Climate change impacts on Robusta coffee production in Vietnam

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Key Points:

- Climate change has a negative impact on the largest Robusta coffee-growing area of the world (the Central Highlands of Vietnam)
- Key factors affecting suitability are minimum temperature during growing and harvest, precipitation during flowering and late growing period
- Significant losses are found in low-elevation areas, particularly below 800 m

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Abstract

The Central Highlands of Vietnam is the biggest Robusta coffee (*Coffea canephora* Pierre ex A.Froehner) growing region in the world. This study aims to identify the most important climatic variables that determine the current distribution of coffee in the Central Highlands and build a "coffee suitability" model to assess changes in this distribution due to climate change scenarios. A suitability model based on neural networks was trained on coffee occurrence data derived from national statistics on coffee-growing areas. Bias-corrected regional climate models were used for two climate change scenarios (RCP8.5 and RCP2.6) to assess changes in suitability for three future time periods (i.e., 2038-2048, 2059-2069, 2060-2070) relative to the 2009-2019 baseline. Average expected losses in suitable areas were 62% and 27% for RCP8.5 and RCP2.6, respectively. The loss in suitability due to RCP8.5 is particularly pronounced after 2060. Increasing mean minimum temperature during harvest (October-November) and growing season (March-September) and decreasing precipitation during late growing season (July-September) mainly determined the loss in suitable areas. If the policy commitments made at the Paris agreement are met, the loss in coffee suitability could potentially be compensated by climate change adaptation measures such as making use of shade trees and adapted clones.

Plain Language Summary

Coffee has been identified as a highly vulnerable crop to climate change. This study aims to identify the impact of climate change on the world's biggest Robusta coffee-growing region, i.e., the Central Highlands of Vietnam. Our analysis identifies the key variables that determine the current distribution of coffee: mean minimum temperature during growing and harvest seasons and precipitation during flowering and late growing periods. We assess changes in climate suitability using climate scenarios based on our suitability impact model and bias-corrected regional climate simulations. The results show that climate change may decrease the suitable Robusta coffee-growing area by 62% and 27% in the high and low emissions scenarios, respectively.

1 Introduction

Agriculture is very vulnerable to climate change, particularly in the tropics. Coffee, a perennial tropical crop providing a vital livelihood to millions of smallholder farmers, has been identified as a highly vulnerable crop, with farmers mostly lacking the resources to invest in adaptation measures (Bunn et al., 2015; Verburg et al., 2019). There are two main economically important coffee species: Arabica coffee (*Coffea arabica* L.) and Robusta coffee (*Coffea canephora* Pierre ex A.Froehner). The latter has a broader environmental niche and higher genetic diversity (Herrera & Lambot, 2017) and therefore is expected to be less sensitive to climate change than Arabica coffee. Supra-optimal temperatures as a result of climate change negatively affect the coffee quality and yields which is further exacerbated by unsuitable rainfall distribution (Bertrand et al., 2012; Läderach et al., 2017; Kath et al., 2021). Due to the high sensitivity of Arabica coffee to changes in temperature, most studies have focused on this species, while only a few studies have studied potential climate change impacts on Robusta coffee. Recent research, however, suggested that Robusta coffee yield is more sensitive to temperature increase than previously expected (Kath et al., 2020).

Most climate change impact assessments for coffee relied on global climate models (GCMs) as inputs for future climate projections. However, their coarse spatial resolution is often lacking detailed regional information. In addition, GCMs could introduce large uncertainties, especially over some specific regions, e.g., Southeast Asia (SEA), where the climate is complex and spatially heterogeneous. Regional climate models (RCMs) could be considered as a better alternative source for climate change impact studies (Teutschbein & Seibert, 2010; Nguyen et al., 2022). Therefore, this study considers several RCMs of the Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA).

Correlative species distribution models have been predominantly used to assess climate changes in coffee suitability, e.g., in Davis et al. (2012), Bunn et al. (2015), or Moat et al. (2017). This approach often relates the present occurrence locations with climatic variables expected to determine the environmental niche for the species distribution. A classification algorithm is used to determine a relationship between the labeled data set (i.e., the presence and absence of coffee) and the selected input variables. It, therefore, identifies areas that are similar in terms of the most important variables selected to determine the distribution of the crop occurrence data. This relationship is used to determine climate suitability, which represents the assumption that strong deviations in key climate characteristics relevant to the crop distribution will negatively affect the climate suitability of the crop. However, this approach needs to be treated with care as the relationship might not capture all relevant aspects determining the actual climate suitability for coffee. This can be due to biases in the occurrence data, missing climatic drivers, or biases in the climate data.

Here, we investigate the possibility of obtaining a robust coffee suitability model. For instance, concerning the occurrence data, we develop a systematic scheme to identify the presence of coffee based on the statistical coffee-growing areas at the district level. In addition, previous studies often used a set of bioclimatic variables (Bunn et al., 2015; Ovalle-Rivera et al., 2015). However, this set might not be the best option, especially in a statistical approach where the model is sensitive to overfitting (Dinh & Aires, 2022). Thus, a careful selection of potential climate variables can help improve the robustness of the coffee suitability model. Moreover, a calibration (or bias correction) method is used to post-process regional climate data before being used in the suitability model. This calibration is essential to minimize systematic biases and bring the climate simulations as close as possible to the observations.

In the following, Section 2 introduces the data, including the study area, coffee-growing areas, potential climate predictors, and the selected climate data. Then, the methods used in this study are described in Section 3. Section 4 presents the results of the model validation and climate suitability. The results are discussed and concluded in Section 5.

2 Data

2.1 Study area and coffee-related data

The study area is located along the longitude 104.22°E to 109.94°E and latitude 9.02°N to 17.82°N, which covers the Vietnamese high-intensity Robusta coffee production area. A map of the study area is shown in Figure 1. In detail, Figure 1a shows the Southeast Asia domain covered by the regional climate models (see Section 2.3). Then, Figure 1b provides a close-up of the study area with the elevation information. Digital elevation data, SRTM 1 Arc-Second Global data (USGS EROS Center, 2018), are downloaded from `https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-1`. The data on planted coffee areas at the district level are obtained from the General Statistics Office of Vietnam (GSO). Figure 2a shows the planted coffee area (in ha) averaged from 2014 to 2018.

2.2 Potential predictors

We chose a set of 12 environmental variables (Table 1) as the potential model predictors. These potential predictors are derived from precipitation, temperature, and evaporation, characterizing growing conditions such as the flowering (i.e., from January to March), the growing season (i.e., from March to September), or the harvest period (i.e.,

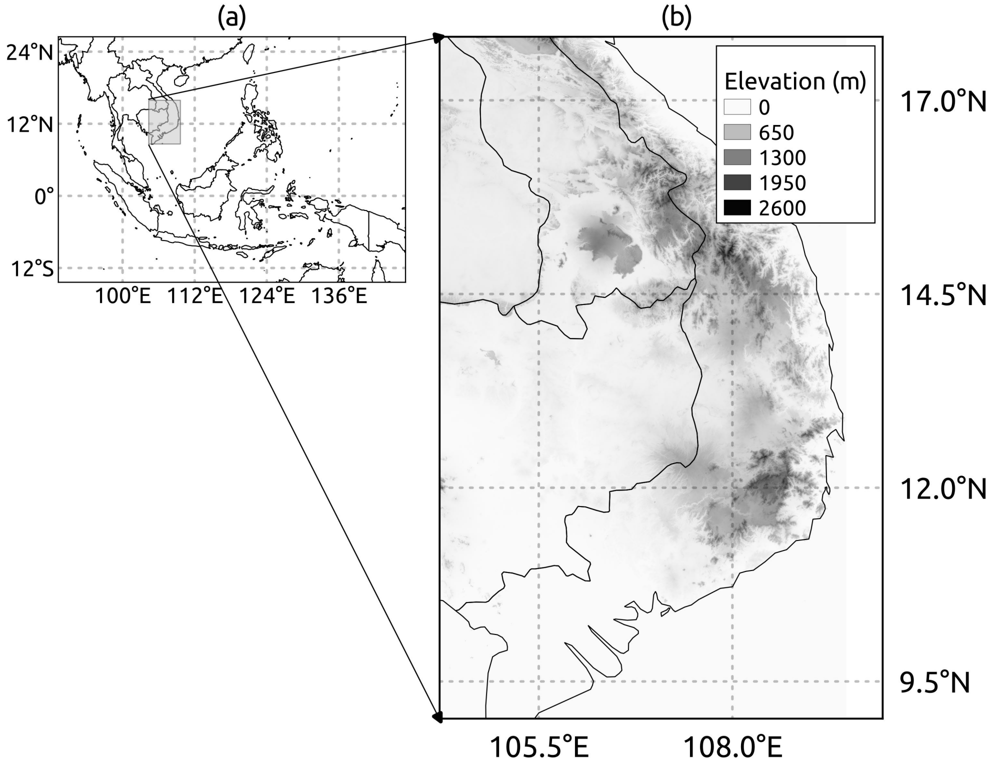

Figure 1. Study area: (a) the Southeast Asia domain with a focus on (b) the study area (104.22 - 109.94 °E and 9.02 - 17.82 °N) and topography elevation (m).

from October to December). They have been selected according to expert knowledge on coffee and a literature review (Bunn et al., 2015; Lambot et al., 2017; Kath et al., 2020, 2021; Dinh et al., 2022).

2.3 Climate data

Monthly data on total precipitation, mean temperature, maximum and minimum daily temperature, and evaporation are considered for both current and future climate. For the current climate (1981-2019), we used the Era5-Land reanalysis dataset (Muñoz Sabater, 2019). This dataset is available at a $0.1° \times 0.1°$ resolution (about 10 km × 10 km at the Equator), and can be downloaded at `https://cds.climate.copernicus.eu/cdsapp#!/home`. We then integrated these data into a $0.22° \times 0.22°$ grid to be consistent with the future climate data, which will be presented in the following.

Regional climate simulations and projections are obtained from several model simulations of the Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA), with $0.22° \times 0.22°$ resolution. The data are available at `https://esg-dn1.nsc.liu.se/search/cordex/`. The list of regional climate models (RCMs) carried out in this study is presented in Table 2. We considered the historical period from 1981 to 2005, used for the calibration (or bias correction) in Section 3.3. We will investigate the future period from 2031-2077 for the Representative Concentration Pathway (RCP) scenarios of the Coupled Model Intercomparison Project – Phase 5: the low (RCP2.6) and high (RCP8.5) greenhouse gas concentration scenarios (van Vuuren et al., 2011). The RCP2.6 scenario is a so-called "peak" scenario, which implies that the radiative forcing

No	Variables	Name	Months	Units
1	P1012	Precipitation during harvest	Oct. - Dec.	mm
2	P79	Precipitation during late growing season	Jul. - Sept.	mm
3	P39	Precipitation during growing season	Mar. - Sept.	mm
4	P13	Precipitation during flowering	Jan. - Mar.	mm
5	Tmin1012	Mean minimum temperature during harvest	Oct. - Dec.	°C
6	Tmin39	Mean minimum temperature during growing season	Mar. - Sept.	°C
7	Tmax39	Mean maximum temperature during growing season	Mar. - Sept.	°C
8	Bio2	Annual mean diurnal range		°C
9	Bio5	Maximum temperature of warmest month		°C
10	Bio7	Annual temperature range		°C
11	Bio15	Precipitation seasonality (CV)		Percent
12	NDM	Maximum number of consecutive dry months		Month

Table 1. Description of the 12 environmental variables used in this study as potential predictors for suitability model.

level reaches 3.1 W m^{-2} by mid-century but returns to 2.6 W m^{-2} at the end of the century. On the other hand, RCP8.5 represents a future with a radiative forcing of 8.5 W m^{-2} by 2100.

No.	Abbreviation of RCM experiment	Driving model (GCM)	Realisation	RCM	RCP2.6	RCP8.5
1	SMHI_CNRM	CNRM-CM5 (CNRM, France)	r1i1p1	RCA4 (SMHI, Sweden)		x
2	SMHI_Had	HadGEM2-ES (Hadley Centre, UK)	r1i1p1	RCA4 (SMHI, Sweden)		x
3	ICTP_Had		r1i1p1	RegCM4 (ICTP, Italy)	x	x
4	GERICS_Had		r1i1p1	REMO2015 (GERICS, Germany)	x	x
5	ICTP_NCC	NCC-NorESM1-M (NCC, Norway)	r1i1p1	RegCM4 (ICTP, Italy)	x	x
6	GERICS_NCC		r1i1p1	REMO2015 (GERICS, Germany)	x	x
7	ICTP_MPI	MPI-ESM-MR (MPI-M, Germany)	r1i1p1	RegCM4 (ICTP, Italy)	x	x
8	GERICS_MPI		r1i1p1	REMO2015 (GERICS, Germany)	x	x

Table 2. List of regional climate models used in this study.

3 Methods

3.1 Learning database identification

To develop a coffee suitability model, we need a database of samples indicating the presence (coffee samples) or absence (background samples) classes. Such a database can therefore be used to calibrate a statistical suitability model. Here, the presence data are based on observations (i.e., data from GSO); the absence data are generated and not observed. The detailed methodology to identify these two data is presented as follows.

The current coffee samples are built from the available coffee areas with respect to the climate-gridded cell (0.22° × 0.22°). Here, we neglected coffee-growing districts with less than 500 ha as they are relatively small compared to the size of one climate cell. For districts with a coffee-growing area of 500 ha, one corresponding gridded cell will be selected as a coffee sample (or coffee cell): (1) if the shape of the district is smaller than the cell or it contains only one cell, we chose that gridded cell; (2) if the shape is overlapped by several cells (e.g., often two cells), the cell with higher overlap surface was selected; (3) if the shape contains several cells which was seldom the case, the coffee cell was randomly chosen among these cells. For districts with coffee-growing areas higher than 500 ha, several corresponding cells were considered and classed as current coffee samples. For each district, the number of cells was defined by a scaling factor S_f, which is computed by the ratio of the coffee area over 500 ha. For instance, let's consider a district with 5000 ha of coffee. The corresponding scaling factor is $S_f = \frac{5000}{500} = 10$, meaning that there will be ten coffee cells associated with this district. We identified these ten cells by replicating the corresponding gridded cell(s).

The background samples are randomly selected from a 4.4° buffer around present regions. The ratio of background samples to current coffee data is set to 1:1, as recommended in Barbet-Massin et al. (2012). Too few (or too many) background samples can lead to false alarms as the model is biased toward the coffee samples (or the background samples).

The learning database was used to explore the corresponding elevation of the coffee and background samples. This information was used to exclude points that are unsuitable for coffee for both current climatic conditions and future climate projections. Figure 2a shows the map of the learning database — coffee (red points) and background (blue points) samples — together with the coffee area data over the study area. We also plot the normalized histogram of the elevation (in m) corresponding to these coffee and background points in Figure. 2b. The learning database suggests that Robusta coffee in the Central Highlands of Vietnam requires an elevation higher than 100 m and mostly from 450 m to 1100 m. Thus, in the climate change impact assessments, we excluded all cells below 100 m.

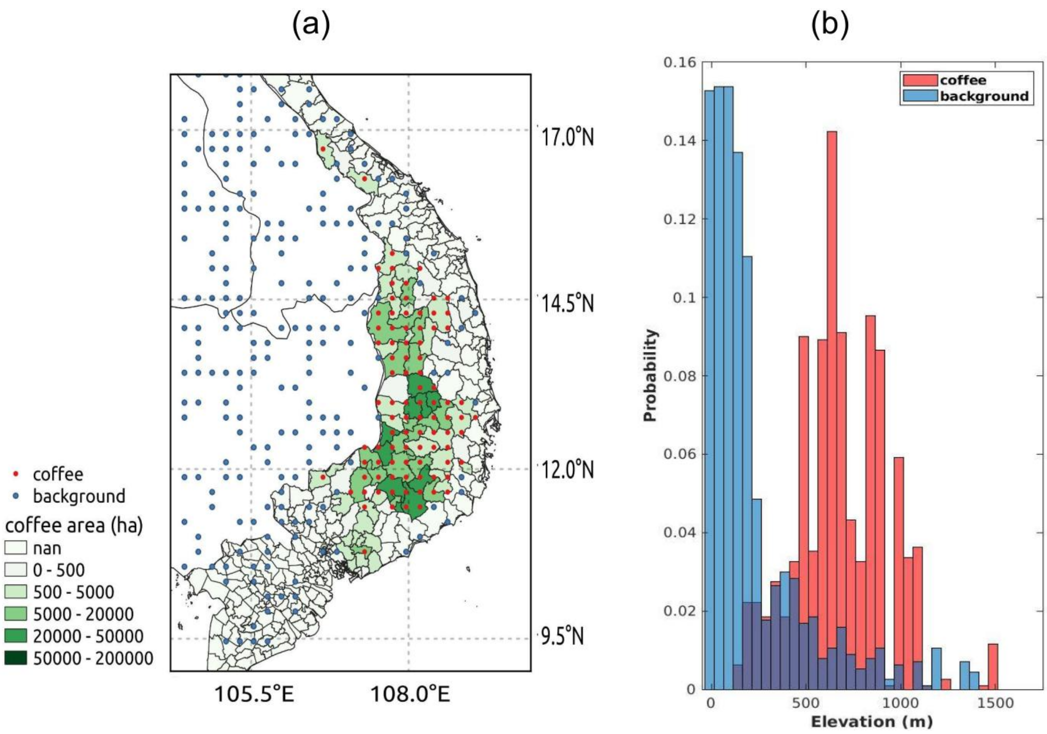

Figure 2. (a) The coffee planted area (in ha) averaged from 2014 to 2018, and the learning database including current coffee (in red) and background (in blue) samples; (b) normalized histogram of the learning database in term of elevation (in m).

3.2 Suitability model

3.2.1 Model selection

Our suitability model relies on neural networks (NN) (Schmidhuber, 2015). As in a classification task, NN trains the generic feedforward neural network to map each input vector into its corresponding target vector. The target is based on the learning database introduced previously. The inputs are chosen from 12 potential predictors (Section 2.2). A forward selection method is used: the first selected input is the one that gives the best-performing network (i.e., the smallest mean squared error). The second one is selected among the remaining potential predictors. The two selected inputs define a two-input model that gives the best-performing network. We continue this process until all potential predictors are selected to obtain the hierarchy of the explanatory variables. However, for the final model we only used four inputs as the use of more inputs leads to overfitting related to a poor generalization ability (Dinh & Aires, 2022).

3.2.2 Model training and evaluation

To assess the model's generalization, we divided our database into three sets: training (60%), validation (20%), and testing (20%). The model is then evaluated using performance metrics derived from the confusion matrix, which are commonly used for evaluating classification models. We considered two common metrics:

- precision p: the measure of correctly identified coffee samples over the number of all correctly identified samples;
- recall r: the measure of correctly identified coffee samples over the count of actual coffee samples.

3.2.3 Impacts

We first trained and tested the model on the learning database for the current climate (2009-2019) to obtain optimal model parameter values. Then, the model is applied to all cells in the study area for different periods: current (i.e., 2009-2019) and future (i.e., 2038-2048, 2049-2059, and 2060-2070 periods). The results are visualized as maps with continuous scores, which are normalized from 0 (not suitable) to 1 (suitable). A threshold is used to determine if a cell is suitable or not for coffee. The threshold is based on the probability density functions of these two classes in the actual learning database (Figure 3) and the coffee area. As shown in Figure 3, a threshold of 0.5 helps to distinguish very well between the coffee and background samples. In addition, with this threshold, our model was able to identify about 70×10^4 ha of suitable areas in the Central Highlands, which is comparable to the actual coffee-growing area in this region (i.e., 57×10^4 ha). The area is computed by summing the entire land area within suitable cells (i.e., a pixel cell of $0.22° \times 0.22°$).

For suitability assessments of future climate projections, we first applied the suitability model for each of the eight calibrated RCMs (Table 2) for the high-end emission scenario RCP8.5. Then, we compared the suitability changes under RCP2.6 and RCP8.5 scenarios using only six RCMs, i.e., all models presented in Table 2 except SMHI_CNRM and SMHI_Had as they do not have simulations for the RCP2.6 scenario. We investigated the area changes respective to elevation.

3.3 Calibration of climate simulations

3.3.1 Calibration method

A calibration (also known as a bias correction) is a necessary prerequisite for climate change impact studies as climate models often suffer from substantial biases and

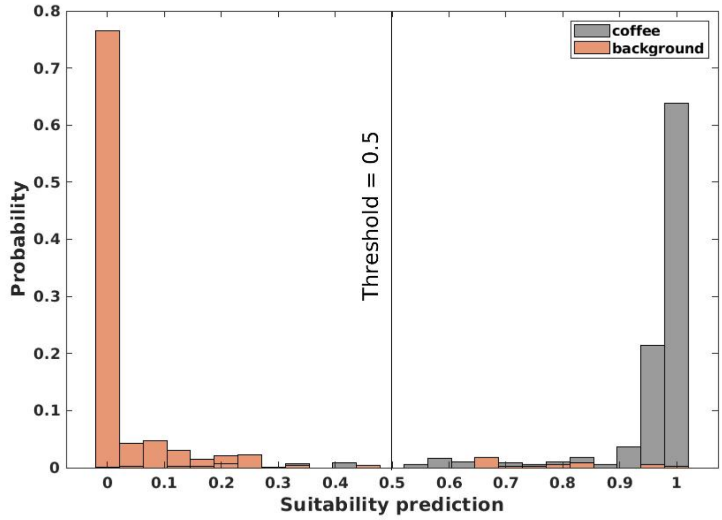

Figure 3. Normalized histogram of the coffee suitability prediction. A threshold of 0.5 is chosen for the coffee or background (no coffee) classification.

errors (i.e., structural biases or parametric uncertainties) compared to the observations (Hawkins & Sutton, 2011; Teutschbein & Seibert, 2012; Chen et al., 2013; Maraun & Widmann, 2018). This study used the equidistant quantile mapping (EqQM) (Li et al., 2010; Pierce et al., 2015) or equiratio CDF matching (Wang & Chen, 2014) to calibrate the CORDEX-SEA data before using them in the coffee suitability model. The calibration was done using three datasets, including:

- the historical observations $X_{O,h}$ (integrated Era5-Land, 1981-2005),
- the corresponding simulations $X_{M,h}$ on the historical record (CORDEX-SEA22, 1981-2005),
- and the simulations $X_{M,f}$ for the future (CORDEX-SEA22 for 3 periods 2031-2055, 2042-2066, and 2053-2077).

The calibrated data $X_{C,f}$, for the 2031-2055 period, for instance, are computed as:

$$X_{C,f}(i) = X_{M,f}(i) + F^{-1}_{O,h}[F_{M,f}(X_{M,f}(i))] - F^{-1}_{M,h}[F_{M,f}(X_{M,f}(i))] \tag{1}$$

for temperature variables, and

$$X_{C,f}(i) = X_{M,f}(i) \times \frac{F^{-1}_{O,h}[F_{M,f}(X_{M,f}(i))]}{F^{-1}_{M,h}[F_{M,f}(X_{M,f}(i))]} \tag{2}$$

for precipitation and evaporation variables. In Equations (1) and (2), i is the time step, F is the cumulative distribution function, and F^{-1} is the inverse of F.

3.3.2 Temporal configuration

To better preserve the temporal evolution of climate change, the calibration is done for several time blocks (Switanek et al., 2017). In detail, we used 25-year periods with an 11-year sliding window to calibrate the 11 middle years. For instance, the 2038-2048 period was calibrated using a model set up in the 2031-2055 (future) versus the 1981-2005 (historical) periods. Next, we calibrated 2049-2059 data using the future 2042-2066 period and the same historical period. Finally, we used the model set up in the 2053-2077 and 1981-2005 periods to obtain the 2060-2070 calibration.

4 Results

4.1 Model validation and variable contribution

The suitability model, which is trained and tested over the learning database, shows a good predictive performance for the current period (2009-2019). The model precision is $p = 95.4\%$, meaning that less than 5% of background samples are misclassified as coffee regions. We also obtain a high model recall of $r = 96.9\%$, which implies that the model can identify the actual coffee cells very well on the historical record, based on actual observations.

Among 12 potential predictors, the most important variables are (1) the mean minimum temperature during the harvest and growing season (i.e., Tmin1012 and Tmin39 shown in Table 1); (2) the precipitation variables are also crucial for robusta coffee, including precipitation during the late growing season (P79) and flowering (P13). The least important variables are the mean maximum temperature during the growing season (Tmax39) and the maximum temperature in the warmest months (Bio5) (Supplementary Material Table S1).

4.2 Climate suitability

4.2.1 Current and future suitabilities

The (trained and tested) suitability model is applied over all study cells for the current period, i.e., 2009-2019 (Figure 4). The highly suitable areas are located in higher elevation areas of the Central Highlands of Vietnam. We then applied this suitability model for eight RCMs (presented in Table 2) under the RCP8.5 emission scenario. Figure 4 shows the mean and standard deviation of the future suitabilities resulting from these eight simulations for three different future periods, i.e., 2038-2048, 2049-2059, and 2060-2070. Compared to the current suitability, highly suitable areas will decrease significantly in the future. These areas become smaller and smaller in time. For example, the suitable area is about 81×10^4 ha for the current period (2009-2019); however, it will be reduced by half in the 2065s ($\approx 42 \times 10^4$ ha). In addition, the eight simulations give similar predictions by showing small standard deviation values, i.e., 15% on average, for all three projected periods.

4.2.2 Sensitivity to climate scenarios

We now study the suitability model's sensitivity to different climate scenarios. As presented in Table 2, only six of the eight RCMs provide the simulations for both RCP2.6 and RCP8.5 scenarios. Therefore, in the following comparisons, we will use only six RCM simulations (all models in Table 2 except SMHI_CNRM and SMHI_Had).

First, let us look at the changes in suitability (the difference between future and current suitability) for different future periods under the RCP2.6 and RCP8.5 scenarios shown in Figure 5. As expected, climate change impacts are less pronounced in the low CO_2 emission scenario (a1 to a3) than in the high CO_2 emission scenario (b1 to b3). For the 2038-2048 period, for instance, the number of magenta cells, which signify the negative change, is much less and lighter in (a1) than (b1). Similar behaviours are obtained for two other considered periods, as shown in (a2) versus (b2) and (a3) versus (b3). In addition, both scenarios show that most of the study regions suffer negative impacts or could become unsuitable for coffee, i.e., shown in many magenta cells in Figure 5. Nevertheless, a small area in the northern Central Highlands could actually become more suitable for coffee. This area covers high mountains ranging from 875 to 1200 m. The change in climate is compatible with the increase in elevation. For the RCP2.6 scenario, the impact of climate change is relatively constant over time. On the other hand, for the RCP8.5 scenario, the negative impacts become stronger toward the end of the century:

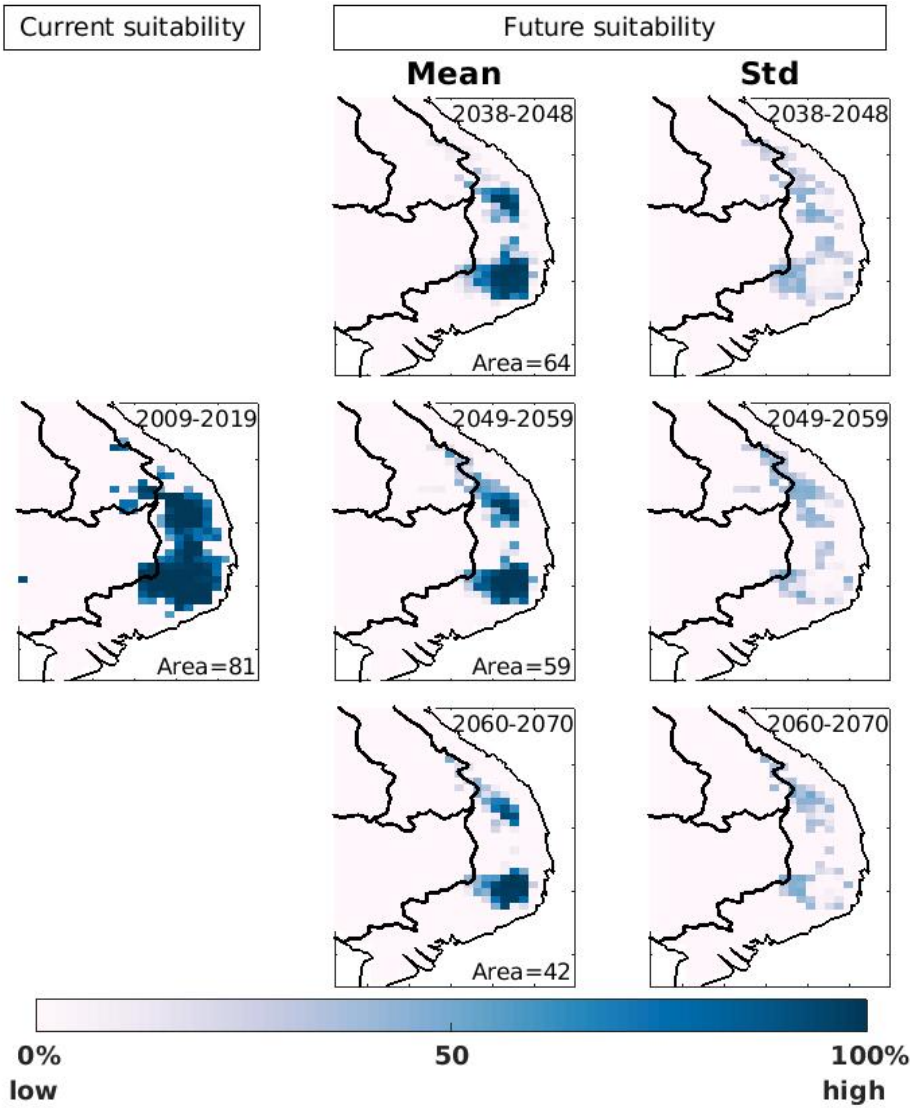

Figure 4. Current and future suitability for coffee. The mean and standard deviation (std) of future suitabilities are computed from eight RCMs presented in Table 2 under the RCP8.5 scenario. Dark blue (or 100%) indicates high suitability, and white (or 0%) means low suitability. The corresponding suitable areas (in 10^4 ha) are indicated in each panel. The area is computed by summing the entire land area within suitable cells.

more regions suffer from negative impacts in the 2060-2070 period (b3) than in the 2038-2048 period (b1).

4.2.3 Distribution of climate change impacts

Figure 6 shows the distribution of the suitable regions by elevation for three future periods (i.e., 2038-2048, 2049-2059, and 2060-2070). Here, we compute the suitable areas by summing the entire land area within suitable cells across 100 m elevation classes.

In general, suitable areas under the RCP2.6 scenario (green lines and shaded areas in Figure 6) are somewhat comparable to the currently suitable areas (black lines

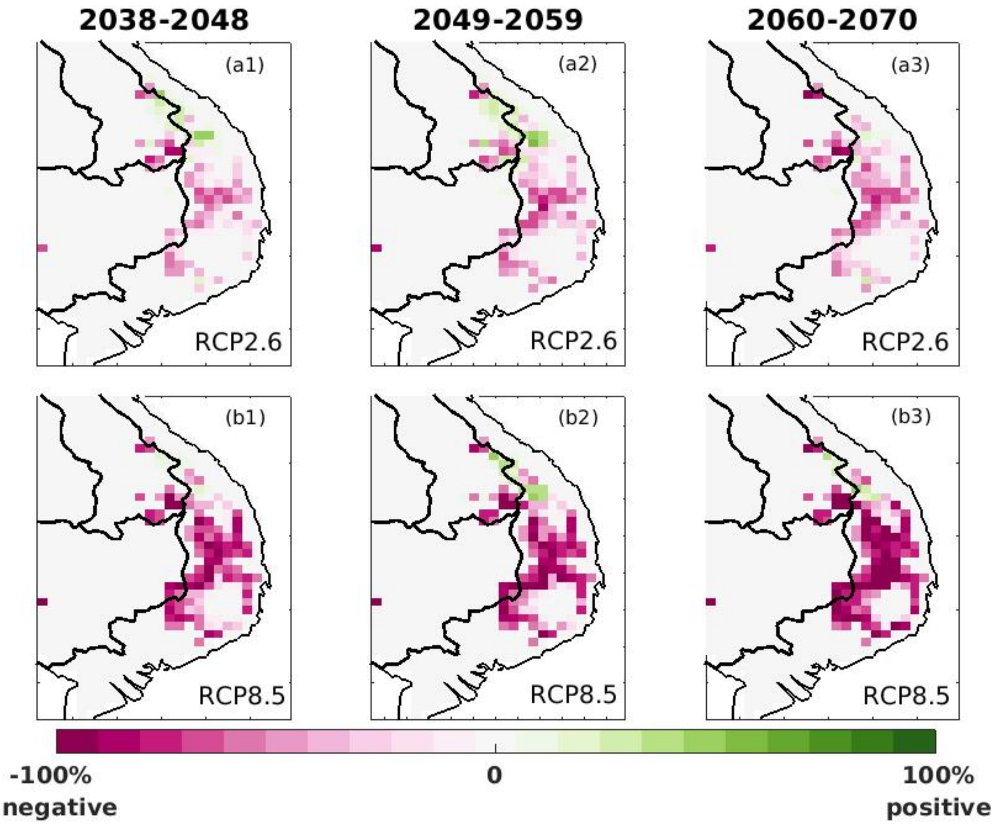

Figure 5. Suitability change (future suitability - current suitability) for three future periods (2038-2048, 2049-2059, and 2060-2070) in the RCP2.6 and RCP8.5 scenarios. Dark magenta (or -100%) presents areas with drastic changes from suitable to unsuitable, and dark green (or 100%) indicates positive changes.

in Figure 6). The average losses are about 27% over three projected periods. The most considerable loss of suitable area could be up to 36% for the 2060-2070 period. For the high impact scenario RCP8.5, the suitable areas decrease significantly for three projected periods, with the losses ranging from 39% up to 83%. The total suitable areas do not change very much from 2038-2048 to 2049-2059. However, we observe a substantial decrease (i.e., about 15%) after the 2060s compared to the two previous projected periods. The suitability is very sensitive to the elevation. The major losses are found in low-elevation areas (i.e., below 800 m). In contrast, the total suitable areas do not change much in higher elevations, especially above 850 m.

5 Conclusions and Discussions

This study assessed climate suitability for Robusta coffee within a climate change context in the world's largest Robusta coffee-growing area, i.e., the Central Highlands of Vietnam. This is the first climate change impact study for the climate suitability of coffee using bias-corrected RCMs rather than GCMs. The RCMs are considered here as they provide finer spatial resolution outputs and more adequately represent the climate and weather processes over a complex and spatially heterogeneous Southeast Asia region that includes mountains and coastal areas. The coffee suitability model indicates that projected climate change scenarios will negatively impact the suitability for growing coffee in the Central Highlands of Vietnam. The degree of suitability change depends

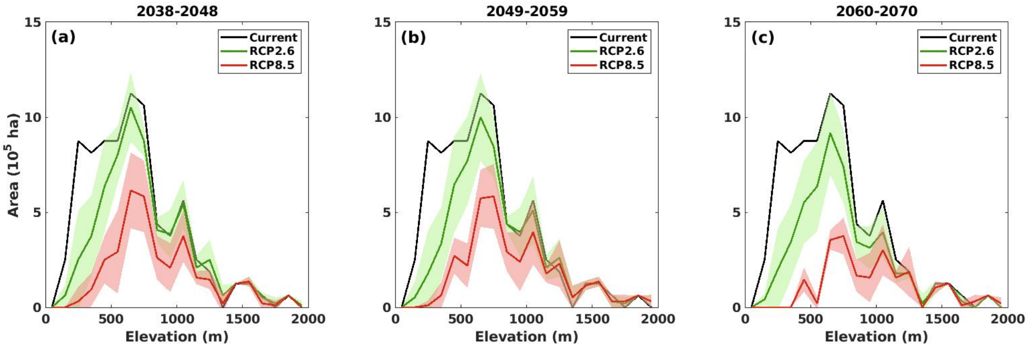

Figure 6. Distribution of suitable areas by elevation for three future periods (i.e., 2038-2048, 2049-2059, and 2060-2070). Black lines indicate the current (2009-2019) suitable area. Color lines and corresponding shaded areas present the mean and standard deviation of future suitable areas induced from six RCMs (all models in Table 2 except SMHI_CNRM and SMHI_Had) under RCP2.6 (top) and RCP8.5 (bottom) scenarios. The areas are calculated by summing the entire land area within suitable cells across 100 m elevation classes.

on the emission scenarios (RCPs) and time periods. As expected, suitability decreases over time, particularly in the period 2060-2070. Towards the mid-century (2038-2048), suitability is negatively affected under the RCP8.5 scenario with a loss in suitable areas of about 56.5%, while changes are more subtle under the RCP2.6 scenario with 21.7% losses. The RCP8.5 scenario is the worst-case emissions pathway assuming no policy success towards climate change mitigation, high population growth and a lot of coal use,. The RCP2.6 is more consistent with current trajectories pointing to a 2°-3°C warming range (Hausfather & Peters, 2020; Pielke Jr et al., 2022) yet it does not mean that RCP8.5 is impossible. The suitable area could decrease up to 83% with the RCP8.5 emissions scenario with significant losses below 800 m. However, if policy action continues with the current path, including the planned actions committed to at the Paris agreement, suitable areas are expected to decrease by 27%, mainly at the lowest elevations (i.e., below 500 m). Losses in suitable areas are particularly striking in Dak Lak province where current climate is hotter and drier compared to other coffee-growing areas in the Central Highlands.

Not surprisingly, and consistent with previous studies focusing on the climate sensitivity of Robusta coffee (Bunn et al., 2015; Kath et al., 2020; Dinh et al., 2022), temperature is a major determinant of the distribution of climate suitability of coffee. Increased temperature accelerates bean development and ripening and increases plant respiration (DaMatta et al., 2019). Under the RCP2.6 scenario, changes in agronomic practices (e.g., the use of shade trees) and the use of more adapted clones could potentially compensate for the loss of suitability. However, further research is required to translate changes in climate suitability into changes in coffee quality and yield. Kath et al. (2020) identified that Robusta coffee yields in Vietnam were highest at low temperatures and that every 1°C increase in mean minimum/maximum temperatures above 16.2/24.1°C during the growing season results in yield decreases of about 14%. The most important climate variables identified by our suitability model (i.e., mean minimum temperature during the growing season and harvest, precipitation during flowering and the late growing season) are in agreement with Kath et al. (2020) who used correlative models on actual yield time series rather than coffee occurrence alone.

In this study, we only sampled the environments close to where Robusta coffee is grown in Vietnam to assess the suitability of these specific Robusta coffee clones (Tram et al., 2021) under specific management conditions. Robusta coffee genotypes from other regions might thrive better under the projected future climate conditions and could therefore be considered for climate-resilient breeding efforts. Further research is needed to analyze how climate variability and climate extremes affect the economic viability of Robusta coffee growing, an aspect that cannot be fully accounted for when using correlative species distribution modeling. Short-term climate hazards, for example, heat stress during peak days of flowering, could be more harmful to Robusta coffee than what can be identified from climate predictors based on monthly averages.

Data availability statement

The coffee area data can be obtained from Vietnam's General Statistics Office (GSO) for the 2000-2018 period. These data are available from GSO on reasonable request. For any inquiries, please send an email to `banbientap@gso.gov.vn`. Digital elevation data (USGS EROS Center, 2018) are from `https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-1` (last access: 02 Mar 2022). The current climate data (Era5-Land reanalysis dataset) can be downloaded from `https://cds.climate.copernicus.eu` (Muñoz Sabater, 2019) (last access: 22 Apr 2021). The future climate simulations are available at `https://esg-dn1.nsc.liu.se/search/cordex/` (last access: 27 Jun 2022).

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