnam, Indonesia and the Philippines. Surprisingly, the declination in the habitat in north Indian regions of Uttarakhand and Himachal Pradesh is not alarming, even showing a scattered increase, under this SSP in FE1 in contrast to the previous two scenarios. However, a prominent decrease up to 30–40% in the states of Uttarakhand is observed in FE2 in comparison to FE1 (Fig. 14b). It is also observed from Fig. 14b that there is a 20–30% declination in the habitat distribution in the Indian states of Manipur and Nagaland. The next epoch of FE3 possesses a little differences with respect to the previous one (Fig. 14c), showing less than 10% decrease or increase in all over the study area. However, a notable recovery (up to 40%) is observed in a narrow region of the state of Uttarakhand. Moreover, 10–20% declination is still noticeable in some places of Nepal and Vietnam. The future epoch FE4 attains a retrieval phase (Fig. 14d) with respect to FE3 in some regions of the study area whereas strong declination of 30–40% with respect to FE3 is observed in the states of Uttarakhand, Nagaland and Manipur of India, some places of Thailand and Indonesia. Notably, the decrease in the habitat in FE4 with respect to FE3 is the most alarming in this projection pathway (SSP3) among all the scenarios considered so far.

3.4.4 Prediction under ssp585

The matter of concern in terms of declination in species' niche in the near future of FE1 with respect to current scenario lies with Nepal, north-east India (Arunachal Pradesh, Nagaland and Manipur) and Chinese Taipei under fossil-fuelled development (SSP5) (Fig. 15a) whereas a strong increase up to 80% in the whole region of east and south-east China is observed. In FE2, a little change from FE1 is visible (Fig. 15b), though up to 30% declination is probable in the regions of Jammu and Kashmir, Thailand and Indonesia. A slight retrieval in FE3 from FE2 is noticeable in Nepal and some parts of the states of Uttarakhand (Fig. 15c) whereas a worsening up to 20% with respect to the previous epoch is present in Punjab, Jammu and Kashmir, west Indonesia and some parts of east China. Alarming decrease up to 30–40% in the states of Punjab, Uttarakhand, some parts of Nepal, middle to southeast Indonesia, some parts of Myanmar and Indonesia is noted in the far most future epoch of FE4 with respect to its preceding one (Fig. 15d). However, the regions of east and southeast China gain a stability with a minor change from the period of FE3 under this pathway till the end of the century, claiming to be the most suitable future habitat under SSP5.

4 Discussion

A broad-sale (spatial and temporal) assessment of the impact of climate change on the distribution of the endangered important species leads us to the discussions regarding its conservation mechanisms. A broad-sale (spatial and temporal) assessment of the impact of climate change on the distribution of the endangered important species leads us to the discussions regarding its conservation mechanisms.

4.1 Ecological response of the species

The distribution of the species shows positive response with the abundance of precipitation whereas it decreases with the increase in temperature (Fig. 3). This suggests that the habitat suitability of *T. wallichiana* is associated with ample rainfall and cold temperature. Strong contributions of the precipitation of the warmest quarter and isothermality are evident in guiding the species' distribution. The Himalayan mountainous regions facilitating abundance in monsoon rainfall associated with cooler temperature provides with the ecology for harbouring the species. As a result, the majority of the current distribution is found to occur within the belt of Himalayas with about 80–90% probability of occurrences in north and northeast India, Nepal, Bhutan and south-east China (Fig. 7). These areas are associated with north-facing slopes retaining moisture, cold and humid environment (Måren et al. 2015). *T. wallichiana* being a moisture-loving species shows its abundance in these north-facing slope regions.

4.2 Effect of climate change on species' distribution

All possible projection pathways (ssp126, ssp245, ssp370 and ssp585) suggest a clear decay in the niche distribution in the regions of north and north-east India along with Nepal and Bhutan and a remarkably strong increase in east and south-east China in the near future of 2021–2040. Thus, prominent indication of range-shift towards northeast to the montane tree-line regions of south-east China is evident. This is possibly due to the warming of lower elevation regions and precipitation irregularities. Researchers (Rathore et al. 2019; Rana et al. 2020) have also noticed such shift for this species as well as similar other species in 2050s and 2070s. However, less attention was paid on the distribution in the regions of Myanmar, Vietnam, the Philippines and Indonesia where some real occurrences and possible distribution have been found in the current scenario (see Fig. 1 and Fig. 7). Interestingly, niche loss is not alarming in the near future (FE1) in these regions. On the contrary, effects of climate change is notably profound in these regions in FE2 for all the future pathways (see Fig. 12-15b). The regions of Uttarakhand, Himachal Pradesh and Nepal also draw attention suffered by further declination in habitat in FE2 over FE1. This progressive declination continues to FE3 as well as FE4 in some parts (see Fig. <link rid="fig8">12</link>-15c and 12-15d). However, the regions of southeast China shows a stability with a minor change with preceding period offering a suitable niche up to the period of 2061–2080 (FE3). The future epoch of FE4 shows stability of distribution in southeast China under most of the SSPs. A slight increase in the probable niche is noticeable in the high altitudinal regions of south China (Tibet) in the far future of end of the 22nd century under all pathways. This shift, though sounds to be astonishing, is possibly guided by the shift in climatic envelop in far future. However, the suitability of niche in Myanmar, Vietnam and Indonesia is declining as well throughout the periods.

4.3 Inter-comparison of projection pathways

Among all the shared socio-economic pathways, SSP5 comes out to be the most alarming in terms of the declination in the habitat suitability in the nearest future period. This decrease is possibly caused due to the indiscriminate use of fossil fuels associated with the highest temporal slope of CO2 emission rate under this pathway (Eyring et al. 2016; O'Neill et al. 2016). Though the most sustainable pathway (SSP1) shows a declining slope of CO2 emission rate in this period, the emission amount is still higher than the baseline with its peak near 2020. As a result, effect of warming is visible, though not alarming, in this period. Other two pathways having positive emission slopes in this period impart **Fig. 14** Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP370; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

probable range-shifts towards northeast.

Contrast between the projection scenarios of SSP3 and SSP5 is interesting for the next period of FE2. The regional rivalry and competitiveness in SSP3 with a lesser CO2 emission amount than SSP5 imparts significant declination in the regions of north India, Myanmar, Singapore and some parts of east China, whereas increase in habitat suitability is present in Vietnam and Beijing. On the contrary, fossil-fuelled development SSP5 imposes notable declination in Indonesia and Cambodia. Increase in habitat suitability in east and northeast China is more in SSP5 than SSP3. Also, declination in India is less in SSP5 than SSP3, in spite of higher emission amount of greenhouse gases in SSP5, possibly due to optimistic human development with controlled conservation mechanisms. Interestingly under SSP2, the emission amount reaches to the peak in this period. As a result, decrease in the niche in North India and Nepal and shifting towards east China are clearly visible owing to the shift of climatic envelop due to global warming. The sustainable pathway SSP1 does not impart a major change in the species **Fig. 15** Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP585; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

distribution except for northeast China.

During the future-period of FE3, increase in habitat suitability is found in northeast Mongolia under SSP1 and SSP2 and in east Russia under SSP3. This is due to possible shift of climatic-niche towards northeast over the preceding period. It is noted that a slight increase in the habitat suitability occurs in Nepal under SSP5 in this period over FE3 indicating a retrieval phase in this region. The most contrasting phenomenon under different SSPs in this period is observed in Indonesia. Under SSP1, northeast Indonesia shows to be alarming in decay whether slight suitability is observed in mid of the country. Whereas, under SSP2, decay in habitat is observed to occur in some places of mid of the country. Habitat suitability slightly increases all over the country under SSP3 where a strong declination in west of the country is noted. Attainment of a stability (a slight to no change) in more or less the whole study area under SSP5 in this period over FE2, in spite of increasing CO2 emissions, is possibly attributed to the drastic change in the previous epoch (FE3 falls beyond the point of inflection of CO2 emission curve).

Strong decay in habitat suitability (more than 30%) in the regions of north and northeast India and Nepal along with a possible increase (10–20%) in east Russia and northeast China than the preceding period are visible in FE4. However, the projection pathway of SSP3 does not yield such trend in this period of far future. Rather, some places of Middle East India show an increase in habitat suitability under this pathway. A clear indication of range-shift towards northeast is visible in FE4 from FE3 under SSP2. This shift is attributed to the strong decay in niche suitability in north Indian Himalaya associated with an increase in southeast China. The most sustainable projection pathway expectedly does not yield any major change between the periods of FE3 and FE4 except for some places near Thailand and Vietnam with a decay (more than 20%) in habitat suitability. Thus, different projection pathways may yield drastically different habitat suitability scenarios at different phases of time in future. Some places of north and northeast India and Nepal draw attention with successive declination in habitat suitability for most of the projection scenarios considered. Conservation strategies should be adopted and monitored time to time for those places.

5 Conclusion

The present study investigates the effect of the climate change on the distribution of T. wallichina with the help of an ensemble species distribution model. Different plausible future climate scenario driven by different socio-economic pathways for four different future epochs are adapted to predict the future distribution of the species. The period wise change in the distribution of suitable habitat is also assessed in this study. From a detailed time-frame estimation of the niche distribution, following conclusions may emerge out.

1. A clear range shift in the suitable niche distribution is visible towards north and north east in future from the northern part of India and Nepal. Thus urgent conservation mechanism is required in those areas.
2. The projection pathway driven by fossil-fuelled development imparts the most alarming effect in terms of declination in the habitat suitability in the nearest future. Along with other projection pathways, even the most sustainable pathway shows declination in the habitat suitability.
3. On the foregoing period, the projection pathway of regional rivalry may come out to be more devastating than the pathway of fossil-fuelled development. Thus conservation strategy should be carried out based on the niche distribution prediction driven by all possible projection pathways for any period of time.
4. The prolonged effect of the climate change is alarming in northern India and some places of Vietnam and The Philippines requiring conservation mechanism to be followed up time to time.

Based on spatial-temporal assessment of suitable habitat distribution of an endangered Himalayan medicinal plant our study suggests similar assessments of other threatened species to come up with the best conservation strategies across time to time. Further study involving different explanatory variables like soil parameters, aspect, slope, land use and land cover etc. may be evaluated for better estimation of the future distribution of the species' suitable habitat.

Declarations

Acknowledgements

The authors thank the officials of the department of Information Technology of Jadavpur University, Salf Lake Campus, Kolkata, West Bengal, India for permitting to access the laboratory and assisting during work.

Funding *The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.*

Author Contributions All authors contributed to the conceptualization. Data collection and analysis were performed by Dhriti Chakraborty. Somnath Mukhopadhyay and Kartick Chandra Mondal mutually supervised the work. The first draft of the manuscript was written by Dhriti Chakraborty and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Competing Interests The authors have no financial or non-financial interest to disclose.

Data Availability The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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Figures

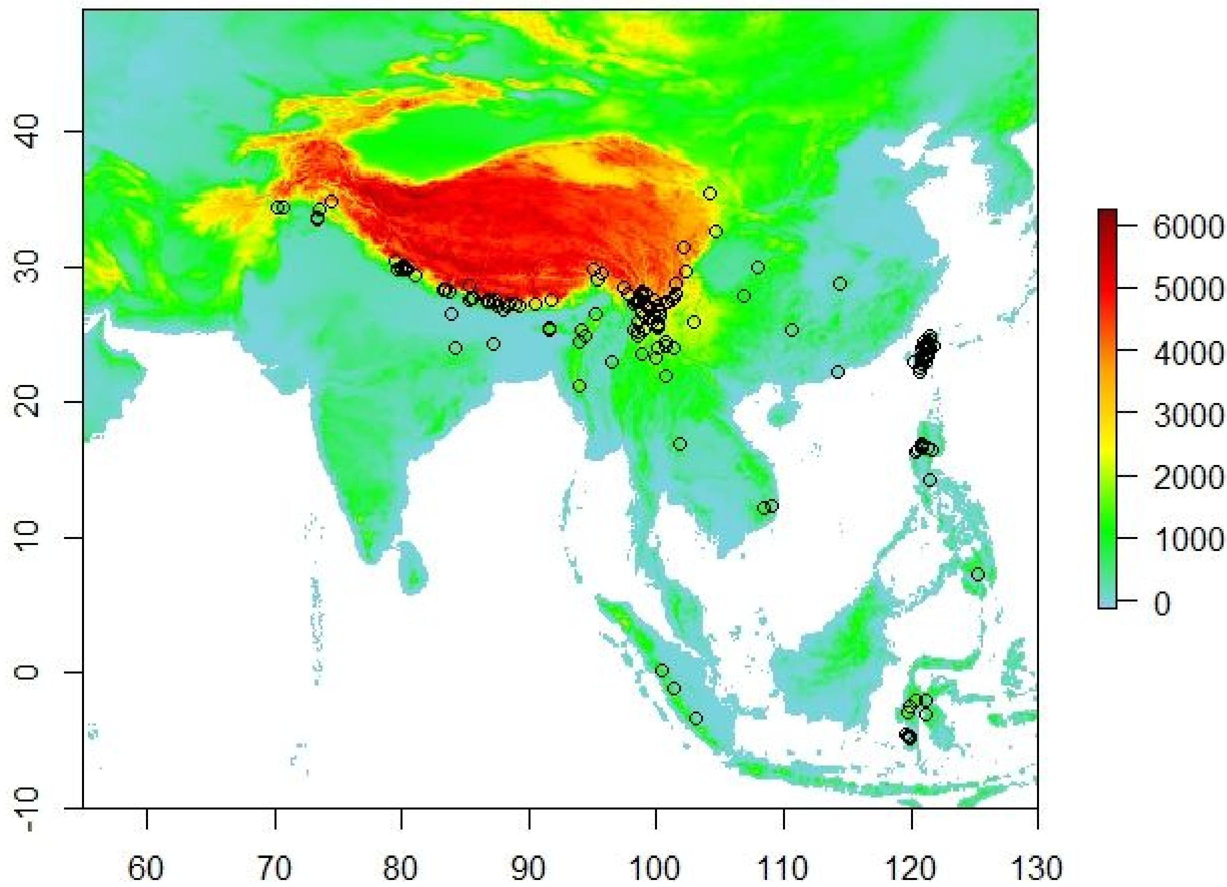

Figure 1

Study area layered with different elevation range along with species occurrence points

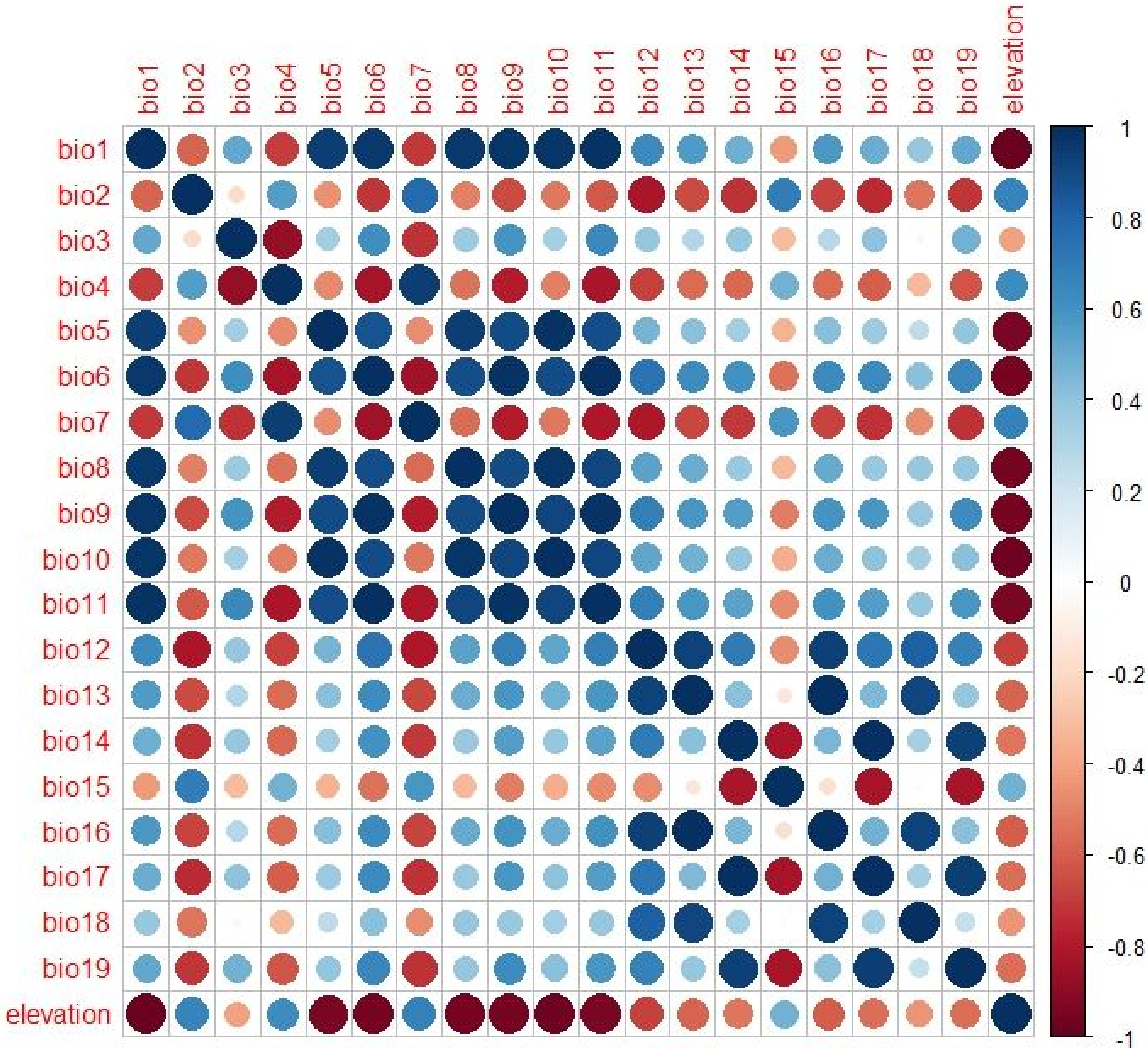

Figure 2

Collinearity matrix for predictor variables (dark blue and red indicate high collinearity and light colours indicate low collinearity)

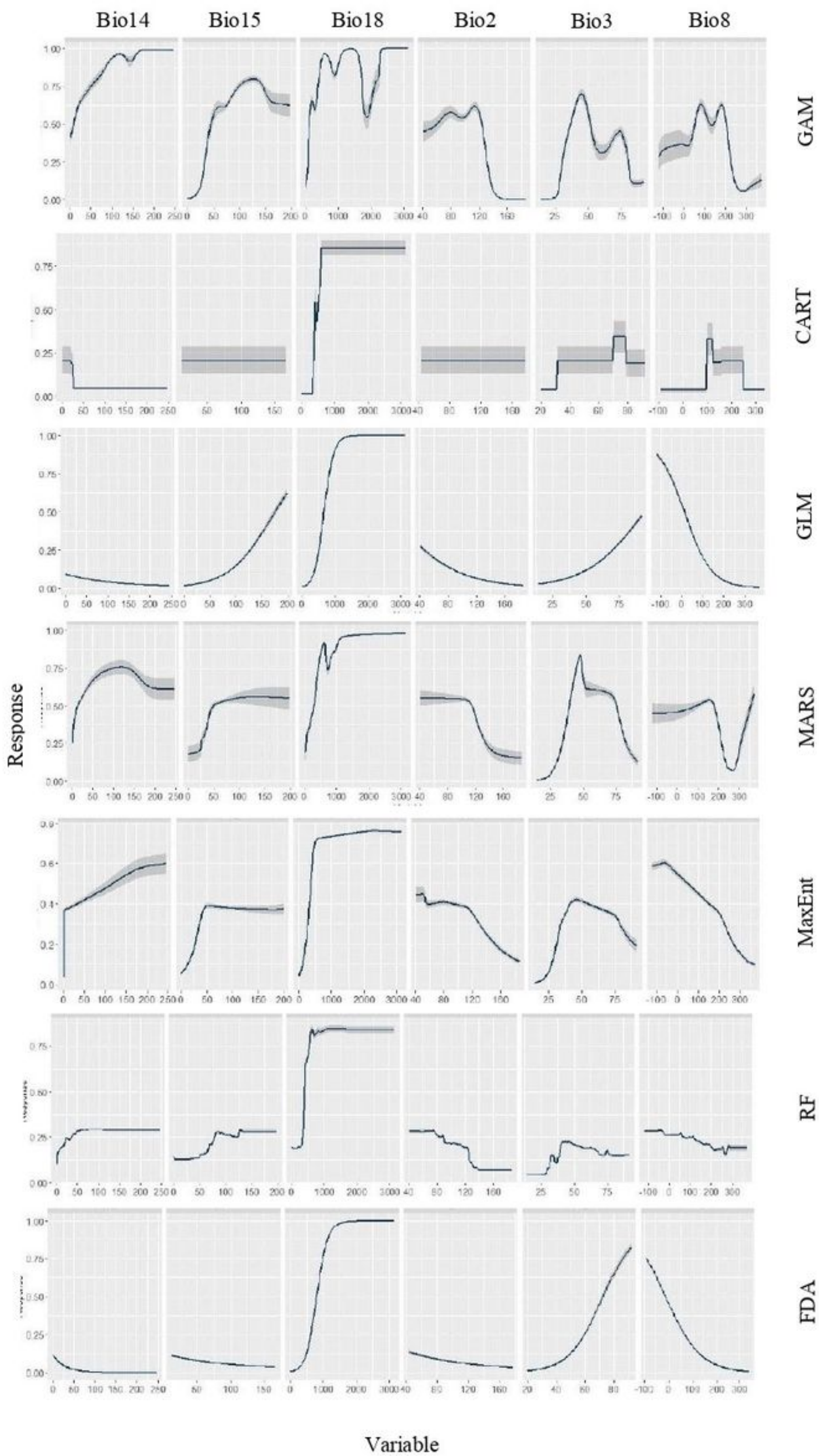

Figure 3

Predictor-probability relationship for different participating models using smoothed curves for each contributing explanatory variables,

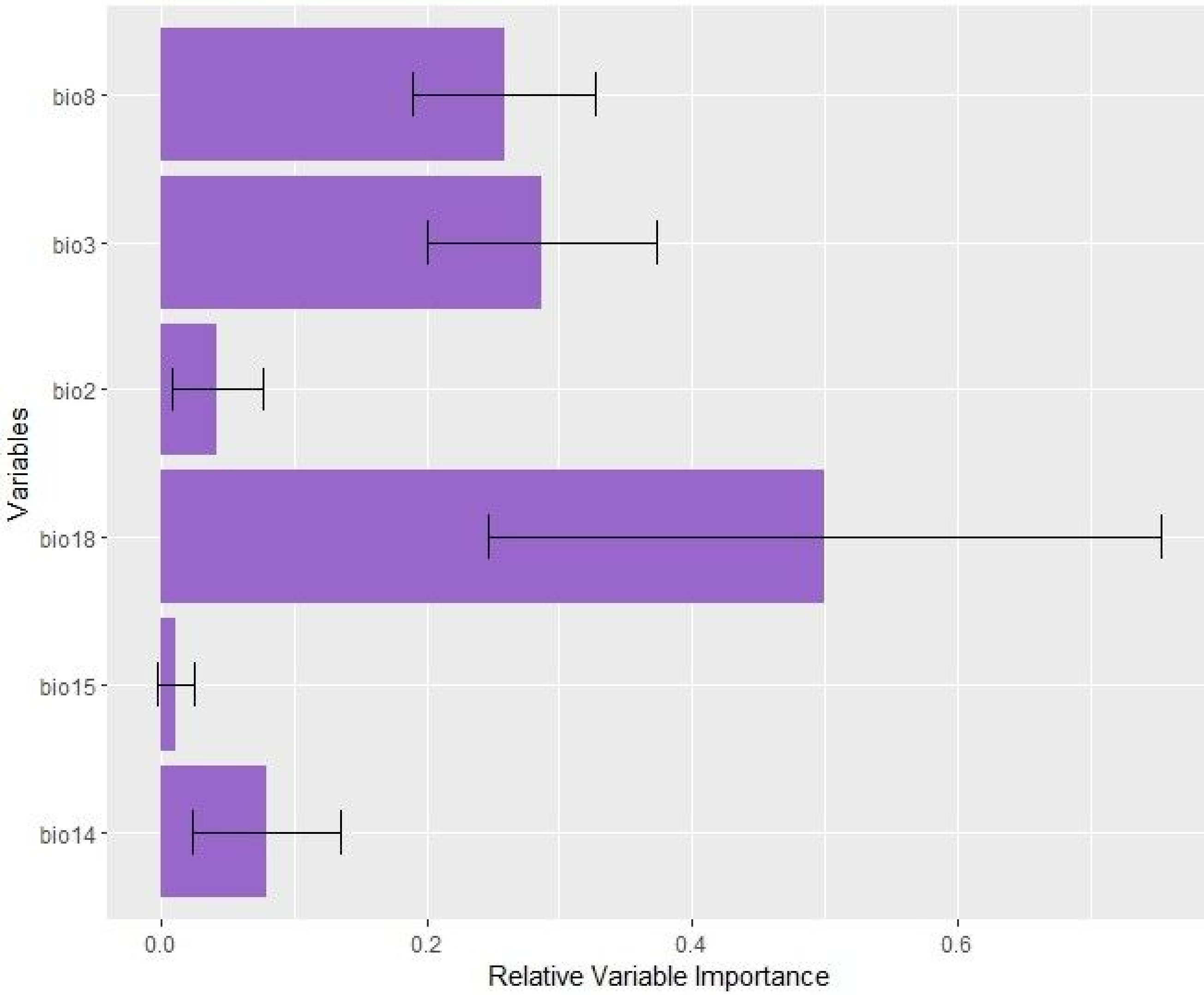

Figure 4

Contribution of variables in ensemble model assessed in terms of relative variable importance.

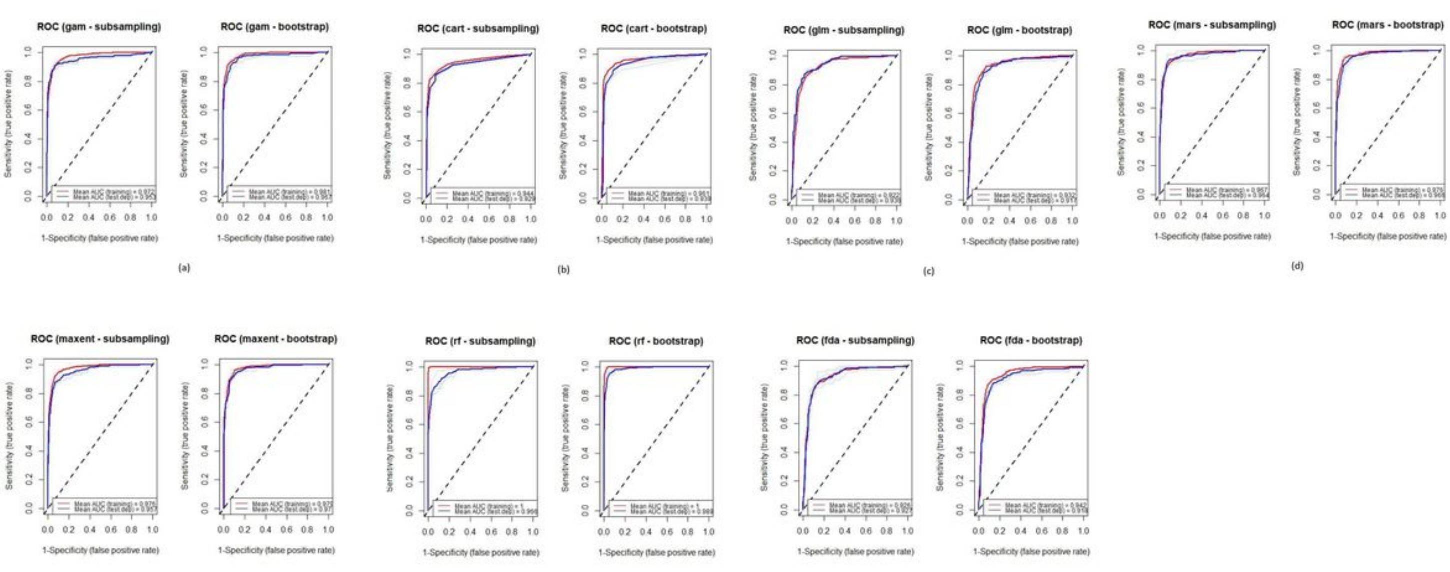

Figure 5

Results of the Receiver Operating curve for different niche modelling algorithm participating in ensemble i.e. (a) GAM, (b) CART, (c) GLM, (d) MARS, (e) MaxEnt, (f) RF, (g) FDA; for each of the two sampling procedure adapted

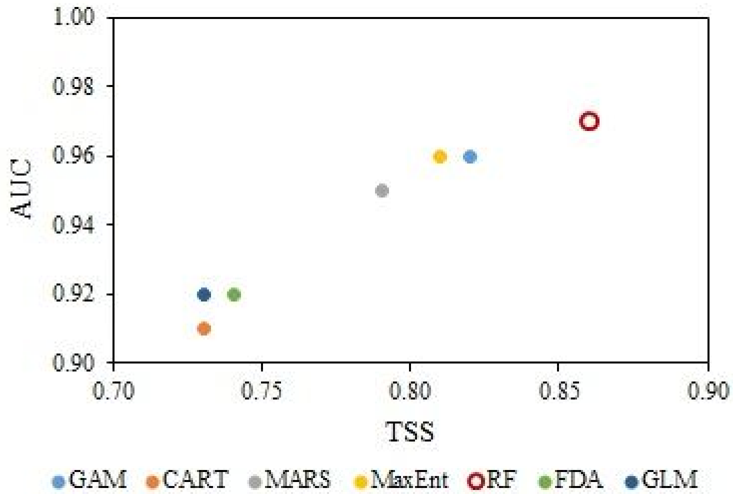

Figure 6

Efficacy of the participating models in the ensemble in term of AUC and TSS

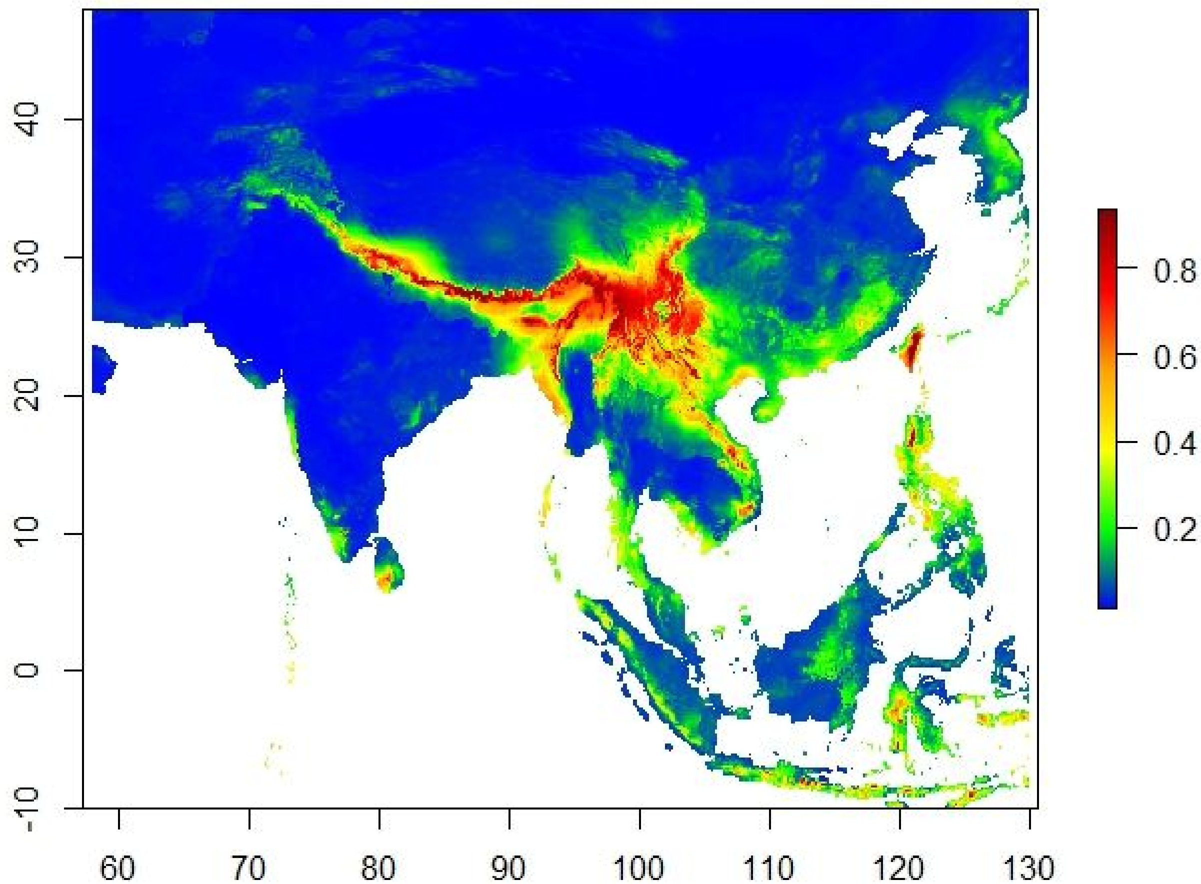

Figure 7

Probabilistic habitat suitability of T. wallichina in the study area of consideration under current (1970-2000) climatic condition in colour mapping with the color code indicated on the right side of the figure (blue to sky blue indicating low to very low probability of presence and red to dark red indicating high to very high probability of occurrences).

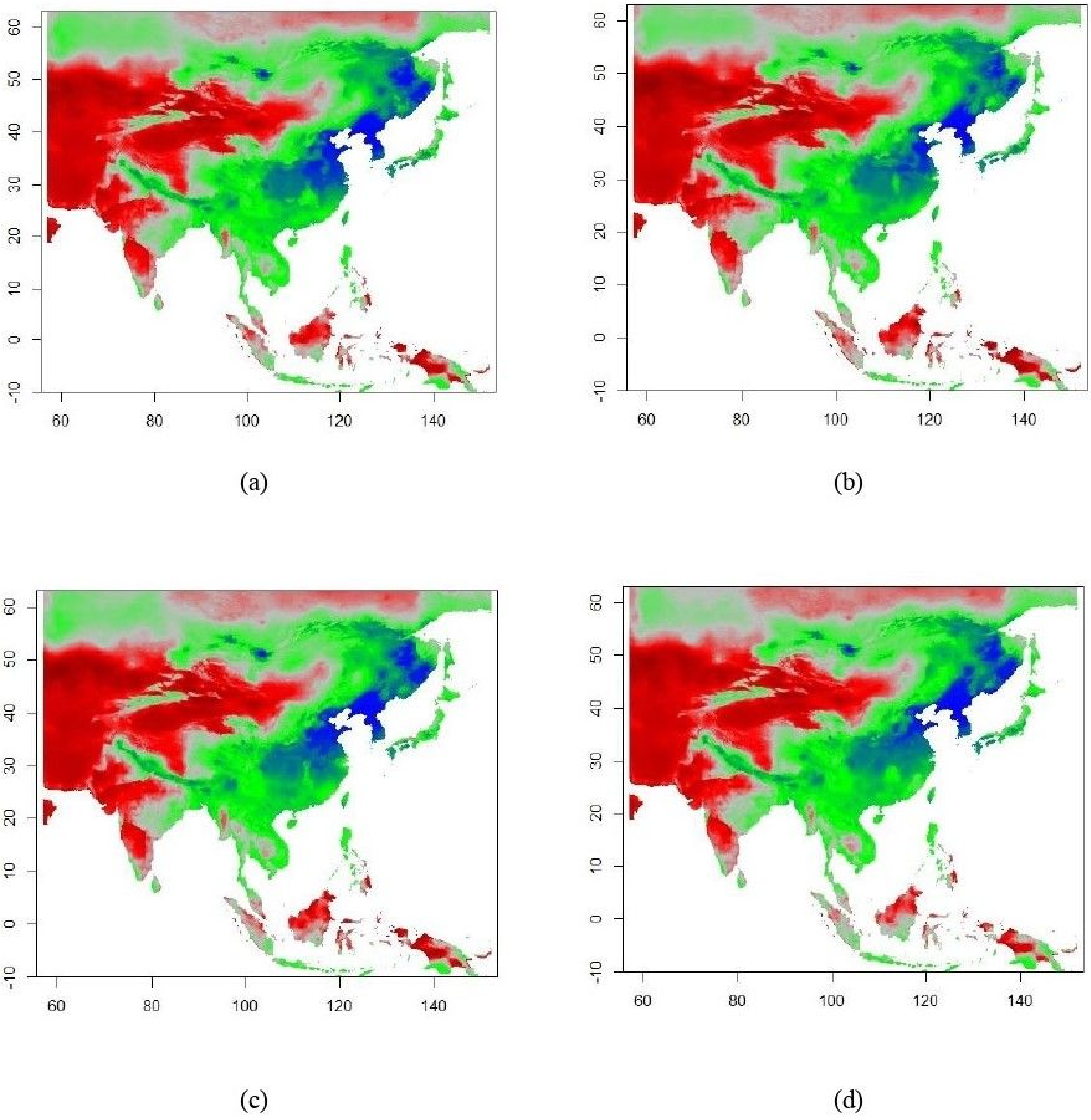

Figure 8

Probabilistic niche distribution under future climatic scenarios driven by the most favourable projection pathway of SSP126 for four different future periods i.e. (a) FE1 (2021- 2040), (b) FE2 (2041-2060, (c) FE3 (2061-2080) and (d) FE4 (2081-2100).

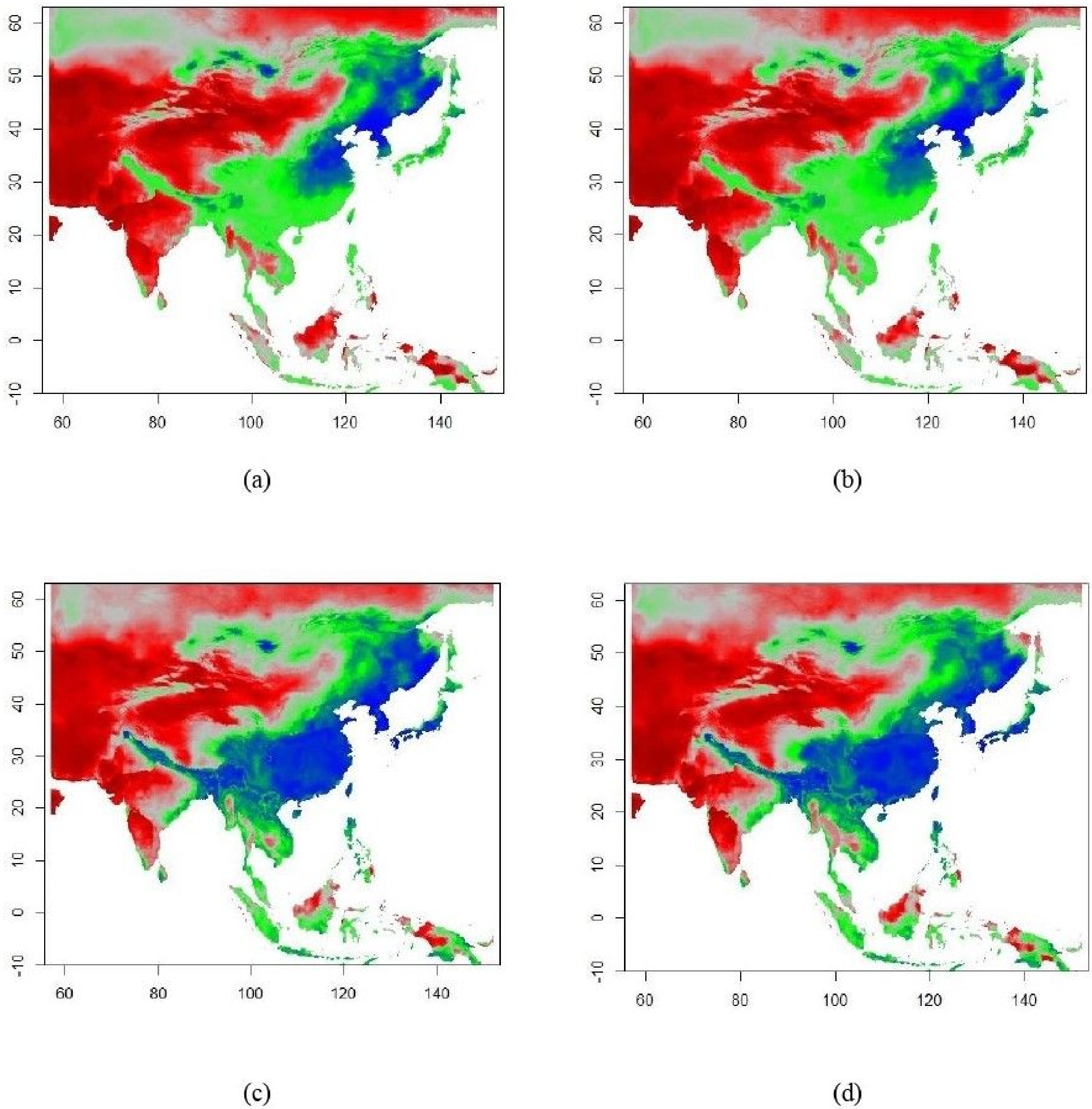

Figure 9

Probabilistic niche distribution under future climatic scenarios driven by middle of the way of SSP245 for four different future periods i.e. (a) FE1 (2021-2040), (b) FE2 (2041-2060, (c) FE3 (2061-2080) and (d) FE4 (2081-2100).

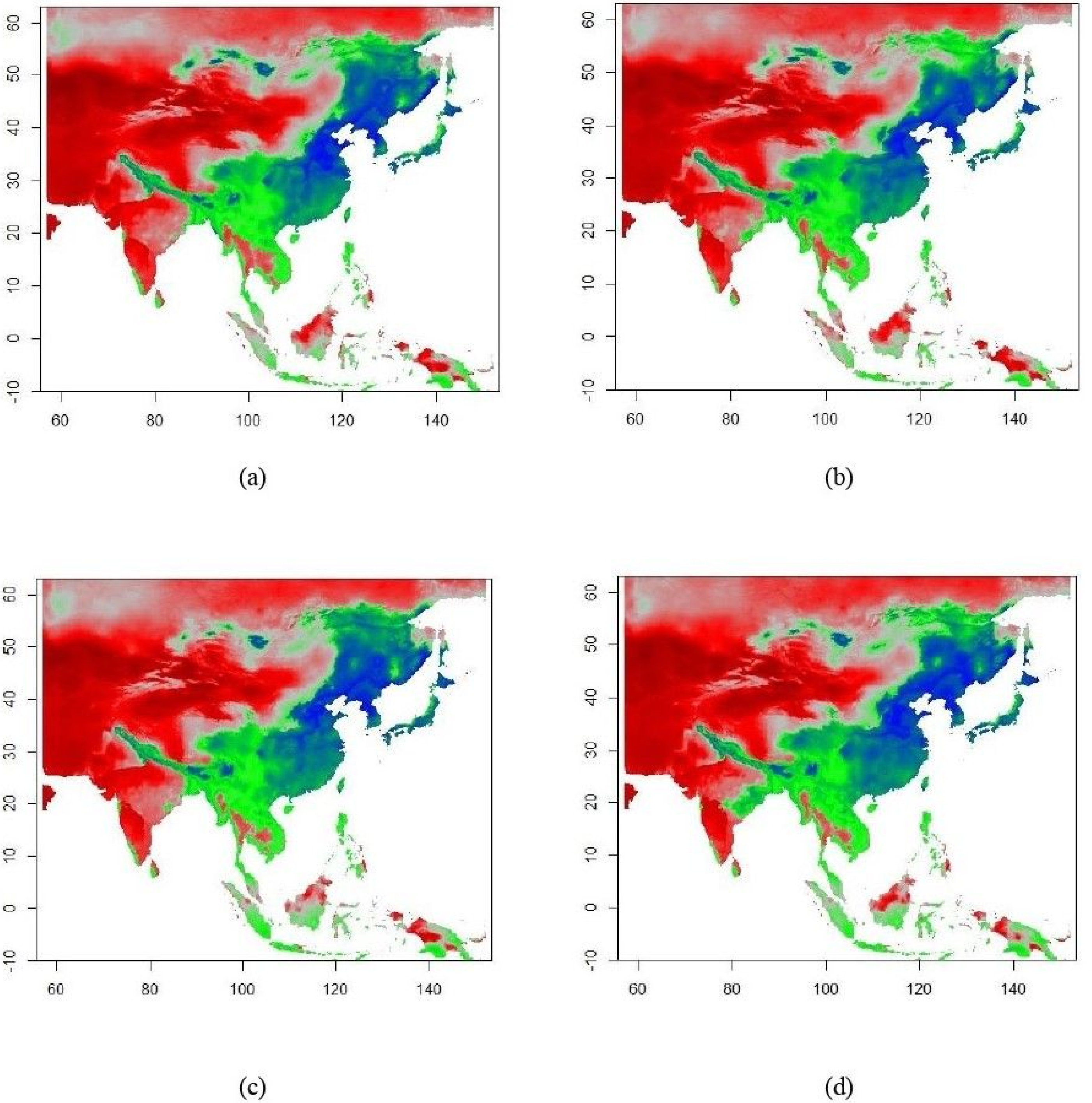

Figure 10

Probabilistic niche distribution under future climatic scenarios driven by regional rivalry of projection pathway of SSP370 for four different future periods i.e. (a) FE1 (2021-2040), (b) FE2 (2041-2060, (c) FE3 (2061-2080) and (d) FE4 (2081-2100).

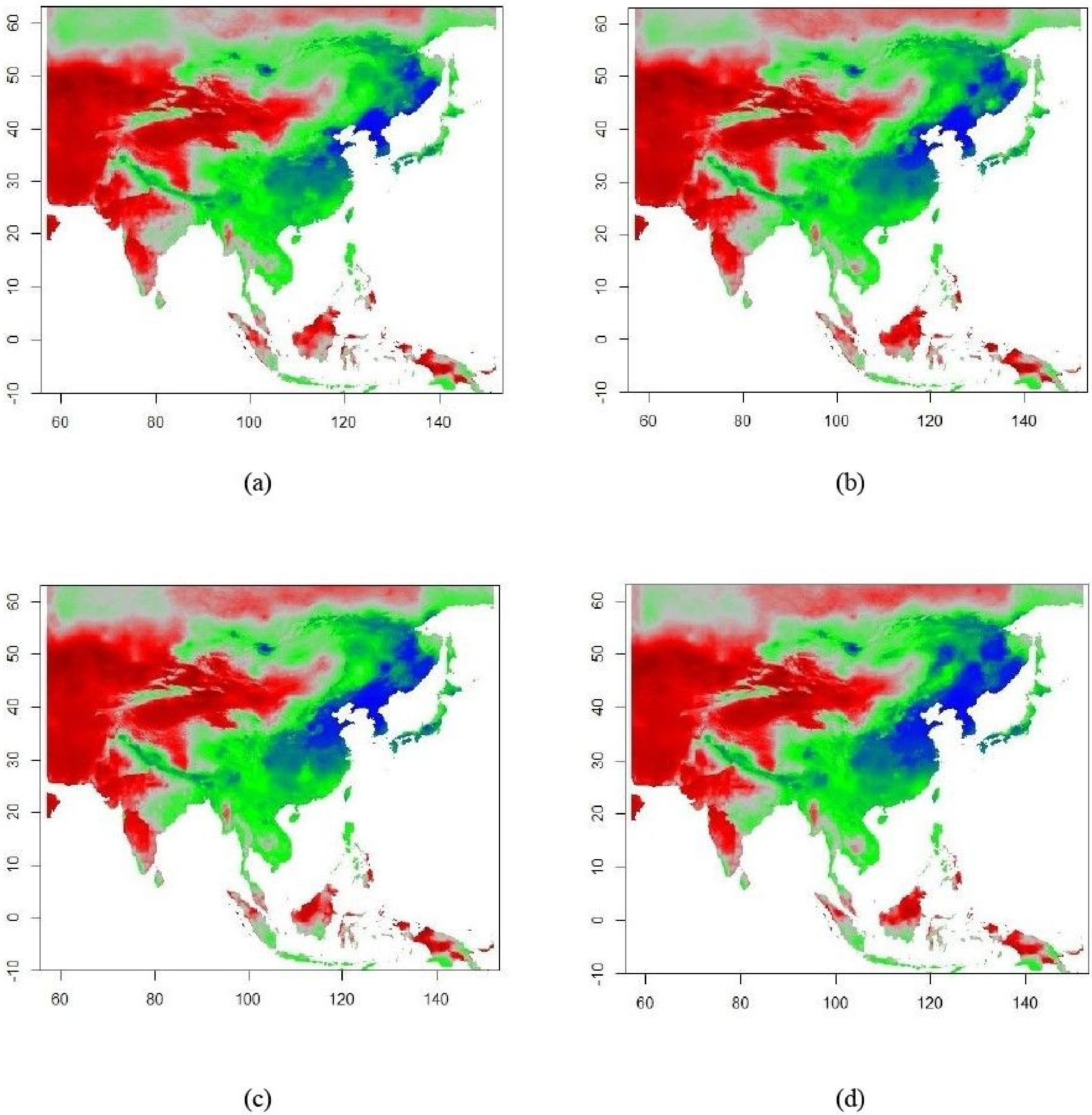

Figure 11

Probabilistic niche distribution under future climatic scenarios driven by the fossil-fuelled development of SSP585 for four different future periods i.e. (a) FE1 (2021-2040), (b) FE2 (2041-2060, (c) FE3 (2061-2080) and (d) FE4 (2081-2100).

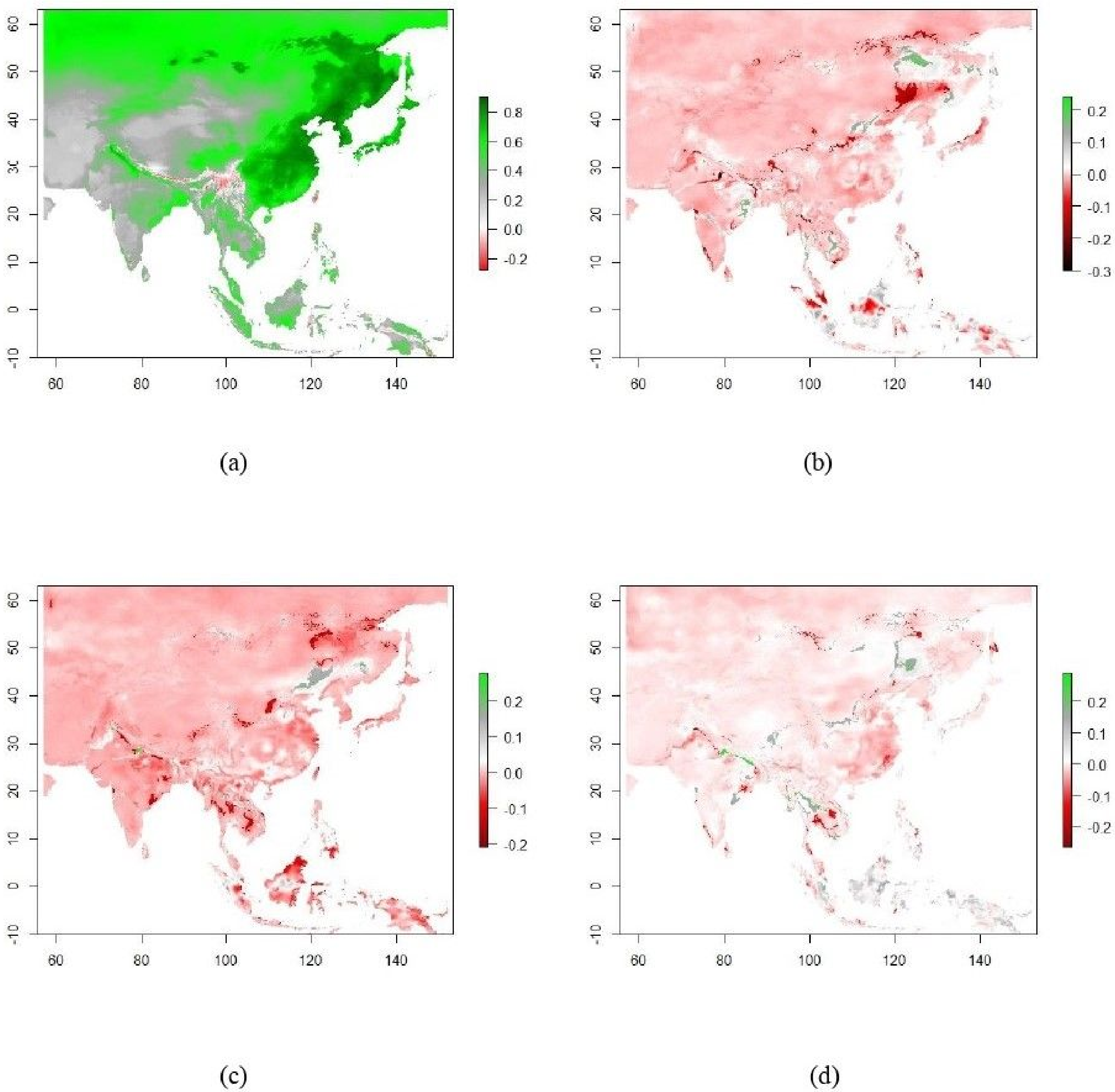

Figure 12

Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP126; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

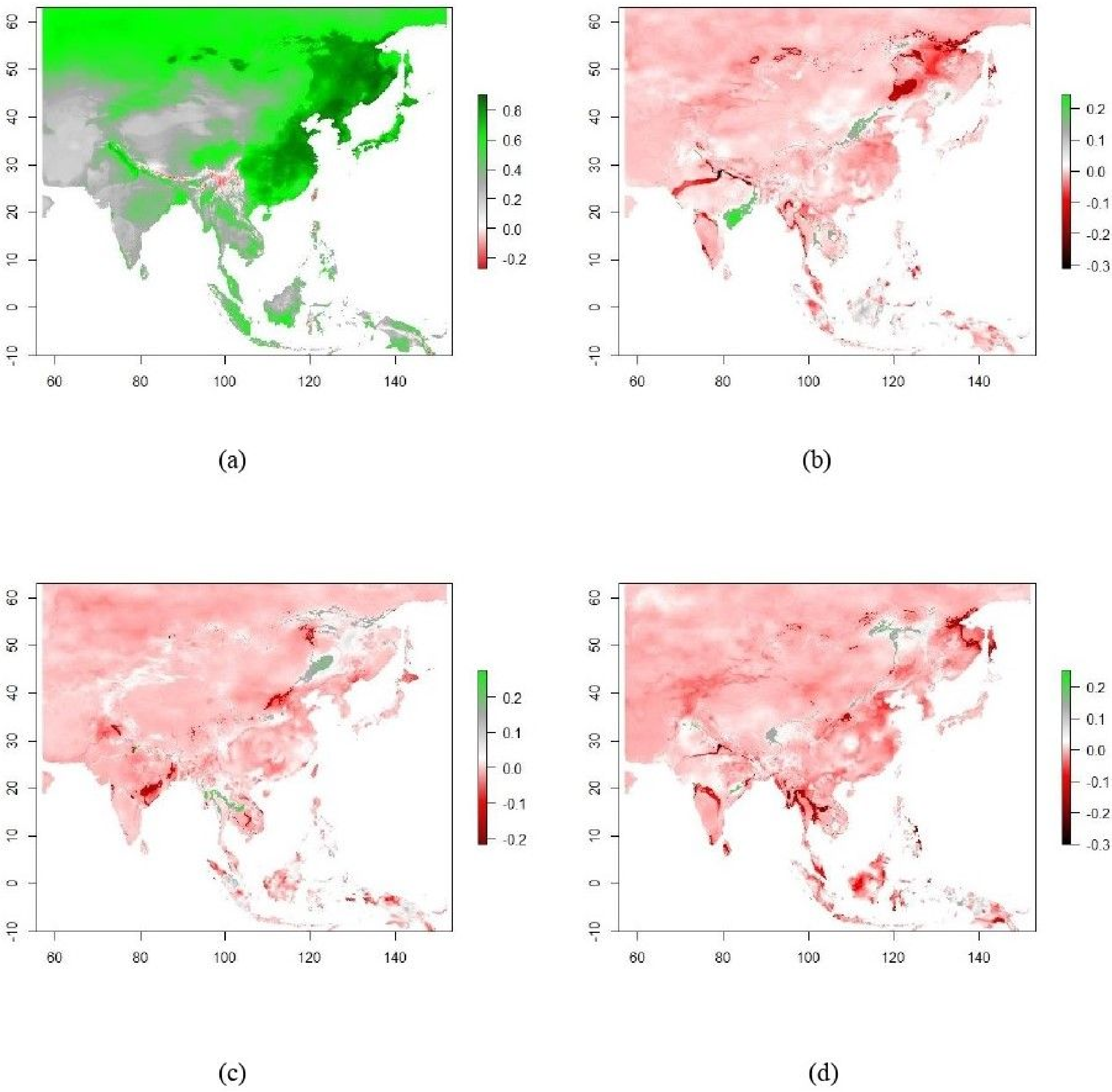

Figure 13

Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP245; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

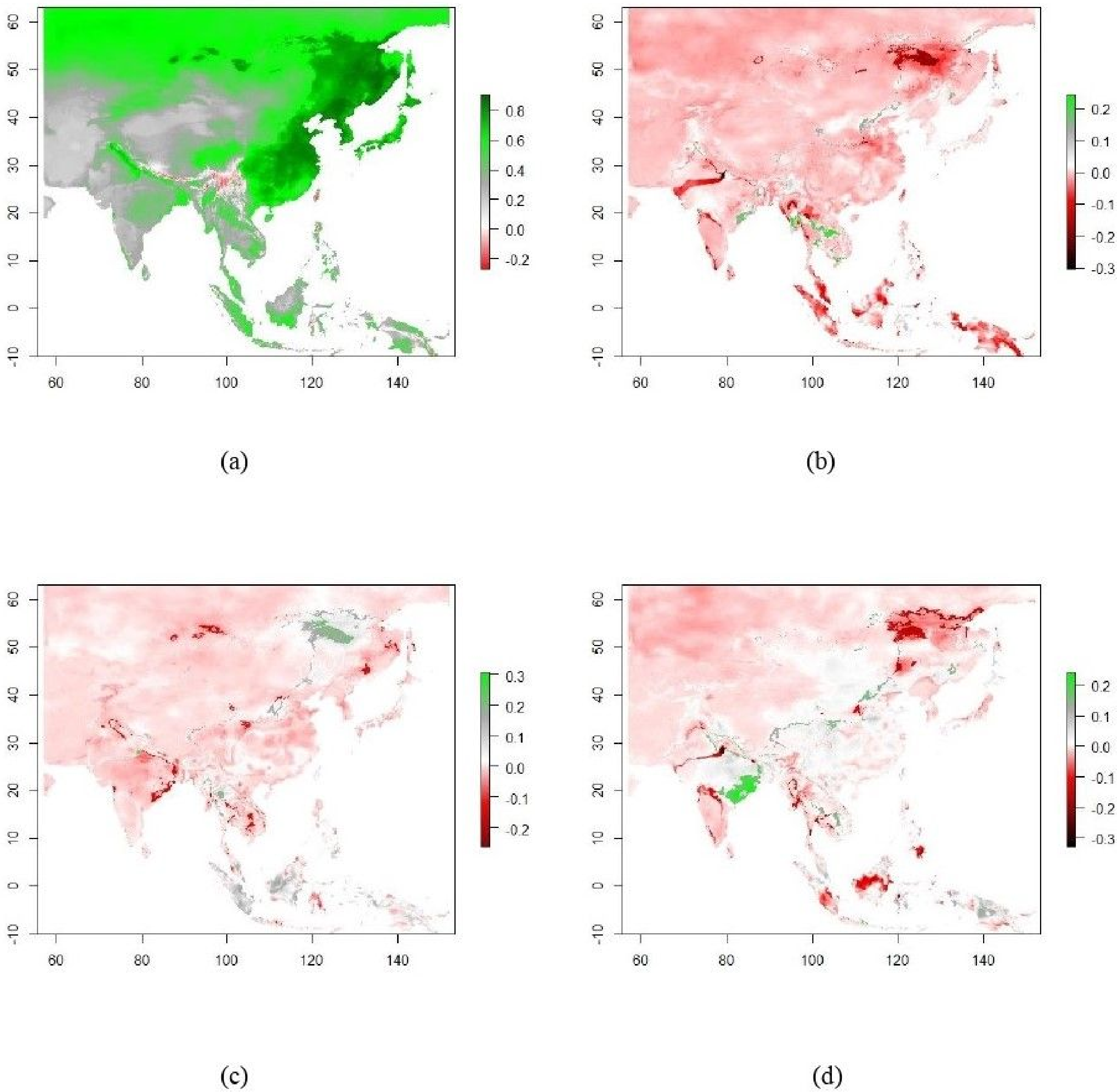

Figure 14

Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP370; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

probable range-shifts towards northeast.

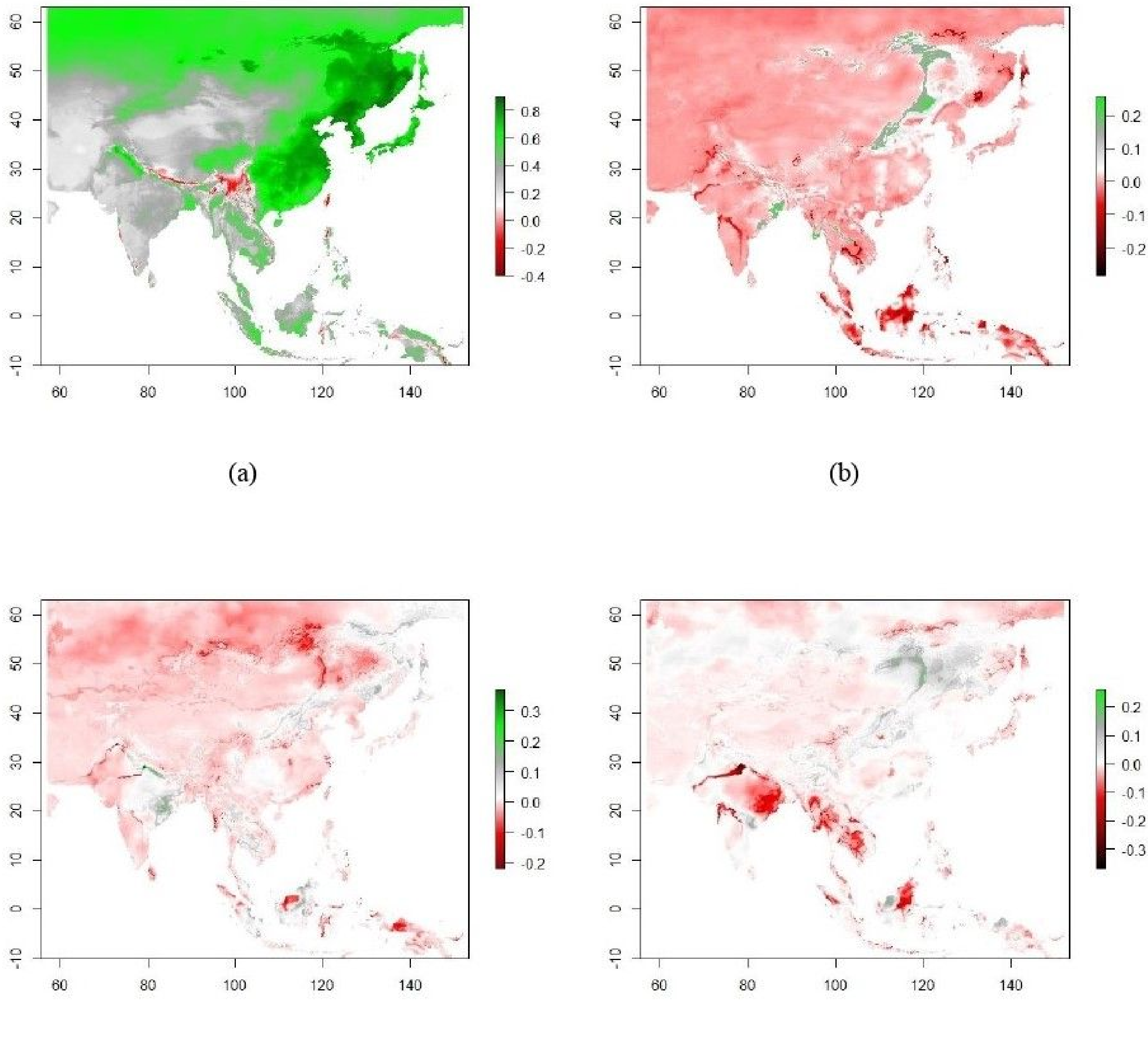

Figure 15

Period to period (on succession) variation in habitat suitability distribution under the projection pathway of SSP585; (a) differences incurred in FE1 over baseline scenario, (b) differences incurred in FE2 over FE1, (c) differences incurred in FE3 over FE2, (d) differences incurred in FE4 over FE3.

distribution except for northeast China.