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Impacts of Climate Change on Hazelnut (*Corylus avellane* L.) Cultivation in Bhutan

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Abstract

This study was conducted to evaluate the factors contributing to the spatial distribution of European hazelnut (*Corylus avellane* L.) in Bhutan and determine the suitable areas for cultivation of the crop in the near future (2040-2060) and distant future (2060-2080) under different climate scenarios of Representative Concentration Pathway (RCP) 2.6 and RCP 4.5 in Bhutan. The environmental layers were obtained from WorldClim and processed in ArcGIS and R software prior to running the model in MaxENT. The multicollinearity test showed six bioclimatic factors and three topographical factors contributing to the distribution of European hazelnut in Bhutan. The findings indicated that approximately 10,744.8 sq. km is potential for hazelnut crop cultivation in Bhutan, with Wangduephodrang District harboring the highest area of 1,227.9 sq. km (11.4%) and Gasa district the least at 130 sq. km. The primary factors affecting climate suitability of European hazelnut were elevation, contributing 87.9%, followed by Bio3 (3.7%), BIO2 (3%), and Bio1 (2.5%), and the least factors were Bio15 and aspect at 0.1% each. The model showed that the most suitable elevation for the growth of hazelnut ranges from 1500-1900 masl. The suitability area for the crop projected under the RCP 2.6 and RCP 4.5 scenarios showed a decline in the near future (2040-2060) in the southern part of the country and a slight increase in the distant future (2061-2080) in Central, Eastern, and Western Bhutan. Therefore, there is an urgent need for climate risk assessment, community-based mitigation measures, and spatial monitoring techniques on agriculture crops in Bhutan.

Keywords

General climate model, hazelnut crop, representative concentration pathways, suitability

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Introduction

Forest ecosystems and agriculture have been affected by increasing temperatures due to climate change (Dorji *et al.*, 2016;

Arunanondchai *et al*., 2018; Raza *et al*., 2019). Climate change has also affected the livelihoods of millions of people dependent on agriculture worldwide, which in turn has affected cropping patterns and yields (He & Zhou, 2012; Huong *et al.*, 2019; Kogo *et al.*, 2019). Furthermore, the emission of carbon from terrestrial ecosystems due to unsustainable uses of natural resources has also led to an increase in the atmospheric carbon dioxide concentration (280 μmol^{-1} to 400 μmol^{-1}) (Zeppel et al., 2012; Walker et al., 2017; Dingkuhn et al., 2020) leading to global warming. Erratic climatic patterns affect the productivity of plants due to biotic and abiotic stresses (Raza *et al*., 2019).

Hazelnut (*Corylus* spp.) is a deciduous tree belonging to the birch family (Betulaceae) within the *Corylus* genus (Baldwin, 2015). There are nine hazelnut species distributed in Central Europe and Eastern Asia. European hazelnut is native to Central Europe and Eastern Asia (Mehlenbacher, 2014). The crop has a high market demand among nuts (Baldin, 2015). As a tree, hazelnut stabilizes mountain slopes, reduces soil erosion, improves watershed retention, mitigates climate change, and ensures agro-ecosystem services (Shared Value Project Hong Kong, 2020). Since its commercial introduction in 2008 by an American couple, 12,000 active growers have cultivated the crop on 7,000 hectares of land in Bhutan (Shared Value Project Hong Kong, 2020). However, the spatial distribution and growth of European hazelnut under different climate scenarios are understudied.

It is critical to understand how the suitability of a particular crop will change with global warming. Bhutan is vulnerable to climate change, so proper climate risk assessments on hazelnut plantations and studies focusing on the impacts of climate change on livelihoods are crucial. Species distribution modelling (SDM) is considered an effective tool for monitoring and the management of species (Goetz & Dubayah, 2011; West *et al*. 2016). SDM identifies potential areas for cultivation using environmental factors as covariates (Phillips *et al*., 2006). Thus, to have a better understanding of the impacts of climate change, the objectives of this study were to (i) evaluate the factors contributing to the spatial distribution of European hazelnut in Bhutan and (ii) determine the suitable areas for cultivation of hazelnut in the near future (2040-2060) and distant future (2060-2080) under different climate scenarios of the representative concentration pathway (RCP) 2.6 and RCP 4.5 in Bhutan.

Methodology

Study area

Bhutan is located at 26.45°N to 28.10°N and 88.45°E to 92.10°E and cultivates most of its hazelnut at 1600 and 3000 masl (Shared Value Project Hong Kong, 2020). The annual average rainfall in Bhutan is 2,076.7mm and the average annual maximum and minimum temperatures are 22℃ and 11.8℃, respectively (National Center for Hydrology and Meteorology [NCHM], 2020).

Ecological niche modeling using MaxENT

For ecological modelling, an open-source modelling software called the maximum entropy model (MaxENT) (Phillips, 2017) was used, which can be downloaded from http://biodiversityinformatics.amnh.org/open_source/maxent/ (American Museum of Natural History, 2020). MaxENT is widely used in species distribution modeling to predict the habitat of target species, predict the spread of invasive species, and in agricultural science, to study potential areas for cultivation (Hernandez *et al*., 2006; Kogo *et al*., 2019). MaxENT is user friendly, accepts presence-only data, is batchable, performs with the least number of occurrence data, produces useful models (produces robust results), and handles continuous and categorical variables using regularization parameters (Baldwin, 2009; Kumar & Stohlgren, 2009; Moreno *et al*., 2011; Pramanik *et al.*, 2018)

Modeling in MaxENT requires two types of data, i.e., geographic coordinates (presence only) and environmental covariates. Species occurrence points were collected from the field where hazelnuts are currently grown. A total of 8,373 points were recorded with the help of the

Garmin Global Positioning System (GPS) with a precision error of ± 5m. GPS points were converted into comma-separated values (.csv file) for running the model algorithm.

The environmental covariates were bioclimatic data of 30 arc-seconds (~1 sq. km) spatial resolution, obtained from Worldclim.org. (**Table 1**). Two representative concentration pathways (RCP 2.6 and RCP 4.5) for the periods of the near future (2040-2060) and the distant future (2060-2080) were selected from the Coupled Model Inter-Comparison Project Phase 6 (CMIP6) (WorldClim, 2020).

Processing of environmental layers

Jayasinghe & Kumar (2019) stated that biologically informative and generalizable information can be obtained from the model using predictor variables having a direct relationship. The multicollinearity among bioclimatic variables can lead to overfitting or poor model development leading to misinterpretation of model output (Ahmadzadeh *et al*., 2013; Merow *et al*., 2013; Jayasinghe & Kumar, 2019). Highly correlated bioclimatic variables were removed through a multicollinearity test performed in ArcGIS using the Species Distribution Modelling toolbox. A total of six bioclimatic variables which had a Pearson coefficient (R) of $r < 0.8$ were selected for model development. The model for Interdisciplinary Research on Climate version 6 (MIROC6) of the GCM was used for the projection (Lamsal *et al*., 2018; Chogyel *et al*., 2020).

Table 1. Bioclimatic variables obtained from WorldClim (WorldClim, 2020

No.	Acronyms	Climatic variables
1	BIO1*	Annual Mean Temperature
2	BIO2*	Mean Diurnal Range
3	BIO3*	Isothermality (BIO2/BIO7) (*100)
4	BIO4	Temperature Seasonality (Standard Deviation *100)
5	BIO5	Maximum Temperature of Warmest Month
6	BIO6	Minimum Temperature of Coldest Month
7	BIO7	Annual Temperature Range (BIO5 - BIO6)
8	BIO8	Mean Temperature of Wettest Quarter
9	BIO9	Mean Temperature of Driest Quarter
10	BIO10	Mean Temperature of Warmest Quarter
11	BIO11	Mean Temperature of Coldest Quarter
12	BIO12	Annual Precipitation
13	BIO13*	Precipitation of Wettest Month
14	BIO14*	Precipitation of Driest Month
15	BIO15*	Precipitation Seasonality (Coefficient of variation)
16	BIO16	Precipitation of Wettest Quarter
17	BIO17	Precipitation of Driest Quarter
18	BIO18	Precipitation of Warmest Quarter
19	BIO19	Precipitation of Coldest Quarter
20	Sl*	Slope
21	As*	Aspect
22	Eleve*	Elevation

Note: The variables marked with asterisk signs were selected for the modelling after running a Pearson correlation coefficient test.

Settings for running MaxENT

Ecological niche model evaluation (ENM evalute) (Kass *et al.*, 2021) was performed in R studio software using package ENMeval ver. 0.3.1 to optimize the MaxENT model. The cross-validation technique of the MaxENT algorithm with ten model replicates was selected since it obtains a realistic model average and uses data efficiently (Elith *et al.*, 2011; Merow *et al.*, 2013). A total of 48 models were developed, among which the model with the lowest delta, Akaike's information criterion (AIC) value, was selected. The selected model required a random multiplier of 2.5 with all **L Q H P T** features. To represent the pseudo-absence location and to ensure adequate accuracy (Kogo *et al.*, 2019), 10,000 background points with 5,000 iterations were used.

Model validation

The area under the curve (AUC) of the receiver operating characteristics curve (ROC) and the true skill statistic (TSS) were used (Phillips *et al.*, 2006; Merow *et al.*, 2013) for model validation. TSS is a threshold-dependent statistical matrix that is not affected by the prevalence and size of the validation set. TSS accounts for both omission and commission error and ranges from -1 to +1 (+1 = perfect agreement, 0 = random fit) (Jayasinghe & Kumar, 2019). If the AUC value is greater than 0.5, it means the model performs better than random estimation. An AUC value between 0.9 and 1.0 shows excellent model performance; 0.8-0.9 = good; 0.7-0.8 = average; 0.6-0.7 = poor; and 0.5-0.6 = insufficient (Phillips *et al.*, 2006; Jayasinghe & Kumar, 2019; Mudzengi *et al.*, 2020).

The model result indicated the probability of the presence of a species, and the logistic value ranging from 0-1 (0= unsuitable, 1= highly suitable) was used (Pramanik *et al.*, 2021). The binary map was produced using Maximum sensitivity plus the specificity threshold (MaxSSS) of 0.4991 (Almadrones-Reyes *et al.*, 2018; Pramanik *et al.*, 2018). The predicted suitable areas were classified into four classes, namely extended suitable area, area with no occupancy, unchanged suitable area, and constricted suitable area, using distribution changes between binary SDM.

Limitations of the study

The limitations of this study included (i) absence of soil data in the analysis, (ii) absence of geological data, and (iii) use of global climate data from WorldClim with coarse pixels (~1 km resolution) for Bhutan. The model was applied to horticulture crops in Bhutan, thus the results give an idea about suitable cropping areas in the present and future conditions but do not represent natural succession by the species.

Results

Variable importance and model performance

The MaxENT generated a suitable model for current and future scenarios of the years 2040-2060 and 2060-2080 for the Intergovernmental Panel on Climate Change (IPCC) RCP 2.6 and 4.5 using nine variables (**Table 2**). Elevation had the highest influence on the model at 88%, and aspect and precipitation seasonality had the least impacts (0.1%) as shown in **Table 2**. The permutation importance value showed elevation (74.7) as the major factor and precipitation as a minor factor in the prediction of suitable areas for European hazelnut cultivation in Bhutan. The model had a moderate performance (TSS = 0.66) with very good accuracy (AUC_{mean}=0.819) as shown in **Figure 1**.

Suitable areas for hazelnut cultivation in Bhutan

The model predicted 10,744.8 sq. km as the current suitable area for hazelnut cultivation in Bhutan. The highest suitable area of 1,227.9 sq. km. (11.4%) was predicted in WangduePhodrang District followed by Chhukha with 856.5 sq. km (8%), and the least in Gasa 130 sq. km (1.2%) (**Figure 2** and **Table 3**).

The model predicted that the most suitable elevation for hazelnut cultivation ranged from 1500-1900 masl with a probability of the presence of hazelnut of 0.78. Isothermality (Bio3) showed a linear growth from 35 to 44. The most suitable annual mean temperature ranged from 14°C to 17.5°C and the best

Table 2. Variables' contribution in modelling

Variable	Percent contribution (%)	Permutation importance
Elevation	87.9	74.7
Isothermality	3.7	3.6
Mean Diurnal Range	3	12.9
Annual Mean Temperature	2.5	6.5
Slope	1.3	2.1
Precipitation of Driest Month	0.9	0
Precipitation of Wettest Month	0.6	0
Precipitation Seasonality	0.1	0
Aspect	0.1	0.1

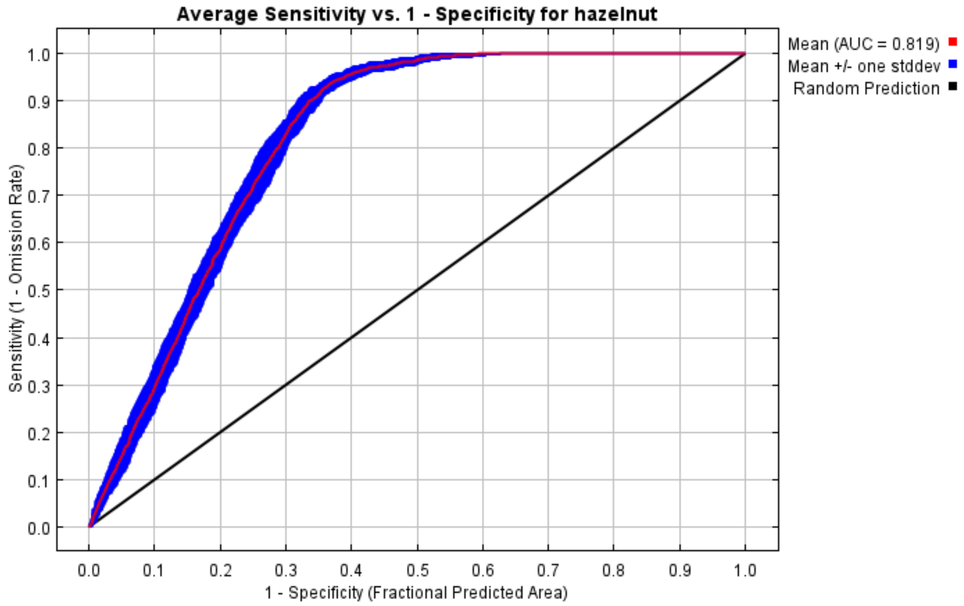


Figure 1. The receiver operating characteristic (ROC) curve. The values shown are the averages of the ten replicate runs. The red colored line shows the model AUC value and the blue line indicates the standard deviation of ±1.

estimation of the mean diurnal range of a suitable habitat was 10℃-13℃. The slope of the highly suitable area ranged from 0º to 35º. Precipitation of the wettest month, precipitation of the driest month, and precipitation seasonality had minimal effects on crop distribution in Bhutan (**Figure 3**).

Future projection and distribution changes

The distribution changes between binary SDM showed an extension of the suitable European hazelnut area (1.69%) in RCP 2.6 and an extension of 1.40% in RCP 4.5 for the years 2060-2080. The study depicted a constriction of 3.82% of the suitable area in RCP 2.6 for the years 2040-2060 and a constriction of 8.29% in RCP 4.5 for the years 2040-2060 (**Table 4**).

Dicussion

Hazelnut cultivation is growing globally due to increased nut demand (Tercan *et al*., 2022). With its potential to sequester atmospheric carbon, ability to stabilize the agro-ecosystem, and economic benefit, hazelnut is an important horticultural crop in climate-vulnerable countries like Bhutan. (Shared Value Project Hong Kong, 2020). While investigating the impacts of climate change on crop cultivation in Bhutan using two

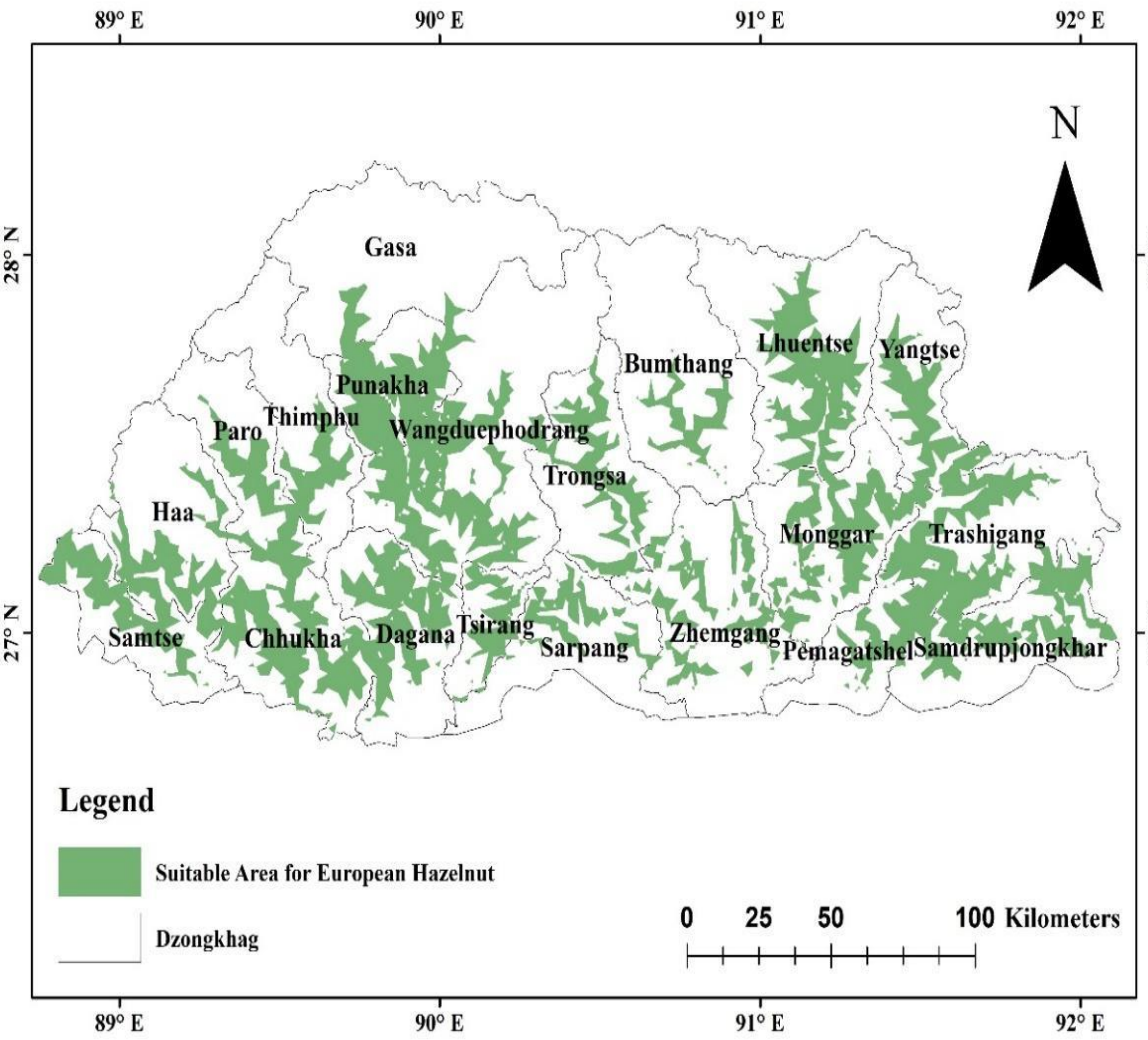


Figure 2. Predicted suitable areas for European hazelnut cultivation in Bhutan for the current scenario

IPCC climate scenarios, the current suitable area for cultivating hazelnut is 27% of the total area of the country, which is approximately 10,744.8 sq. km. The climate suitability for hazelnut is likely to decrease over the next 40 years based on the MaxENT model. The constriction of the suitable area is primarily due to increasing temperatures in the near future (RCP 2.6 and 4.5, years 2040-2060). This study predicts the constriction of suitable cultivation areas in southern districts mostly in RCP 2.6 and 4.5 for the years 2040-2060 (**Figure 4**). This could lead to reduced production from southern and central districts in the future similar to the study conducted in Turkey (An *et al*., 2020), which predicted an approximate 13% reduction in the yield of hazelnut during the years 2020-2050. The model predicts less constriction of the suitable areas in the two RCPs (2.6 and 4.5) for the years 2060-2080.

Commercial hazelnut plantations are usually found in Mediterranean-type climates in the latitude range of 40-45°N with mild and humid winters and cool summers (Baldin, 2015). The countries that lie in this region are Turkey (Giresun), Italy (Viterbo), Spain (Reus), and the state of Oregon (Corvallis) in the U.S., where the mean maximum temperature of these four regions is 25-30^{o}C and the minimum mean temperature is 0-5°C (Baldin, 2015). This indicates that these regions and Bhutan share

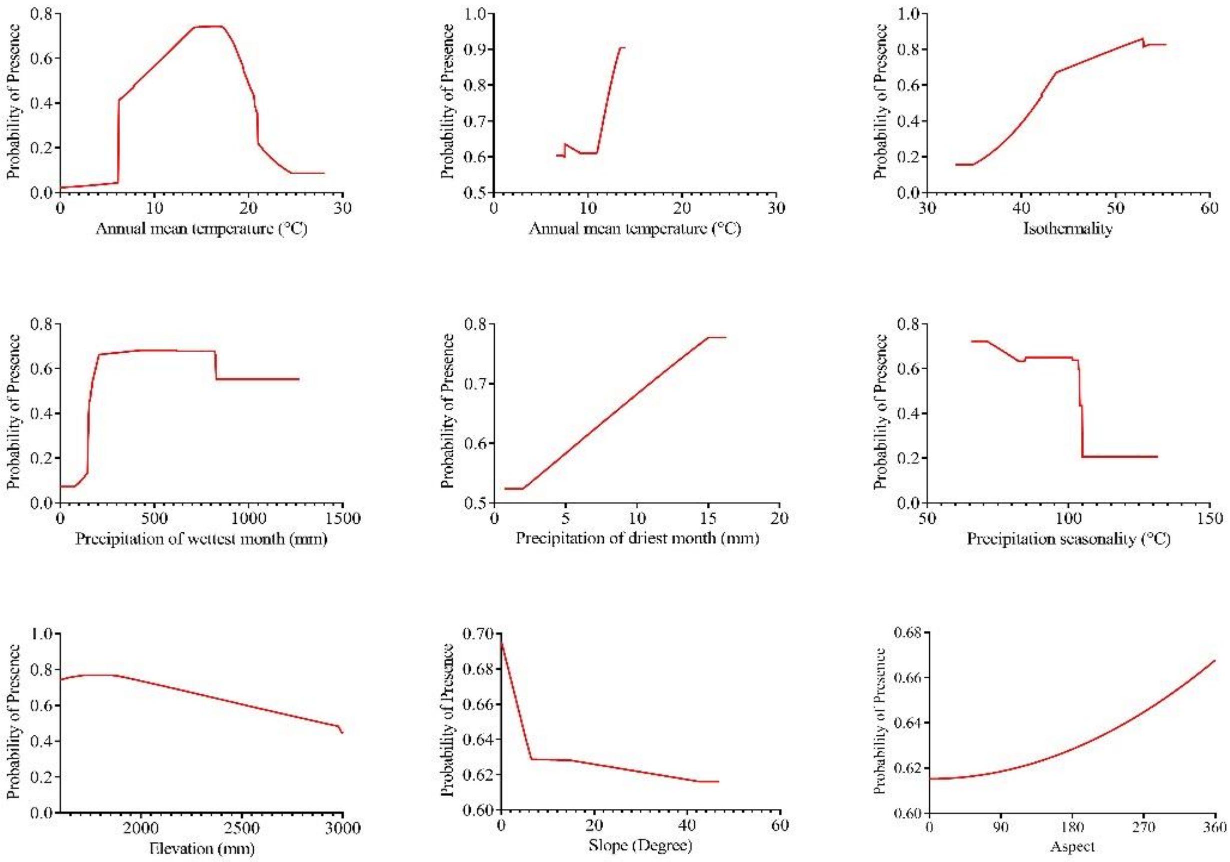
Table 3. District wise suitable areas for hazelnut cultivation for the current scenario

Dzongkhag (District)	Area (Sq. km)	Suitable Area (Sq. km)	% suitable
Bumthang	2717.33	237.99	2.21
Chhukha	1879.77	856.46	7.97
Dagana	1722.83	662.34	6.16
Gasa	3134.45	130.66	1.22
Haa	1904.87	460.43	4.29
Lhuentse	2858.70	852.42	7.93
Monggar	1944.26	679.13	6.32
Paro	1287.13	348.74	3.25
Pemagatshel	1022.10	305.19	2.84
Punakha	1109.57	709.00	6.60
Samdrup jongkhar	1877.07	621.58	5.78
Samtse	1304.85	500.87	4.66
Sarpang	1655.38	293.68	2.73
Thimphu	1795.87	276.88	2.58
Trashigang	2203.96	828.46	7.71
Trongsa	1813.71	523.58	4.87
Tsirang	637.83	246.08	2.29
Wangduephodrang	4035.65	1227.92	11.43
Yangtse	1449.05	463.23	4.31
Zhemgang	2416.58	520.16	4.84
Total area	38770.96	10744.83	100

similar temperature variability making the areas potential sites for the growth of hazelnut. In Bhutan, the maximum temperature ranges from 37.5℃ in Punakha, Sipsu (Samtse), Phuentsholing (Chukha), Bhur (Gelephu), Tangmachu (Lhuntse), Punakha, and Bajo (Wangduepgodrang) to the minimum of -12℃ in Haa, Gasa (NCHM, 2020), and Paro, concentrating the favorable areas in south and central Bhutan in the current and near-future climate scenarios.

The suitable areas in south, west, and central Bhutan are likely to be impacted by climate change and the changes in suitable areas across the different belts are not consistent in RCP 2.6 and RCP 4.5. This could be due to the effects of topoclimate (Lamsal *et al*., 2018), which is a spatial variation of climate due to elevation change. Dorji *et al*. (2016) also reported an average temperature lapse rate of 0.5℃ per 100 m of change in elevation in Bhutan, indicating a high probability of changes in land use and cover.

The simulated results indicated an AUC value of 0.81, which is under the good category, thus the model had good predictive accuracy (Pearce & Ferrier, 2000; Merow *et al*., 2013; Kebede *et al*., 2014). The model performance assessed through true skill statistics (TSS) showed a TSS of 0.66, which falls under category 0.4-0.8, which is considered as a moderate performance (Wei *et al*., 2018; Kogo *et al*., 2019). The elevation was the most influential factor in the distribution of hazelnut in Bhutan, and similar results were reported in Turkey (Aydinoglu, 2010). The study predicted an annual temperature range of 14℃-17.5℃ as suitable for cultivating hazelnut, and a similar finding was reported in Turkey (Aydinoglu, 2010).



Note: V_1 = BRRI dhan28, V_2 = BRRI dhan47, S_0 = Control, S_1 = Quarter strength marine water, S_2 = Half strength marine water, S_3 = Full strength marine water

Figure 3. Response curves of the nine environmental layers affecting the distribution of European hazelnut in Bhutan

The majority of the population in Bhutan (57%) is agrarian, and they live on the sloppy terrains (Chhogyel & Kumar, 2018). Bhutanese farmers are vulnerable to climate change impacts when they apply traditional farming approaches leading to irrigation uncertainties (Climate-law.org, 2020). Agriculture contributes approximately 15.8% to the country's gross domestic product (GDP) (Royal Monetary Authority of Bhutan [RMA], 2020) and the cultivation of hazelnut is predicted to increase an additional 5% to the overall GDP of Bhutan (Shared Value Project Hong Kong, 2020). A single matured hazelnut tree can sequester a total of 8 million tons of atmospheric carbon dioxide (Shared Value Project Hong Kong, 2020), which can help Bhutan to keep its promise of staying carbon neutral for all time to come (Climate-law.org, 2020). Thus, hazelnut cultivation can help to mitigate climate change and the impact of the climate crisis on the agro-economy (Idh-sustainable trade initiative, 2017).

Conclusions

The current suitable area (10,744.8 sq. km) for hazelnut cultivation in Bhutan will constrict in future climate change scenarios. The maximum (13.11%) constriction in RCP 2.6 and 4.5 for the year range 2040-2060 affects the southern foothills and Central Bhutan. Constriction of the suitable area in the future may cause huge economic losses to hazelnut growers in Bhutan. Apart from, taking action to mitigate the risk of climate change, we also need to plan crop cultivation in areas where changes due to climate crisis are less susceptible for the crop. Community-based adaption measures such as mobilization of community members to act locally based on their needs, knowledge, and

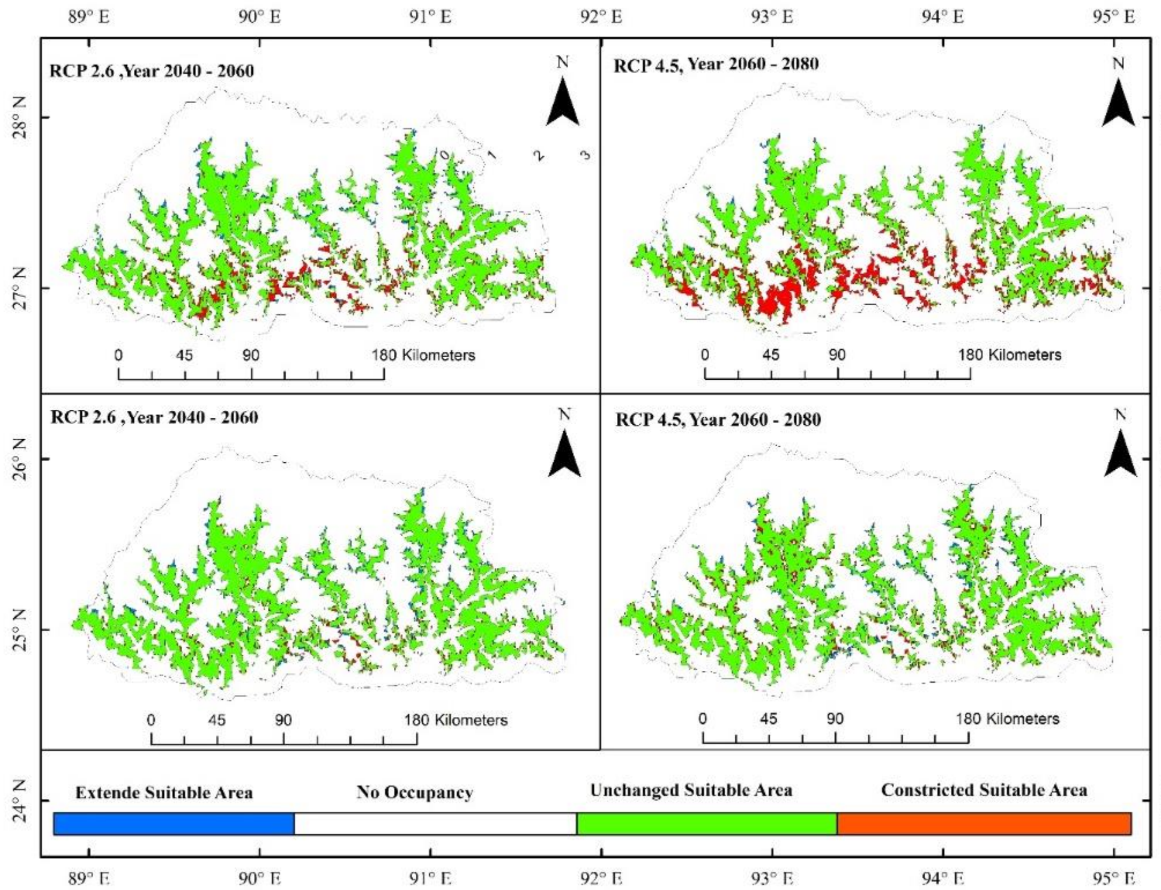


Figure 4. Predicted changes in the suitable areas to cultivate European hazelnut in Bhutan under two IPCC scenarios (RCP 2.6 and RCP 4.5) for the years 2041-2060 and 2061-2080

capacities should be initiated and enhanced. Integrated farming like intercropping could help enhance hazelnut development whilst farmers can earn supplementary income from integrated crops and improve input efficiency if there is a huge impact of climate change on hazelnut production.

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