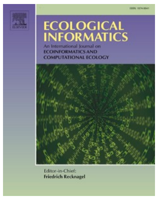
Ecological Informatics 91 (2025) 103392

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf



Local-scale analysis of projected climate change impact on Arabica coffee distribution in selected districts of southwestern Ethiopia: Are the future production areas commercially viable?

Melkamu Mamuye[a], Caleb Gallemore[b], Ng'winamila Kasongi[c,d], Kristjan Jespersen[e,*], Gezahegn Berecha[f]

[a] Department of Natural Resource Management, College of Agriculture and Veterinary Medicine, Jimma University, Jimma, Ethiopia
[b] International Affairs Program, Lafayette College, USA
[c] Department of Geography, University of Dar es Salaam, Tanzania
[d] Department of Geography and Environmental Studies, University of Dodoma, Tanzania
[e] Department of Management Science and Communication, Copenhagen Business School, Denmark
[f] Department of Horticulture and Plant Science, College of Agriculture and Veterinary Medicine, Jimma University, Jimma, Ethiopia

ARTICLE INFO

Keywords:
Coffee
Climate change
Local scale
EUDR
CMIP6
Ensemble

ABSTRACT

Climate change is reshaping the geographies of coffee production globally, impacting the livelihoods of coffee farmers and the international coffee market. A local-scale understanding of these shifts is essential for designing effective adaptation and policy planning. This study assessed the local-scale (district-level) impact of projected climate change on coffee area suitability and how future production geographies intersect with the forest cover in five major coffee-growing districts of southwestern Ethiopia. The study models coffee distribution using an ensemble of three machine-learning algorithms (Maxent, SVM, and RF) to predict suitable areas presently and in the 2030s, 2050s, 2070s, and 2090s under SSP2–4.5 and SSP5–8.5 scenarios. The models perform well in predicting suitable areas with an AUC value of >0.96 for Ale, Goma, Gera, and Yayu and > 0.86 for Limu Seka. Rainfall and temperature variables are the most important factors for predicting coffee area suitability. Under the SSP2–4.5 scenario, the study predicts an overall increase in suitable areas in Ale (+19 %), Gera (+41 %), Goma (+4 %), Limu Seka (+124 %), and Yayu (+21 %) at the end of the century, while most current production areas remain suitable. In the SSP5–8.5 scenario, however, we expect suitable areas to increase in Ale (+16 %), Gera (+52 %), Limu Seka (+71 %), and losses in Goma (−0.5 %), and Yayu (−47 %). Problematically, projected suitable coffee production sites overlap by 25 % to 90 % with areas currently designated as forest under the Global Forest Cover 2020 map, potentially placing production in those areas off limits for export to the European Union under the provisions of the EUDR 2023/1115 regulation. We therefore conclude that many areas in the region that could become newly suitable for coffee production may not be commercially viable. The heterogeneity of primary local drivers of coffee suitability means that micro-scale spatial analyses of climate change impacts on coffee production could provide valuable insights for other regions in planning targeted and effective climate adaptation strategies.

1. Introduction

Coffee is a prominent global cash crop, contributing significantly to the livelihoods of millions of smallholder farmers (FAO, 2015). Coffee producers are expected to enjoy robust demand for some time, with global coffee consumption predicted to exceed production (ICO, 2023). However, with the Intergovernmental Panel on Climate Change (IPCC) predicting global warming of 1.2 °C to 3.0 °C by 2050 (IPCC, 2021), agricultural commodities, including coffee, may be at significant risk. Arabica coffee is grown in a specific climatic and biophysical envelope with average annual temperatures of 18–22 °C (DaMatta and Ramalho, 2006; Sayed et al., 2019; Wintgens, 2012) and annual precipitation of 1400–2000 mm (Adhikari et al., 2020; Ovalle-Rivera et al., 2015; Steinhart, 2005; Wintgens, 2012), and climate change could force many

---

* Corresponding author.
E-mail address: kj.msc@cbs.dk (K. Jespersen).

https://doi.org/10.1016/j.ecoinf.2025.103392
Received 11 March 2025; Received in revised form 10 August 2025; Accepted 11 August 2025

extant production areas outside this range. Indeed, there is strong evidence that coffee-producing regions already face challenges from climate change (Ahmed et al., 2021; Grüter et al., 2022).

In addition to its relatively narrow climatic and biophysical envelope, arabica coffee has limited genetic diversity (Pham et al., 2019). Arabica-producing areas are already experiencing increasing temperatures and variability in the amount and distribution of rainfall, which threaten coffee yield and quality (Kasongi et al., 2024; Mamuye et al., 2024). In consequence, several studies have examined the possible impacts of climate change on coffee at different spatial and temporal scales and found that depending on the scenario, as much as 50 % of areas suitable for coffee production globally might no longer be viable by the 2050s (Bunn et al., 2015; Chemura et al., 2021; Davis et al., 2012; Grüter et al., 2022; Laderach et al., 2011; Ovalle-Rivera et al., 2015). Other works indicated that climate change would likely increase the prevalence of coffee diseases and insect pests and impact yield and quality (Craparo et al., 2015; Jaramillo et al., 2011; Laderach et al., 2011).

Like other production zones, Ethiopia's coffee, grown in forest, semi-forest, plantation, and agroforestry production systems (Labouisse et al., 2008), is potentially under threat (Benti et al., 2022; Chemura et al., 2021; Davis et al., 2012; Moat et al., 2017). Ethiopia is a wild coffee genetic pool, and coffee supports the livelihoods of 25 % of the country's population, generating 5 % of its gross domestic product (GDP) (Olana Jawo et al., 2023).

There is general agreement across previous studies that most current coffee-growing regions will lose suitability in the coming decades, while a few places, mainly at higher elevations or latitudes, might become more suitable. Clearly identifying potential winners and losers at the scales that matter for smallholder coffee producers, however, is challenging. Because of its diverse agroecology, a wide range of altitudes, varying soil types, and divergent microclimates, different regions in Ethiopia may have quite different experiences with respect to coffee production as a result of climate change (Agegnehu et al., 2015). Generally, climate change is expected to negatively affect coffee production in the country and push production into the highlands (Benti et al., 2022; Chemura et al., 2021; Davis et al., 2012; Moat et al., 2017), but national- and local-scale predictions sometimes vary. Furthermore, recent work examining coffee suitability under climate change in other regions suggests that crop suitability can depend on the style of cultivation – particularly whether or not coffee is cultivated in a shade-grown agroforestry setting (Abigaba et al., 2024; Cassamo et al., 2023), suggesting that using local data on currently suitable production locations could lead to more accurate predictions.

Even if some highland areas in countries like Ethiopia become newly suitable for coffee production, the expected shift of coffee to highland areas potentially conflicts with extant highland forest cover. In Ethiopia, coffee forest management involves the removal of some proportion of the overstory canopy trees and clearing competing understory vegetation (Aerts et al., 2011). This is a problem because, under European Union Regulation 2023/1115, firms are not allowed to supply goods derived from lands deforested after December 31, 2020. Given that the European market is the dominant source of export demand for Ethiopia's coffee sector (Keane et al., 2024), even if suitable areas expand, they may not be economically viable. Although Ethiopia's coffee production system plays a relatively minor role in deforestation in comparison with other forms of agriculture (Hirons et al., 2018), there is no guarantee that this will remain the case in the future, particularly if substantial shares of Ethiopia's future coffee-suitable areas were under forest cover as of 2020.

Species distribution models (SDMs) predict species suitability based on environmental conditions by correlating known species occurrence data with environmental variables. They are useful to assess the potential impacts of climate change on crop distribution, including coffee. Correlative SDMs relate species' presence at particular geographic locations to the environmental characteristics of those locations in order to predict their distribution in other geographical regions (Srivastava et al., 2019; Warren, 2012), are often the preferred choice for small-scale suitability analysis under climate change, compared to mechanistic models, which rely on simulating the biological processes that govern species survival and reproduction and require detailed physiological and ecophysiological data rarely available for crops like coffee (Dormann et al., 2012). Although coffee suitability depends on specific climatic and biophysical requirements, few studies evaluate climate change threats to coffee production at small spatial scales while considering all its diverse biophysical requirements, such as local microclimate (rainfall, temperature, humidity, and radiation), topographic (elevation, slope angle, and aspect), soil (fertility, acidity/alkalinity) (Abigaba et al., 2024; Cassamo et al., 2023; Chemura et al., 2021; Scholz et al., 2018; Worku et al., 2019). While global and national-scale models exist and are highly informative, they may nonetheless fail to capture small spatial-scale habitat characteristics and are affected by biased and incomplete occurrence records, especially in under-surveyed, remote areas. Additionally, large-scale models are more difficult to apply for planning local adaptation and conservation strategies (Elith and Leathwick, 2009; Meyer et al., 2016; Wiens et al., 2009).

In contrast, local-scale SDM provides detailed insights that capture variations in local conditions. It allows for more accurate predictions and better validation through field data, making it highly relevant for site-specific conservation and adaptive management (Brambilla et al., 2024; Casas et al., 2022). Assessing local-level climatic threats to coffee and considering all important variables influencing coffee suitability is crucial for designing appropriate local-level adaptation and mitigation strategies (Moat et al., 2017).

Numerous factors influence SDMs' reliability, including the study area extent (Amaro et al., 2023), the modeling algorithms employed (Yackulic et al., 2013), the range of predictor variables used, the relationship between environmental and topographic factors, and the degree of extrapolation from the original data (Elith and Leathwick, 2009). Most previous suitability modeling studies have limitations in that they may not address all ecologically relevant predictors and mostly rely on only a single machine learning algorithm (Santini et al., 2021). Addressing those limitations will help advance scientific framing of potential climate change impacts in the different coffee origins to guide better adaptation planning.

In this study, we examine the potential impacts of climate change on *Coffea arabica* L. in selected districts of Southwestern Ethiopia using an ensemble modeling approach that combines three machine learning algorithms (Maxent, SVM, and RF), trained using an ensemble of three global climate models (GCMs) covering two Shared Socio-economic Pathways (SSP2–4.5 and SSP5–8.5) over four future periods: 2022–2040 (2030s), 2041–2060 (2050s), 2061–2080 (2070s), and 2080–2100 (2090s). In this study, we investigate 1) the current distribution of coffee production areas and their projected shifts in local coffee production areas under different emission scenarios and future time-periods in selected districts of Southwestern Ethiopia, 2) the important environmental determinants of coffee area suitability in each site, and 3) the intersection between projected production areas and the 2020 global forest cover map used by the European Union Deforestation Regulation (EUDR).

2. Methodology

2.1. Study area

Ethiopia has a highly diverse climate, ranging from the equatorial rainforest with high rainfall and humidity in the south and southwest, to the afromontane regions in the summits of the Semien Mountains in north and Bale Mountains in the east, to the desert region in the northeast. Southwest Ethiopia is primarily a tropical highland sub-humid zone (M. Yang et al., 2020). It is the birthplace of *Coffea arabica L.*, which grows indigenously in the wild in the tropical, moist, evergreen montane forest. In the forested highlands of southwestern

Ethiopia, *Coffea arabica* grows wild as a native understory shrub (Samuel et al., 2019). The present study considers five coffee-growing districts from southwestern Ethiopia: Gera, Goma, and Limu Seka from the Jimma zone and Yayu and Ale districts in the Ilubabor zone (Fig. 1). We selected these locations based on their diverse altitudinal ranges, high coffee production potential, diversity of coffee production systems, and dominance of coffee production among smallholders. The selected districts have a diverse topography and wide elevation range (1233 to 3028 m above sea level). They experience unimodal rainfall patterns and have faced increasing temperature trends and mean annual rainfall in recent decades (Mamuye et al., 2024).

2.2. Data collection and analysis

2.2.1. Coffea arabica presence data

Presence data were collected from field observations using a hand-held Global Positioning System (GPS) device with an accuracy of ±5 m from coffee production locations. Assuming coffee farmers grow coffee in all suitable agro-ecological areas, we collected occurrence points across gradients from the lowest to the highest possible altitudes where coffee is currently grown. In the study area, coffee is cultivated in four distinct – though in all cases shaded - production systems: forest, semi-forest, garden, and plantation, each with varying management intensities. Because, as noted above, production regimes can influence the potentially suitable range for coffee cultivation, we collected occurrence points across all production systems to capture the full range of local growing techniques. A relatively large sample size was gathered to encompass the variability in agroecology across the extensive spatial range of coffee plants in the region (Läderach et al., 2017; Magrach and Ghazoul, 2015).

2.2.2. Spatial filtering of the presence data

We employed the ‘spThin’ package (Aiello-Lammens et al., 2015) in R version 4.3.2 (R Core Team, 2023) to randomize the spatial distribution of the coffee presence data set and limit the presence data to no more than one data point per pixel at a resolution of ~1 km^2 (Kramer-Schadt et al., 2013; Steen et al., 2021). After spatial filtering, 119 points for Gera, 89 for Ale, 65 for Goma, 98 for Yayu, and 113 for Limu Seka, a total of 484 valid points, were retained for modeling.

2.3. Predictor variables for suitability modeling

We used three primary classes of agro-climatic variables - bioclimatic, soil, and topographic to estimate Arabica coffee suitability across five coffee-growing districts selected based on previous literature on coffee production.

2.3.1. Bioclimatic variables

We used historical climate data for 1970–2000 obtained from WorldClim version 2.1 (https://www.worldclim.org/data) to model the areas currently suitable for Arabica production in the study sites. To evaluate suitability for arabica coffee production in the future, we used ensembles of three climatic projections from the INM, MRI_ESM2.0, and MIROC6 global circulation models (GCMs), which previous studies have

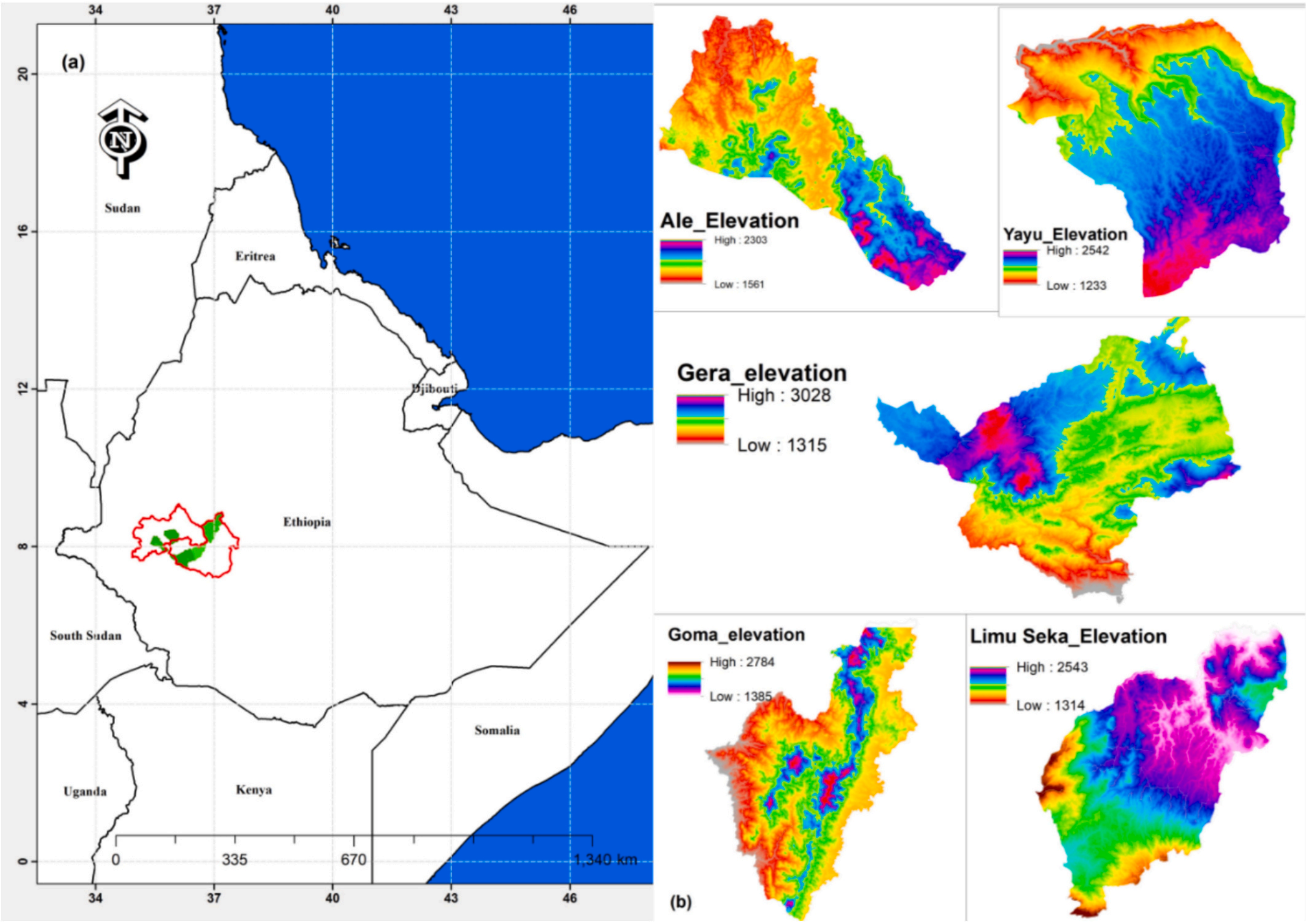


Fig. 1. Location map of the study area (a), elevation ranges (in meters above sea level) of the study districts (b).The Map was produced by Melkamu Mamuye using shapefile data from https://gadm.org/. and DEM from http://e0srp01u.ecs.nasa.gov/srtm/version2/SRTM3/

indicated provide robust median results for Ethiopian conditions (Gebisa et al., 2023; Sime and Dibaba, 2023) (Supplementary Table S1). The GCMs are monthly future climate data from the CMIP6, available in GeoTiff files with a spatial resolution of 30 arc *sec*. We selected two socio-economic pathways (SSPs), SSP2–4.5, regarded as a moderate carbon emission scenario, and SSP5–8.5, a high-emissions scenario (O'Neill et al., 2014), to characterize the possible future of coffee production in the area over four time periods: 2021–2040, 2041–2060, 2061–2080, and 2081–2100. Previous studies have identified these selected GCMs as performing well in East Africa (Ayugi et al., 2022; Ongoma et al., 2018; Gebisa et al., 2023; Rettie et al., 2023; Sime and Dibaba, 2023), and further bias-corrected for all periods under consideration using the delta downscaling method (Navarro-Racines et al., 2020).

From these datasets, we used the Coupled Model Intercomparison Project 6 (CMIP6) bioclimatic variables at a spatial resolution of 1 km. The 19 global gridded bioclimatic variables described in Supplementary Table S2 are climate indices analyzed from average monthly temperature and precipitation values. They represent annual trends (e.g., mean annual temperature, annual precipitation values, and their variations), seasonal characteristics (e.g., annual range in temperature and precipitation), and extreme or limiting environmental factors (e.g., the temperature of the coldest and warmest month, and precipitation of the wet and dry quarters) that impact species growth, physiology, survival, and productivity. These bioclimatic variables have been widely used in previous SDM studies (Abigaba et al., 2024; Benti et al., 2022; Bunn et al., 2015; Chemura et al., 2021; Moat et al., 2017). Supplementary Table S2 provides detailed information for each variable.

2.3.2. *Topographical variables*

The amount of radiation received by coffee plants varies depending on the direction that the slope is facing, and slope angle also has an influence on the accumulation of water and soil depth (Zhou et al., 2023), so we include elevation, aspect, and slope, similar to Guisan et al. (2017). Since topographic variables influence microclimates, solar radiation, and soil moisture, thereby affecting the species occurrence and distribution, incorporating these variables improves the spatial precision of species distribution models (Kharel et al., 2024; Yang et al., 2023). We computed these three topographic variables from a digital elevation model (DEM) derived from the Shuttle Radar Topography Mission's (SRTM) 90 m × 90 m elevation product, downloaded from http://e0srp01u.ecs.nasa.gov/srtm/version2/SRTM3/ using the *terra* package (Hijmans, 2024) in R version 4.3.2 (R Core Team, 2023).

2.3.3. *Soil variables*

Soil types and their associated physical and chemical properties are important determinants in influencing coffee production and land suitability (Getachew et al., 2022; Kufa, 2011; Nair, 2014). Soil properties can also constrain plant distributions and substantially impact their occurrence (Ni and Vellend, 2022). Our models include four soil variables considered good indicators of soil quality and productivity (Maurya et al., 2020): pH, cation exchange capacity (CEC), organic carbon content (OC), and bulk density (BD) (Supplementary Table 3). Soil pH affects coffee growth by influencing plant root development, nutrient availability, and overall plant health (Laekemariam, 2020). Similarly, CEC impacts nutrient retention and supply to the plant's roots (Sánchez-Reinoso et al., 2023). BD influences soil aeration, water infiltration, and root development (Tebekew et al., 2024), and SOC influences soil structure, fertility, and biological activity, thereby indirectly boosting both nutrient availability and CEC (Sánchez-Reinoso et al., 2023).

We obtained gridded soil raster data from the International Soil Reference and Information Centre (ISRIC) Africa soils database (https://soilgrids.org/) at a 250 m resolution (Hengl et al., 2014), later resampled to 1 km to align with the spatial resolution of the bioclimatic variables using the '*aggregate*' functions of the *terra* package (Hijmans, 2024). We used the average resulting value from the 0–100 cm soil depth for the analysis. Soil data were masked to the extent of the study areas using the *terra* and *sf* packages (Pebesma, 2016) in R version 4.3.2 (R Core Team, 2023).

2.4. *Multicollinearity analysis and relative importance of environmental variables*

The Variable Inflation Factor (VIF) step function, available in the *sdm* package, was employed to conduct a multicollinearity analysis for each site by eliminating variables that exhibited a high correlation with a VIF exceeding 10 (Naimi and Araújo, 2016). To determine the relative contribution of the environmental variables to the predictions made by the model, we employed the *usdm*-R package (Naimi et al., 2014), which measures the correlation between the predicted values of a model with the original predictors and predictions of the model with a randomly permuted dataset under evaluation. Since each algorithm produces different variable importance values, we calculated the mean values for the three models to provide relative information on the predictors' importance within the model (Chemura et al., 2021). The percentage contribution of each retained variable was presented for all locations separately to identify their relative importance in predicting Arabica coffee suitability.

2.5. *Modeling approach*

We used an ensemble modeling approach that combines predictions from multiple models to improve accuracy and reduce uncertainty (Pourghasemi et al., 2017), a technique frequently applied in previous research (Chemura et al., 2021; Harris et al., 2024; Kaky et al., 2020). We used three machine learning algorithms: maximum entropy (Maxent; Phillips and Dudík, 2008), random forest (RF; Breiman, 2001), and support vector machine (SVM; Vapnik, 2000), to build the ensemble model discussed here. We selected these algorithms due to their demonstrated high performance in species distribution modeling, especially under limited presence-only or nonlinear environmental data conditions (Elith and Leathwick, 2009; Guo et al., 2005; Phillips et al., 2006). We ran these models in the *sdm* package in R (Naimi and Araújo, 2016). We used a weighted multimodel ensemble of predictions, commonly used in coffee suitability studies (Abigaba et al., 2024; Chemura et al., 2021), by averaging the predictions made by individual machine learning algorithms to increase the reliability of predictions (Tegegne et al., 2020). Ensembling integrates predictions from multiple algorithms, which reduces individual model biases and improves overall predictive accuracy and robustness, particularly valuable in climate-sensitive species like *Coffea arabica* grown under complex ecological interactions (Li et al., 2024; Zhao et al., 2022). After running all three models, we computed the ensemble means using Eq. 1:

$$Weighted\ MME = \frac{\sum_{j=1}^{n} (AUC_j \times \mathrm{M}\_prediction_j)}{\sum_{j=1}^{n} AUC_j} \tag{1}$$

AUC_j is the AUC value of the jth single machine learning algorithm (M_j) and $M\_prediction_j$ is the single machine learning algorithm prediction.

2.6. *Model performance evaluation*

To evaluate model performance, we divided the coffee presence data into training (70 %) and testing (30 %) datasets, using the former for model calibration and the latter for performance evaluation. To assess prediction accuracy, we computed the receiver operating characteristic curve (AUC) (Fielding and Bell, 1997) and the true skill statistic (TSS) using the *ecospat* package in R (Di Cola et al., 2017). AUC measures overall discrimination capacity and varies from 0 to 1 (Swets, 1988), while TSS balances the capacity to correctly predict presences and pseudo-absences that vary from −1 to 1 (Allouche et al., 2006). AUC values above 0.75 are generally considered good (Chang and Bourque, 2020; Elith and Graham, 2009). A TSS value of ≥0.5 is typically considered an acceptable, and a TSS ≥ 0.7 a strong, predictive performance (Allouche et al., 2006).

2.7. Suitability maps

We created binary maps from the continuous suitability raster generated in the modeling to categorize suitable and non-suitable areas using the threshold that maximized the sum of specificity and sensitivity to classify the continuous suitability index raster (Chemura et al., 2016). Coffee suitability maps were then created for present and future periods, and the overall change in suitable areas (loss, gain, or stable) was determined by subtracting the current suitability from predicted future suitability.

2.8. Analysis of the intersection between the projected production site and the global forest cover map

Recent efforts to reduce deforestation linked to international trade have led to a number of voluntary zero-deforestation efforts (Lambin and Furumo, 2023), and with the passage of the European Union Deforestation Regulation (EUDR) in 2023, these initiatives became particularly important for the coffee sector. Because the EU is such a substantial global coffee buyer, the EUDR, which forbids importing a range of deforestation-linked products, including coffee, that have been grown in areas that were identified as forest as of December 31, 2020, could act as an important constraint on coffee expansion (Regulation (EU), 2023). While there is no officially recognized global forest cover map that ensures compliance with the legislation, the EU Forest Observatory has produced a global 10-m-resolution map of forest cover intended to support the EUDR (Forest Observatory, 2023). This map has limitations, as it uses binary classification of forest and non-forest land based on canopy cover thresholds, which can misclassify shaded agroforestry systems as either forest or non-forest (Gallemore et al., 2025). Given its intended purpose and policy relevance, however, we selected this map to assess the share of areas potentially suitable for coffee production that fell under the forest as of the end of 2020. While preliminary tests of the map suggest it over-identifies coffee production areas as forests (European Commission, Joint Research Centre, 2024), such systematic errors could nevertheless also act as impediments to smallholder expansion by increasing regulatory risks. In other words, we are less interested in the layer's accuracy than we are simply in what areas it designates as forested as of December 31, 2020. To assess the overlap between estimated present and future new coffee-suitable areas, we took the binary coffee-suitability rasters discussed above and masked out currently suitable coffee areas. We multiplied the resulting rasters by the binary EU forest observatory global map of forest cover for the year 2020, computing the overlap as a percentage of the newly suitable area using the *terra* package in R version 4.3.2 (R Core Team, 2023).

3. Result

3.1. Model performance and variable importance

The accuracies of all the SDM algorithms were generally excellent across all districts. All models: Maxent, RF, and SVM exhibited the highest AUC and TSS values. The highest AUC value ranged from 0.86 to 0.98 across all algorithms and sites. According to Phillips and Dudík (2008), a model with an AUC value of greater than 0.75 is potentially acceptable; AUC values greater than 0.90 indicate excellent discrimination, while values between 0.80 and 0.89 reflect very good model performance (Jiménez-Valverde, 2012). Similarly, the TSS value was also above 0.84 for all models and sites except Limu Seka (Table 1), where TSS values greater than 0.64 indicate good predictive accuracy. The relatively lower score in Limu Seka may reflect the limited number of species occurrence points used relative to the district's total area. Overall, all three models performed well in predicting Arabica coffee distribution in the study areas.

3.2. Determinants of coffee area suitability across districts

Fig. 2 indicates the relative contribution of climatic variables, soil, and topographical factors in estimating coffee suitability for each district. While climatic factors are the most important predictors of coffee area suitability in the study areas, the percentage contribution of specific bioclimatic variables to the predictions differs across districts. In Ale, precipitation in the driest month (BIO14) and isothermality (BIO3), followed by soil bulk density (BD), were the top contributors to coffee suitability, accounting for 52 % of the total prediction contribution. In Yayu, BIO14, precipitation of the wettest month (BIO13) and precipitation of the coldest quarter (BIO19) were the highest contributors, accounting for 44.3 %. Temperature seasonality (BIO4) contributes 37.5 % in Gera, followed by precipitation of the warmest quarter (12.8 %) and other variables. Similarly, in Limu Seka, temperature seasonality (BIO4) and BIO19 contribute 25.14 %, followed by BIO9 and BD. In Goma, BIO19, BIO4, BD, and BIO15 have almost similar contributions that account for 45.82 %, in addition to other remaining variables.

Topography-related variables (slope and aspect) were identified as the least essential variables for coffee suitability in all sites because coffee distribution is driven more by climatic suitability than by terrain per se. The soil bulk density (BD) value is relatively high in determining suitability compared to CEC and SOC in Ale, Goma, and Limu Seka. Variation was observed for the least contributing variables across districts. Overall, climate variables are essential contributors to coffee suitability and are of varying importance. BD, CEC, pH, SOC, aspect, and slope affect coffee suitability in all districts with varying degrees of contribution.

3.3. Areas suitable for coffee production under current climatic conditions

The multi-model ensemble identifies approximately 4590 km^2 (65.5 %) of the total study sites as suitable for coffee under current climatic conditions, with the largest area coverage in Limu Seka and Gera districts, which is 1155km^2 and 1072 km^2, respectively (Table 2). Suitable areas amount to 857 km^2 in Ale, 887 km^2 in Goma, and 619 km^2 in Yayu

Table 1
Model performance of machine learning algorithms used in suitability modeling.

	Yayu		Limu Seka		Gera		Goma		Ale	
Methods	AUC	TSS	AUC	TSS	AUC	TSS	AUC	TSS	AUC	TSS
Maxent	0.98	0.95	0.86	0.64	0.97	0.89	0.98	0.92	0.96	0.86
RF	0.98	0.93	0.87	0.68	0.97	0.89	0.98	0.92	0.97	0.87
SVM	0.97	0.9	0.86	0.64	0.96	0.85	0.97	0.9	0.95	0.84

AUC stands for "Area under the ROC curve," which provides an aggregate measure of performance across all possible classification thresholds; TSS stands for true skill statistic, which balances the capacity to predict presences and pseudo-absences correctly.

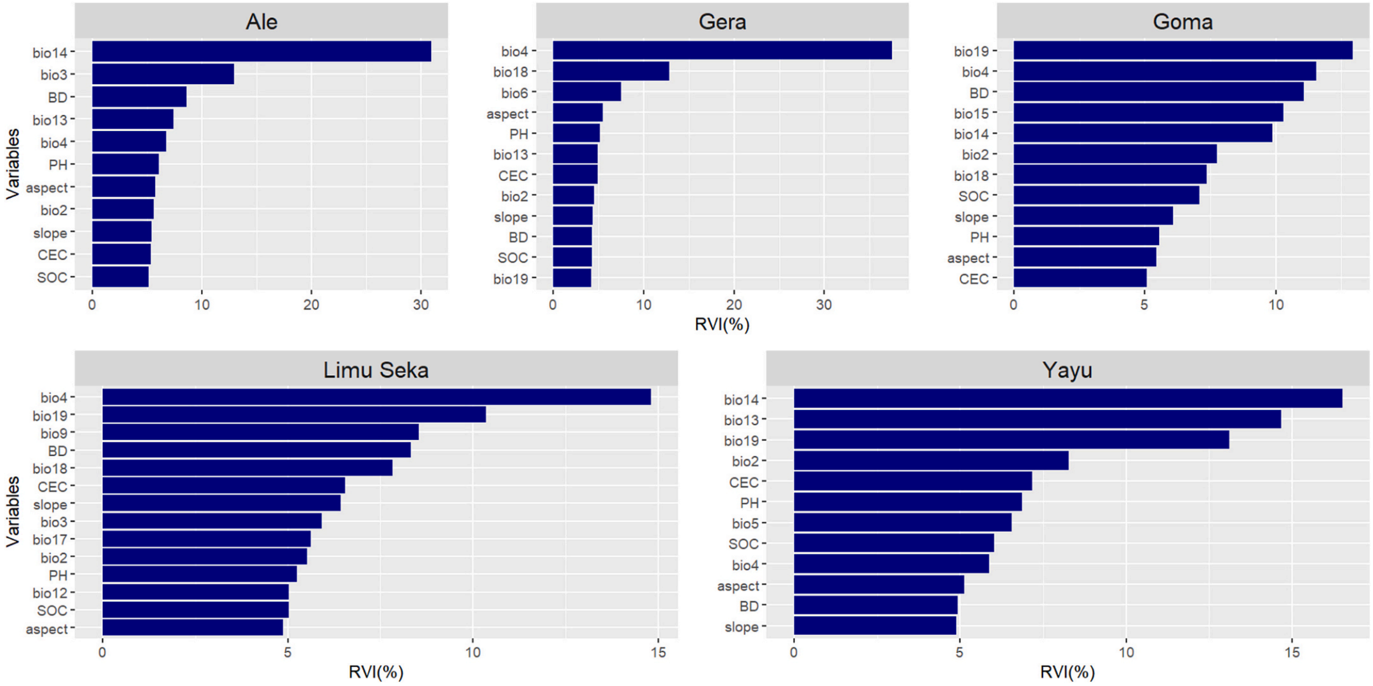


Fig. 2. The relative importance of predictor variables (RVI%) in determining coffee area suitability for specific districts. The variables importance values based on the AUC matrix for all the models were combined (averaged) and presented.

Table 2
Total area of the study districts and percentage of current suitable areas for growing coffee.

Sites	Total area considered for analysis (square km)	Current suitable area (km^2)	Percent suitable from the total area (%)
Ale	1071	857	80
Gera	1783	1072.0	60.1
Goma	1122	887.0	79.1
Limu Seka	2998	1155.0	38.5
Yayu	1017	619.0	61

districts. According to the current suitability map, the existing distribution of climatically suitable areas for coffee matches the occurrence records obtained by the field survey (supplementary Fig. S3).

3.4. Projected changes in coffee arabica suitable area under SSP2–4.5 scenario

Projected suitable areas for Arabica coffee and changes under the SSP2–4.5 scenario are shown in Figs. 3 and 4. The ensemble model predicts that the suitable area for coffee production in Ale, currently 857 km^2, will increase by 17 % (1006 km^2) by the 2030s and in 25 % (1070 km^2) by the 2050s, but only by 20 % (1032 km^2) by the 2070s, and 19 % (1022 km^2) by the 2090s. In Gera, the currently suitable area of 1072 km^2 is expected to increase significantly by 52 % (to 1627 km^2) in the 2030s and 59 % (1700 km^2) in the 2050s, but only by 51 % (1613 km^2) and 41 % (1510 km^2) by the 2070s and 2090s, respectively.

Goma district's coffee-suitable area is also expected to expand by 8 %, increasing from 887 km^2 to 958 km^2, particularly by the 2050s, and is projected to grow by 4.17 % during the 2090s. Limu Seka, which currently boasts 1155km^2 of arabica-suitable areas, is projected to experience the highest positive change, with a growth of 122.2 % (to 2566 km^2) by the 2030s, 127 % (2622 km^2) by the 2050s, 136.1 % (2727 km^2) by the 2070s, and 124.2 % (2590 km^2) by the 2090s. Yayu is also predicted to gain additional suitable areas in the 2030s, though the magnitude of the increase is expected to decline in subsequent years, from 42.81 % (884 km^2) in the 2030s to 35.6 % (838 km^2) in the 2050s, 25.5 % (777 km^2) in the 2070s, and 21.5 % (752 km^2) in the 2090s (Figs. 5 and 6).

3.5. Projected changes in Arabica coffee suitable area under SSP5–8.5 scenario

Figs. 7 and 8 show the current and projected suitable areas under SSP5–8.5 scenarios. In the 2030s, the area suitable for coffee is projected to grow by 21 % (from 857 km^2 to 1036 km^2), 65.1 % (from 1072 km^2 to 1770 km^2), 9 % (from 887 km^2 to 967 km^2), 66 % (from 1155 km^2 to 1914 km^2), and 29 % (from 619 km^2 to 801 km^2) in Ale, Gera, Goma, Limu Seka, and Yayu, respectively. Coffee growing areas are likely to increase in the 2050s and 2070s for all locations compared to the current suitable area, except for Yayu, where they are expected to contract by the 2070s (−5.5 %). By the 2090s, the highest projected loss of suitable area is expected in Yayu district (−46.7 %; 330 km^2). The highest average increase is anticipated in Limu Seka, which is expected to benefit from climate change by gaining 71.0 % more coffee-suitable area by the end of the century (Figs. 9 and 10).

Overall, under both emission scenarios, suitability for growing *Coffee arabica* in the study sites is expected to expand to higher elevations, allowing most currently suitable areas to continue growing coffee, except for some lowland locations. More pronounced expansion is projected under the SSP2–4.5 emission scenario, where coffee will become more suitable in most study sites. Similarly, under SSP5–8.5, most of the highland areas are projected to gain additional suitable areas for coffee production, except Yayu, which is projected to lose suitability in different parts of the district at the end of the century. The largest increase in suitable area is projected for Limu Seka and Gera under both scenarios, while the smallest percentage gain is expected in Goma. Under the SSP2–4.5 emission scenario, projections indicate a more pronounced expansion, with coffee becoming more suitable in most study sites.

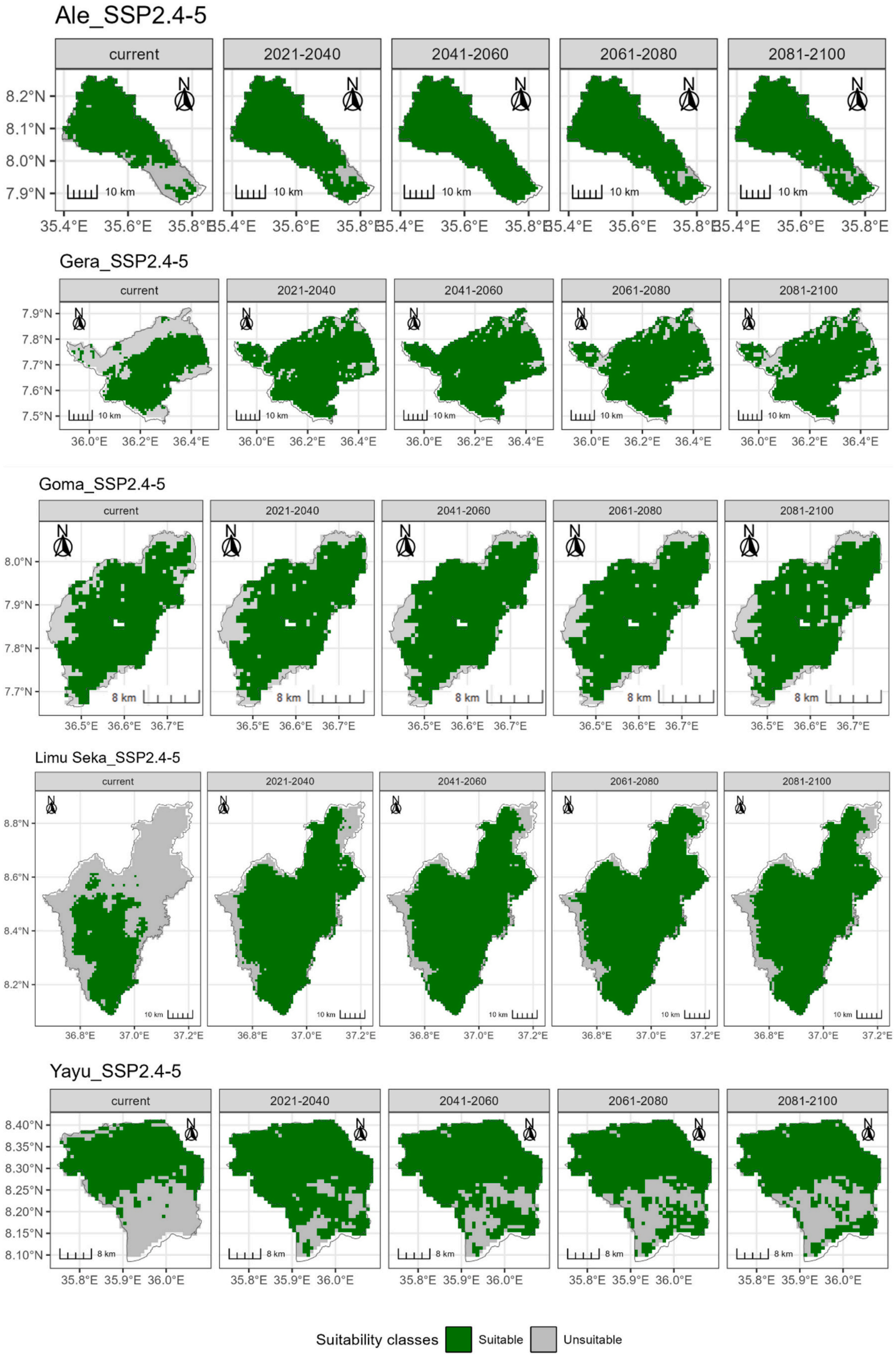


Fig. 3. Projected current and future distribution of coffee arabica under SSP2.4–5.

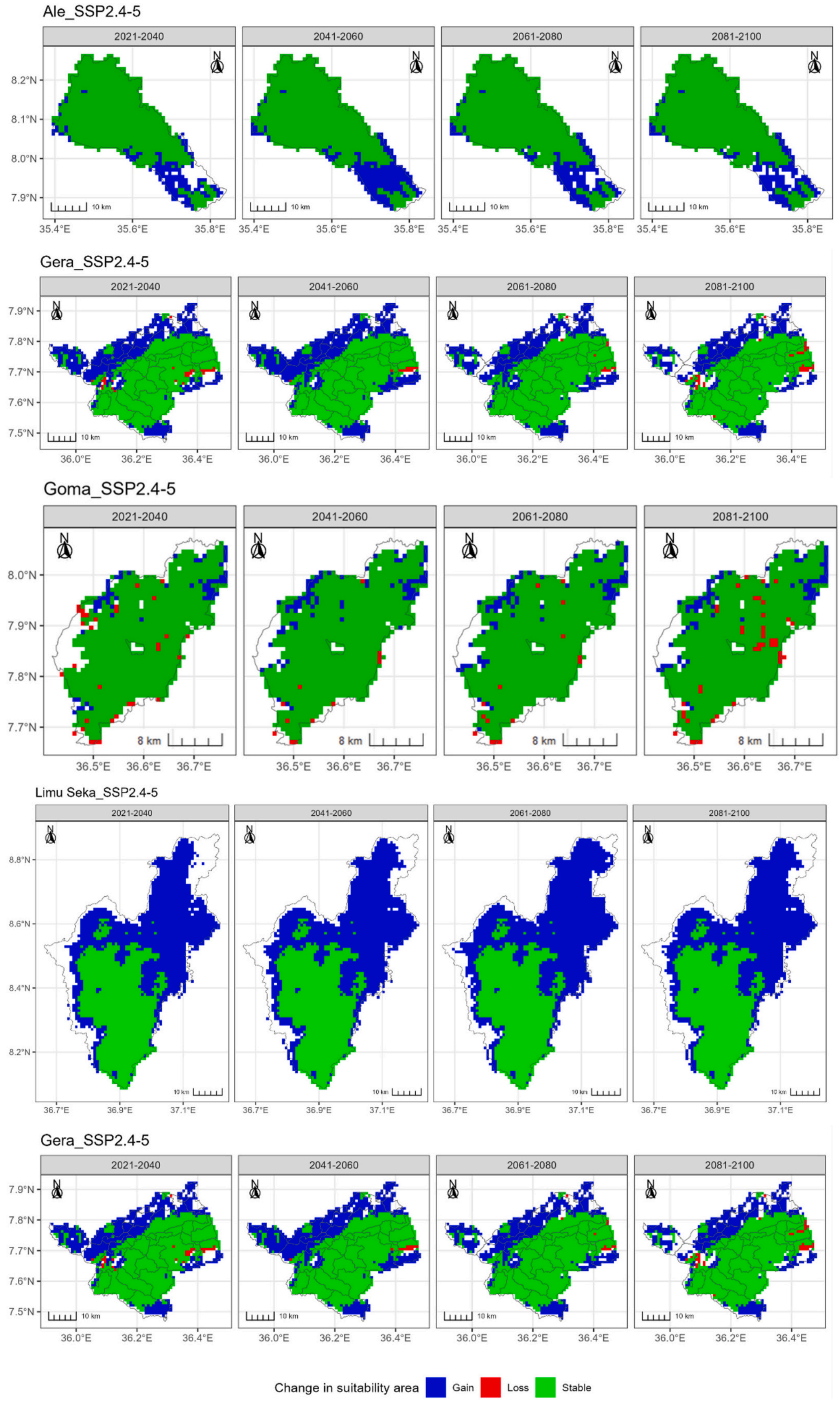


Fig. 4. Projected changes (gains, losses, and remaining suitable) in the Arabica-coffee suitable areas in the study districts under the SSP245 scenario.

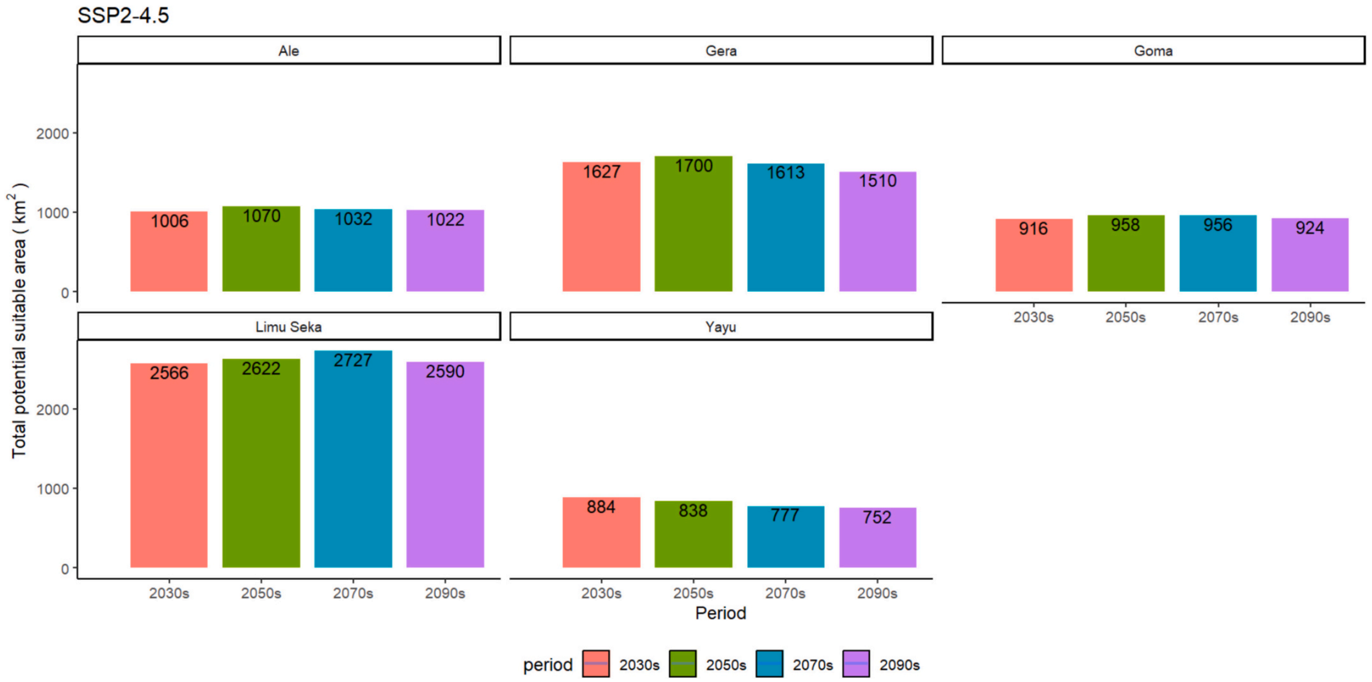


Fig. 5. Projected coffee arabica-suitable areas (km^2) in the study districts under SSP245 scenario.

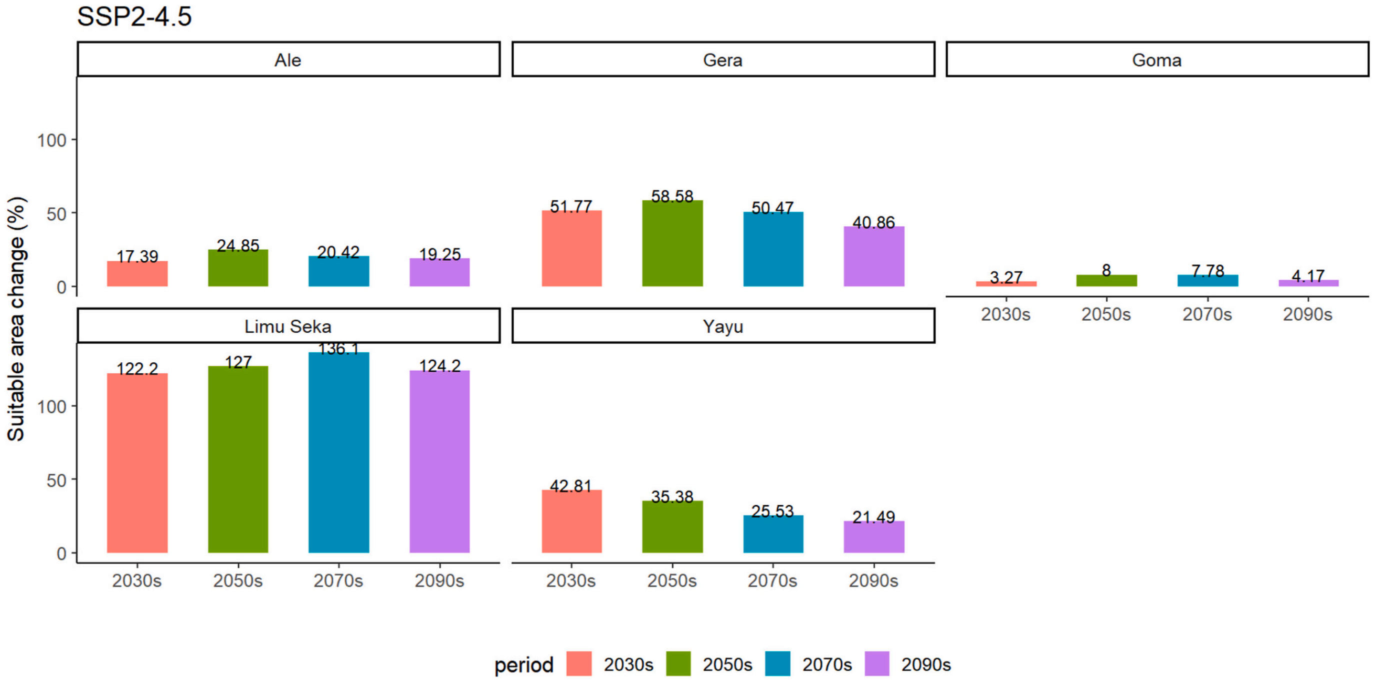


Fig. 6. Change in projected arabica-suitable areas (%) in study districts under SSP245 scenario. Percentage change is calculated relative to the current suitable area.

3.6. *Future coffee production areas' intersection with the EU forests Observatory global forest map 2020*

The percentage of projected suitable areas (Figs. 3 and 7), classified as a forest on the global forest cover map of the year 2020 (https://forest-observatory.ec.europa.eu/forest/gfc2020), designed to support compliance with the EUDR varies substantially across districts (Fig. 11). About 90 % of areas that may become newly suitable for coffee production over the 21st century in Ale and Yayu were under forest cover as of 2020, which, under current EU policy, would effectively render those areas off limits for export to the world's largest coffee market. The rates are lower in the other districts, though about 30 % of newly suitable areas were under forest in 2020 in Gera and Goma, and about a quarter of new areas in Limu Seka.

4. Discussion

4.1. *Determinants of coffee area suitability across districts*

Our results indicate that the environmental variables that predict the

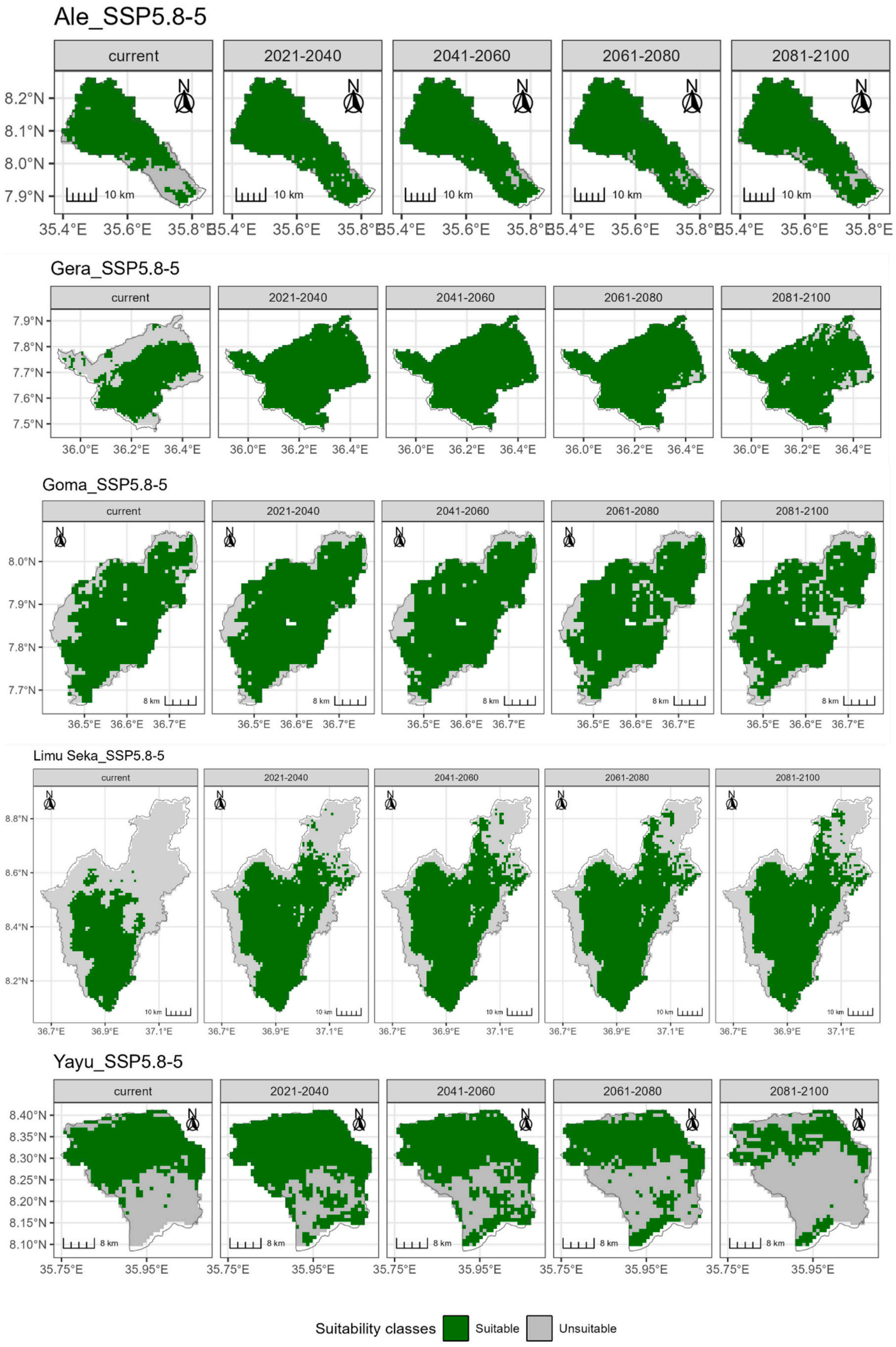


Fig. 7. Potential current and future distribution of coffee arabica under SSP5–8.5.

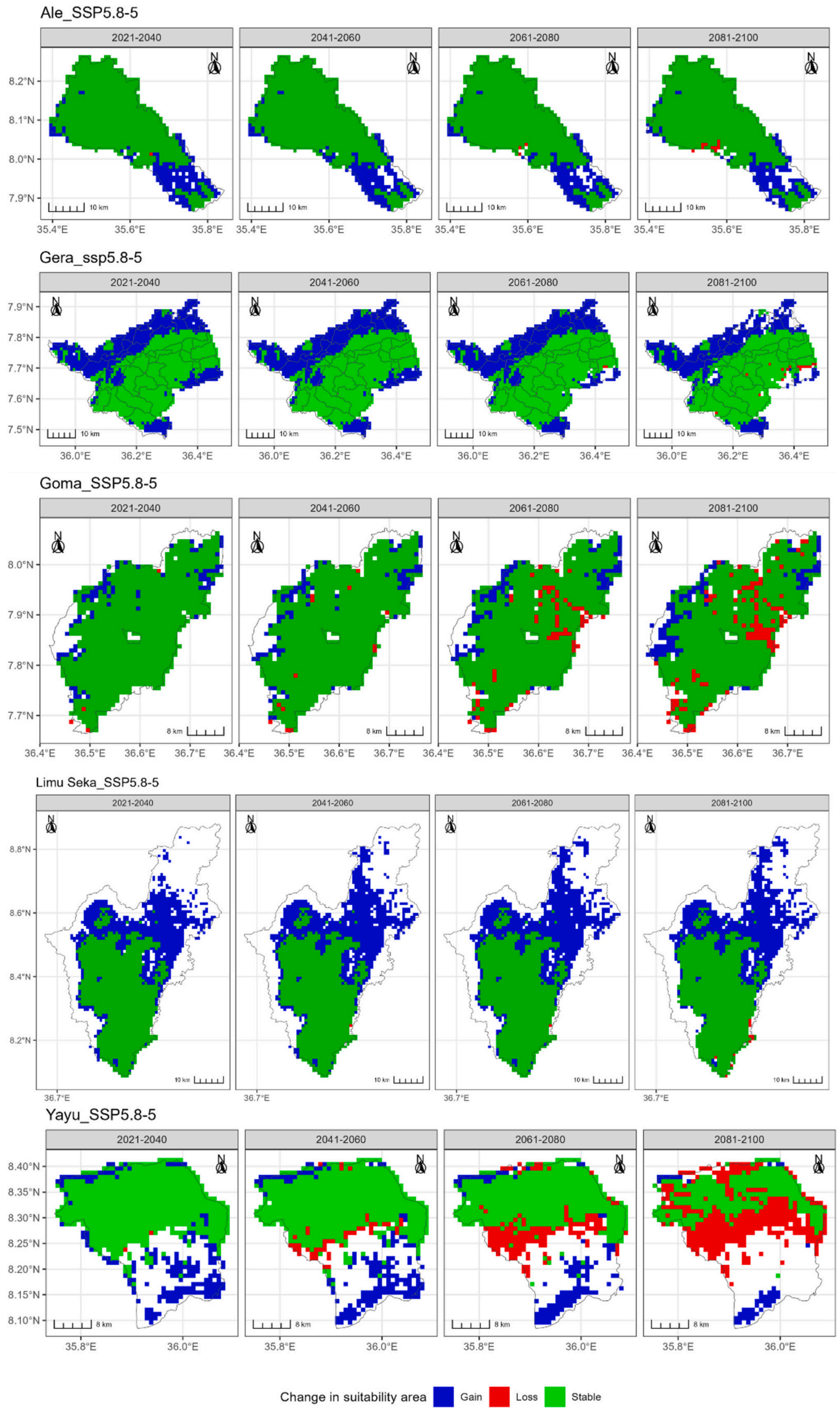


Fig. 8. Projected changes (gains, losses, and stable) in the suitable areas for coffee growth under the SSP585 scenario.

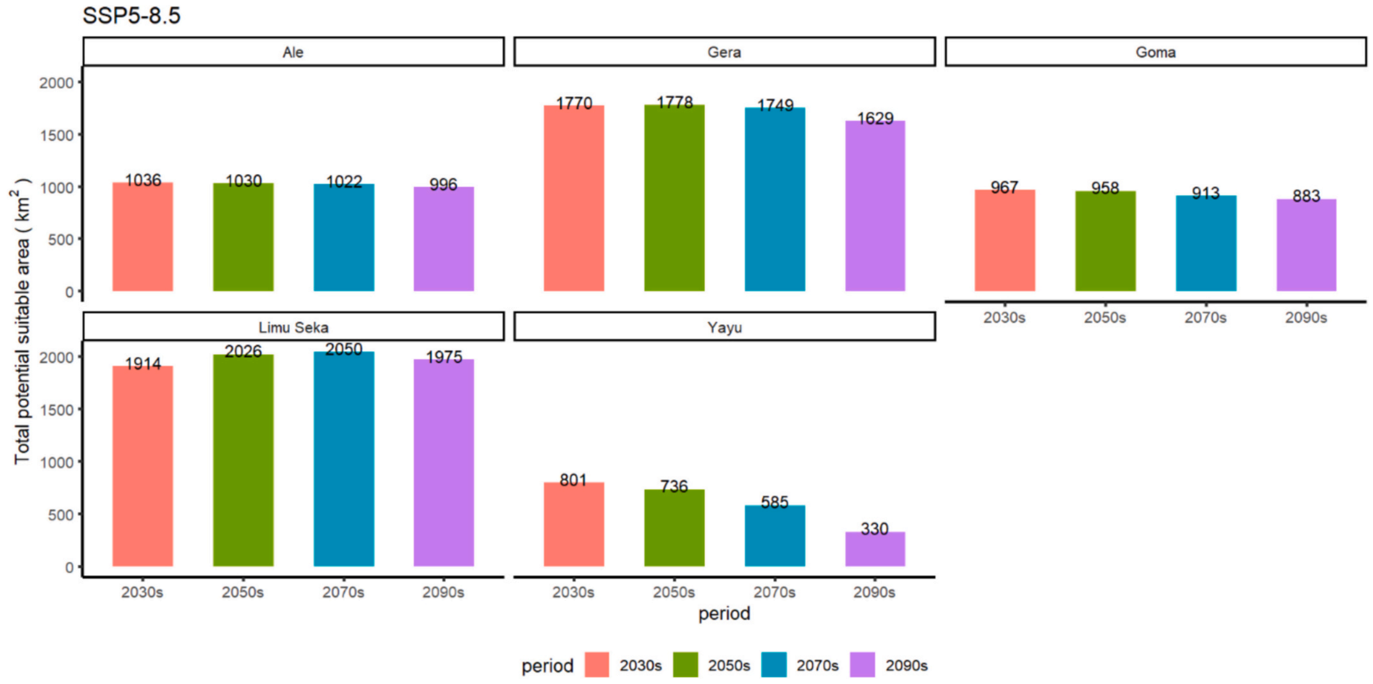


Fig. 9. Projected coffee arabica-suitable areas (km^2) in study districts under SSP585 scenarios.

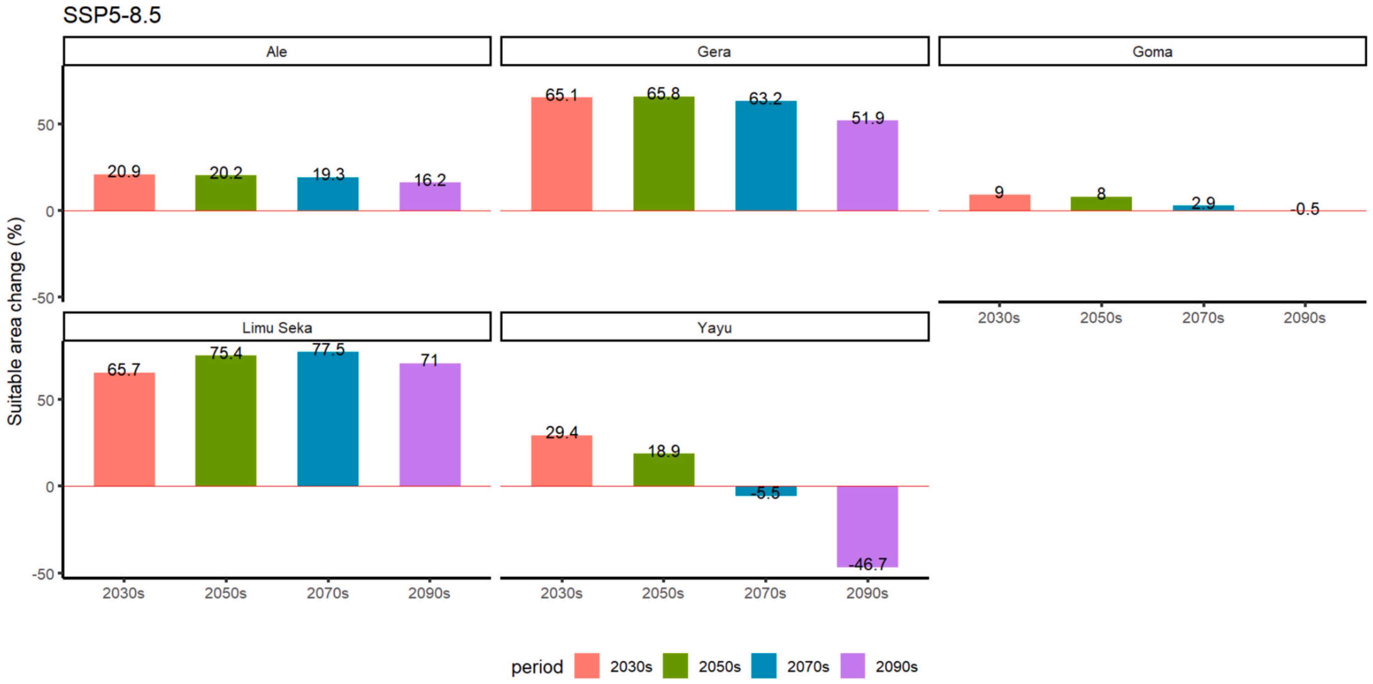


Fig. 10. Change in projected arabica-suitable areas (%) in study districts under the SSP585 scenario. Percentage change is calculated relative to the current suitable area.

suitability of Arabica coffee areas differ between locations, with rainfall-related variables being the best predictor in Ale, Goma, and Yayu, followed by temperature-related variables, while the order of importance is the opposite in Gera and Limu Seka. In a national-scale study of Ethiopia, (Chemura et al., 2021) also found precipitation-related variables to be the most important predictor of coffee suitability. Bunn et al. (2015), conversely, identified temperature factors as determinants of Arabica coffee suitability globally. While their relative importance differs from site to site, however, the contribution of temperature and precipitation factors in predicting coffee area suitability in our study area is high and consistent with previous studies (Benti et al., 2022; Chemura et al., 2021; Moat et al., 2017). The variation in the type and percentage contribution of the predictor variables in different locations suggests that local biophysical factors shape the suitability of coffee areas in individual locations Chemura et al. (2021) or that different factors are close to limits in different areas. In addition, distinct environmental drivers in each site suggest tailored adaptation strategies like using heat-tolerant coffee varieties and agroforestry practices in areas like Limu Seka to sustain coffee production as climate impacts evolve. The contribution of soil and topographical factors in determining coffee

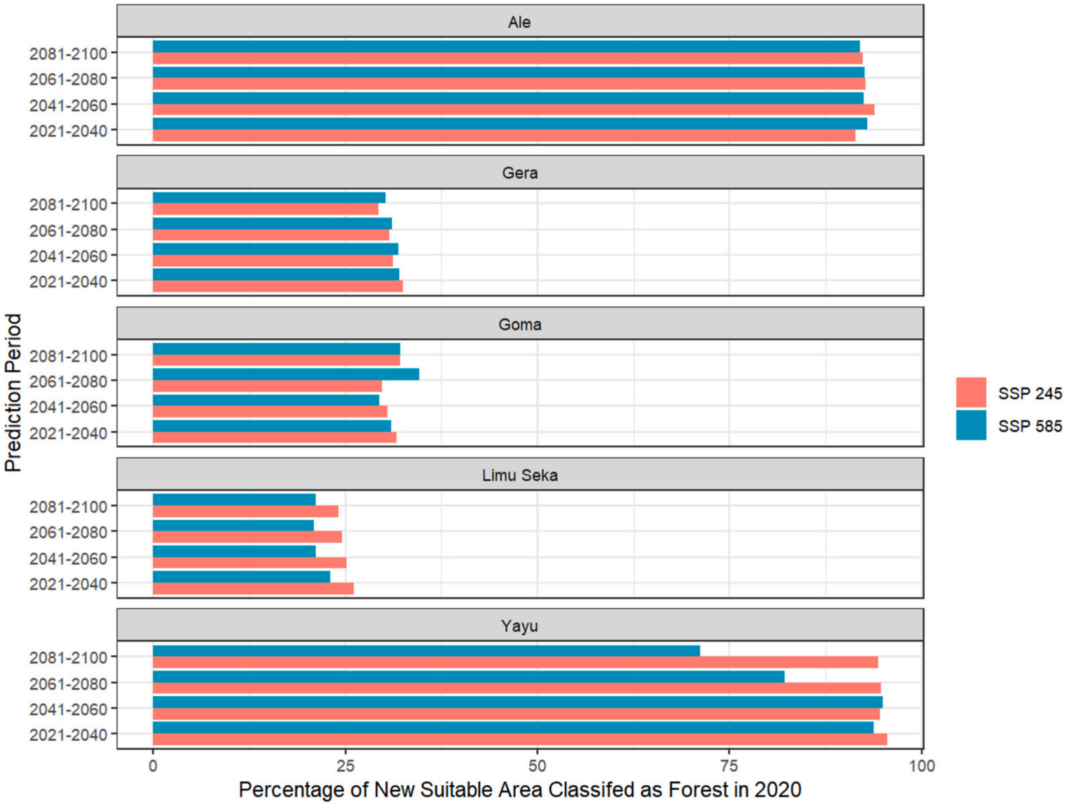


Fig. 11. Percentage of projected new suitable areas classified as forest in 2020.

area suitability also varies in predictive importance across sites, with the contribution of soil-related parameters (BD, pH, and CEC) in predicting suitability being substantial in certain districts because those parameters are pivotal indicators of nutrient availability in the soil (Lara Estrada et al., 2017). Other studies have highlighted the interplay between soil, topography, and climate in determining land suitability for crops like coffee, emphasizing that soil properties such as pH and other fertility indicators are critical edaphic factors influencing coffee suitability by buffering against climate-induced stresses (Salas López et al., 2020; Tebekew et al., 2024; Abigaba et al., 2024). This suggests that coffee farmers must adopt agronomic practices such as agroforestry and soil conservation interventions in the coffee production system as a climate adaptation option (Olana Jawo et al., 2023). The results underscore the crucial role of local-scale modeling in capturing microclimatic and topographic variations affecting Arabica coffee suitability, which national or global-scale studies often overlook. This specificity allows targeted adaptation strategies for each district's unique environmental challenges in areas where coffee is produced within numerous agro-ecological zones and geographical boundaries (Moat et al., 2017).

4.2. Projected changes in suitable areas

Our modeling projects a geographically heterogeneous but overall increasing trend in areas suitable for the production of indigenous Arabica coffee under the influence of global climate change. Suitability is projected to increase in highland regions of Gera, Lim Seka, Ale, and Goma, while declining in low and some mid-elevation zones such as Yayu, reflecting contrasting local climate responses (Figs. 4 & 8). Overall, under the SSP2–4.5 scenario (medium challenges to mitigation and adaptation), all locations are projected to experience an overall increase in suitable areas over future periods. Specifically, the number of bioclimatically suitable areas in the Ale, Gera, Goma, Limu Seka, and Yayu districts is expected to rise by 19 %, 41 %, 4 %, 124 %, and 22 %, respectively, by 2081–2100. Under the worst-case scenarios (SSP5–8-5: high challenges for mitigation, low challenges for adaptation), the highest increases are still expected in Ale (16 %), Gera (52 %), and Limu Seka (71 %) by the end of the century. The highest decline in suitable areas in Yayu might be due to the extensive area coverage of lowland areas currently producing coffee and the highest projected increase in mean temperature and rainfall under the SSP5.8–5 scenario in Yayu and Goma districts, which might affect optimal requirements for coffee (Supplementary Fig. S1).

Due to the upslope shift in coffee area suitability, previously unsuitable areas for coffee production will become biophysically suitable for cultivation (Sisay, 2018), though this does not mean that they will be agroecologically viable. In agreement with our projections, Benti et al. (2022), in their regional analysis in the Jimma zone of southwest Ethiopia, estimated an increase in suitable areas under high-emission scenarios by 2.52 % and 2.25 % in the 2050s and 2070s, respectively. A recent study by Chemura et al. (2021) in the Nekemte area of western Ethiopia also projected increases in suitable areas, depending on the time periods and scenario. Another nationwide study also projected the emergence of suitable regions at higher altitudes of the southwestern and northern Ethiopian coffee areas, forecasting a more than 400 % increase in coffee-suitable areas under a lower emission scenario (Moat et al., 2017). An increase of up to 44.2 % in the suitable coffee-growing areas in Ethiopia, with a westward and northwestward shift of suitable areas, is also reported by Adane (2024). In agreement with these projected positive changes in general, coffee suitability in Ethiopia is expected to increase (Bunn et al., 2015; Moat et al., 2017). Ethiopia, however, is rather unique in this regard: Grüter et al. (2022) present evidence that few higher elevation regions in East Africa are positioned to benefit from climatic change.

One of our study sites, Yayu, is expected to lose 46.7 % suitable areas by the end of the century under the high emission (SSP5–8.5) scenario. Certainly, many other global and national findings have also shown declining trends in coffee-suitable areas. Example: Magrach and Ghazoul (2015), using the MaxEnt modeling algorithm, and Grüter et al.

(2022), using CONSUS, a GIS-based decision support system, in their global-level study, reported a more than 50 % decrease in the currently suitable area for *Coffee arabica*. Using a random forest modeling approach, Bunn et al. (2015), indicated an overall global loss of suitable areas for coffee by the 2050s. Ovalle-Rivera et al. (2015) also reported an average loss of 19 % of suitable area globally by the 2050s. Similarly, Moat et al. (2017) found that under high emission scenarios and in the absence of significant interventions, 39–59 % of currently suitable areas will decline by the end of the century. Davis et al. (2012) also reported a profound negative impact of climate change on Ethiopian Arabica, with a 65–100 % reduction in suitable areas by 2080. Benti et al. (2022), in their regional analysis using the Maxent model, found a decline in total suitability by 4.75 % (2050s) and 6.09 % (2070s) under low-emission scenarios.

In general, our results contrast with some earlier global and nationwide studies that showed areas suitable for Arabica production in Ethiopia would diminish; however, the findings agree with most of microscale projections and more recent regional assessments. Our local-scale projections suggest that the suitability of arabica coffee will increase while the majority of current production sites also remain suitable. The variation between our local-scale analysis and nationwide analysis might be explained by various reasons, including the scales of analysis, details of the data set, and sample size used for modeling. Consequently, analyzing climate change impacts at a broader spatial scale may have, in some previous cases, led to overly pessimistic projections. Studies also suggest that numerous local factors explain coffee suitability in individual locations, and the reliability of species distribution modeling is also affected by the extent of the study area, the type and details of the datasets used for modeling (Amaro et al., 2023; Barve et al., 2011; Elith and Leathwick, 2009). Small spatial scale (location-specific) studies indicate more detailed information about the consequences of climate change on coffee production than broader area ones. Chemura et al. (2021) also recommended region-specific assessment to investigate the detailed consequences of climate impacts on coffee production.

Moreover, in this study, most of our study sites are located at an elevation range of 1233 to 3028 m a.s.l. (Fig. 1), in which areas above ~2300 m a.s.l. are not currently under coffee production. Similar to other coffee modeling studies mentioned above, temperature and rainfall variables were the most important factors explaining coffee suitability (Fig. 4), and increasing trends in historical climate variables characterize our study sites (Mamuye et al., 2024) and an increase in projected mean rainfall and temperature trends (Supplementary Figs. S1 and S2), which might bring the majority of the highland areas to a suitable class for coffee production. As temperatures increase in higher elevations, coffee-producing areas might remain stable, and additional new production sites might emerge (Adane, 2024; Moat et al., 2017). Additionally, a limited number of previous coffee modeling studies take soil and topographic requirements into account, which limits coffee suitability in some of our study sites, which is important in explaining the sites more accurately. The expansion to higher-elevation regions could offer new opportunities for sustainable Arabica coffee production in the face of climate change that may require implementing proactive adaptation strategies, enhancing institutional support, land-use planning, and enabling access to extension support and climate information to align with the emerging requirements from international coffee buyers like the EUDR regulation.

4.3. Projected newly suitable areas classified as forest in the global forest cover map 2020

The majority of Ethiopian coffee is produced under shade-tree cover, which provides significant benefits for biodiversity conservation (Gebremichael et al., 2022; Hylander et al., 2024; Manson et al., 2024) and carbon sequestration (Berhanu et al., 2023; Tesfay et al., 2022). Our suitability analysis indicated that projected coffee production sites could expand towards forested highland areas, which may become a serious concern in the future, as production in such areas would violate the requirements set in the EUDR 2023/1115. Concerningly, between about 25 % and 90 % of projected newly suitable areas, depending on the district, are identified as under forest cover as of December 2020 by the European Forest Observatory's global forest cover 2020 map. With the EU a dominant player in Ethiopian coffee export markets, it would be wise not to regard all the future suitable areas as truly open to coffee production.

Southwestern Ethiopia, in general, and the study districts in particular, are known for coffee-dominated landscapes associated with forest cover (Fashing et al., 2022), with various levels of management gradient, including forest (wild) coffee to intensively managed plantation coffee, which all grow under the tree canopy (Teketay, 1999). Forests are the foundation of livelihoods for forest-dependent people in the tropics, including our study sites (FAO and UNDP, 2020), where 90 % of coffee production in Ethiopia is concentrated in the hands of smallholders who produce coffee under shade (Zhunusova et al., 2022). On the other hand, global climate change is also influencing climatically suitable areas for coffee production, pushing suitable areas for coffee to high-altitude forested areas. These might put smallholders who rely on coffee production for their livelihood in a bind. Smallholders have low education levels, limited access to information, and limited financial resources to cover the costs of complying with this regulation (Zhunusova et al., 2022). Given these concerns, we suggest the EUDR may need to more directly consider the implications of shade-grown Arabica coffee and its impact on the livelihoods of millions of smallholder farmers who rely on coffee production. Muradian et al. (2024) also noted that the EUDR has not been designed to address the current critical drivers of tropical deforestation; it adopts a restrictive notion of EU-driven deforestation based only on consumption. Furthermore, local adaptation could involve promoting agroforestry-based coffee systems that maintain canopy cover in areas projected to be suitable. Negotiation pathways that include advocating for context-specific EUDR interpretations, recognizing low-impact, shade-grown coffee practices as compliant, are also important.

5. Conclusions

This study examined the potentially suitable areas for coffee arabica under future climate conditions and how climate change will affect this at a local scale under different emission scenarios. We applied an ensemble of three machine-learning algorithms (SVM, RF, and MAXENT) to examine the current and future suitability of coffee in five different potential coffee-growing districts of southwestern Ethiopia. This study aimed to understand and identify determinants of coffee area suitability and the impact of climate change on coffee area suitability in the future. We also assessed the extent to which the projected future production geographies may overlap with the global forest cover map of 2020. All three models demonstrated excellent predictive performance across all study sites. Using ensemble modeling algorithms combined with multiple predictor variables enabled us to identify the impact of climate change on coffee area suitability and to identify potential production geographies at a small spatial scale. We found that arabica coffee is currently suitable in distinct areas of the sites, and climate change will allow the areas to gain additional suitable areas, keeping the majority of current production sites suitable in the future, except for very few locations that will lose suitability. Under the SSP2–4.5 scenario, coffee suitability is projected to expand considerably across all time periods in four of our study sites. Under the high-emission scenario, three of our study sites are expected to experience substantial increases in suitable areas by the end of the century, while the remaining two are projected to lose 0.5–46.7 % of the currently suitable areas. In all districts, at least about a quarter and as much as 90 % of projected newly suitable areas were forested as of 2020 and potentially out of compliance with the EUDR.

We drew four important conclusions from the study results. First, there are differences in factors best predicting coffee area suitability across the five districts. Second, all of the study areas are projected to gain additional suitability in all future periods and emission scenarios, except Yayu, which will lose a significant amount of suitability during the 2090s under the high-emission scenario. Projections indicate that new potential production sites will emerge in the high-altitude areas of the districts. Third, the magnitude of the impacts of climate change varies among different scenarios and the periods under consideration, and the highest negative impact will be under the high-emission scenario at the end of the century. Fourth, the considerable overlap of projected suitable areas with the global forest cover map (2020) might challenge coffee producers in the areas to fulfill the export requirements set by the EUDR. For the areas identified as at risk of losing suitability, there are opportunities for adaptation strategies to maintain coffee in its original locations. Further research endeavors should also focus on modeling the impact of climate change on coffee quality, distribution of coffee disease and insect pests, land tenure and land availability issues in the current and projected suitable areas, and their adaptation and mitigation measures to maintain coffee.

Finally, our findings underscore the crucial role of local-scale modeling in capturing microclimatic, soil, and topographic variations affecting Arabica coffee suitability, something national or global-scale studies often overlook. Establishing and integrating local climate-agriculture monitoring programs into district-level planning and coordinated policy frameworks across local institutions can support real-time decision-making. This specificity allows targeted adaptation strategies for each district's unique environmental challenges. To prepare for anticipated losses in suitability, local governments and other actors should invest in drought-resistant crop varieties and diversified agroforestry systems. Additionally, areas projected to gain suitability should adopt strict reforestation and soil conservation practices to comply with the EUDR. While our model effectively captures bioclimatic influences, incorporating socio-economic factors, pest prevalence, and coffee quality in future analyses would provide a fuller picture of the impact of climate change. Further research should explore these aspects to enhance long-term adaptation strategies.

CRediT authorship contribution statement

Melkamu Mamuye: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Caleb Gallemore:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Ng'winamila Kasongi:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Kristjan Jespersen:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Gezahegn Berecha:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this manuscript.

Acknowledgements

This research was conducted as part of the Paradoxes of Climate-Smart Coffee (PACSMAC) project, funded by the Danida Fellowship center (Grant number: DFC File No, 20-07-CBS) implemented in collaboration between Copenhagen Business School, Jimma University, the University of Dar es Salaam, Lafayette College, and ESADE Business School.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2025.103392.

Data availability

All materials, including data and codes related to our findings, are provided as follows. For data obtained from online sources, such as bioclimatic variables from different GCMs, as well as soil and topographic variables, we cited the source links in the body of the manuscript. We provided the species presence data (coffee occurrence locations) used for modeling in .csv format. We uploaded the R code used for SDM and visualization of outputs, projected suitability maps in .tiff file, topographic variables in .tiff file, coffee occurrence locations in .csv and shapefile formats to GitHub repository and can be accessed: https://github.com/MelkamuMamuye/Coffee-SDM-Analysis. The data created in this research follow the guidelines of the journal for reproducibility and transparency (Huettmann and Arhonditsis, 2023).

References

Abigaba, D., Chemura, A., Gornott, C., Schauberger, B., 2024. The potential of agroforestry to buffer climate change impacts on suitability of coffee and banana in Uganda. Agrofor. Syst. 98 (6), 1555–1577. https://doi.org/10.1007/s10457-024-01025-3.

Adane, A., 2024. Analysis of current and future bioclimatic suitability for C. Arabica production in Ethiopia. PLoS One 19 (10), e0310945. https://doi.org/10.1371/journal.pone.0310945.

Adhikari, M., Isaac, E.L., Paterson, R.R.M., Maslin, M.A., 2020. A review of potential impacts of climate change on coffee cultivation and mycotoxigenic fungi. Microorganisms 8 (10), 1625. https://doi.org/10.3390/microorganisms8101625.

Aerts, R., Hundera, K., Berecha, G., Gijbels, P., Baeten, M., Van Mechelen, M., Hermy, M., Muys, B., Honnay, O., 2011. Semi-forest coffee cultivation and the conservation of Ethiopian Afromontane rainforest fragments. For. Ecol. Manag. 261 (6), 1034–1041. https://doi.org/10.1016/j.foreco.2010.12.025.

Agegnehu, E., Thakur, A., Mulualem, T., 2015. Potential impact of climate change on dynamics of coffee berry borer (Hypothenemus hampi Ferrari) in Ethiopia. OALib 02 (01), 1–11. https://doi.org/10.4236/oalib.1101127.

Ahmed, S., Brinkley, S., Smith, E., Sela, A., Theisen, M., Thibodeau, C., Warne, T., Anderson, E., Van Dusen, N., Giuliano, P., Ionescu, K.E., Cash, S.B., 2021. Climate change and coffee quality: systematic review on the effects of environmental and management variation on secondary metabolites and sensory attributes of Coffea arabica and Coffea canephora. Front. Plant Sci. 12, 708013. https://doi.org/10.3389/fpls.2021.708013.

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., Anderson, R.P., 2015. spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38 (5), 541–545. https://doi.org/10.1111/ecog.01132.

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43 (6), 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x.

Amaro, G., Fidelis, E.G., Da Silva, R.S., Marchioro, C.A., 2023. Effect of study area extent on the potential distribution of species: A case study with models for Raoiella indica Hirst (Acari: Tenuipalpidae). Ecol. Model. 483, 110454. https://doi.org/10.1016/j.ecolmodel.2023.110454.

Ayugi, B., Shilenje, Z.W., Babaousmail, H., Lim Kam Sian, K.T.C., Mumo, R., Dike, V.N., Iyakaremye, V., Chehbouni, A., Ongoma, V., 2022. Projected changes in meteorological drought over East Africa inferred from bias-adjusted CMIP6 models. Nat. Hazards 113 (2), 1151–1176. https://doi.org/10.1007/s11069-022-05341-8.

Barve, N., Barve, V., Jiménez-Valverde, A., Lira-Noriega, A., Maher, S.P., Peterson, A.T., Soberón, J., Villalobos, F., 2011. The crucial role of the accessible area in ecological niche modeling and species distribution modeling. Ecol. Model. 222 (11), 1810–1819. https://doi.org/10.1016/j.ecolmodel.2011.02.011.

Benti, F., Diga, G.M., Feyisa, G.L., Tolesa, A.R., 2022. Modeling coffee (Coffea arabica L.) climate suitability under current and future scenario in Jimma zone, Ethiopia. Environ. Monit. Assess. 194 (4), 271. https://doi.org/10.1007/s10661-022-09895-9.

Berhanu, Y., Nigussie, A., Jifar, A.A., Ahmed, M., Biresaw, A., Mamuye, M., Fite, A., Dume, B., 2023. Nitrous oxide and methane emissions from coffee agroforestry systems with different intensities of canopy closure. Sci. Total Environ. 876, 162821. https://doi.org/10.1016/j.scitotenv.2023.162821.

Brambilla, M., Bazzi, G., Ilahiane, L., 2024. The effectiveness of species distribution models in predicting local abundance depends on model grain size. Ecology 105 (2), e4224. https://doi.org/10.1002/ecy.4224.

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32. https://doi.org/10.1023/A:1010933404324.

Bunn, C., Läderach, P., Ovalle Rivera, O., Kirschke, D., 2015. A bitter cup: climate change profile of global production of Arabica and Robusta coffee. Clim. Chang. 129 (1–2), 89–101. https://doi.org/10.1007/s10584-014-1306-x.

Casas, E., Martín-García, L., Hernández-Leal, P., Arbelo, M., 2022. Species distribution models at regional scale: *Cymodocea nodosa* seagrasses. Remote Sens 14 (17), 4334. https://doi.org/10.3390/rs14174334.

Cassamo, C.T., Draper, D., Romeiras, M.M., Marques, I., Chiulele, R., Rodrigues, M., Stalmans, M., Partelli, F.L., Ribeiro-Barros, A., Ramalho, J.C., 2023. Impact of climate changes in the suitable areas for *Coffea arabica* L. production in Mozambique: agroforestry as an alternative management system to strengthen crop sustainability. Agric. Ecosyst. Environ. 346, 108341. https://doi.org/10.1016/j.agee.2022.108341.

Chang, Y., Bourque, C.P.-A., 2020. Relating modelled habitat suitability for Abies balsamea to on-the-ground species structural characteristics in naturally growing forests. Ecol. Indic. 111, 105981. https://doi.org/10.1016/j.ecolind.2019.105981.

Chemura, A., Kutywayo, D., Chidoko, P., Mahoya, C., 2016. Bioclimatic modelling of current and projected climatic suitability of coffee (Coffea arabica) production in Zimbabwe. Reg. Environ. Chang. 16 (2), 473–485. https://doi.org/10.1007/s10113-015-0762-9.

Chemura, A., Mudereri, B.T., Yalew, A.W., Gornott, C., 2021. Climate change and specialty coffee potential in Ethiopia. Sci. Rep. 11 (1), 8097. https://doi.org/10.1038/s41598-021-87647-4.

Craparo, A.C.W., Van Asten, P.J.A., Läderach, P., Jassogne, L.T.P., Grab, S.W., 2015. Coffea arabica yields decline in Tanzania due to climate change: global implications. Agric. For. Meteorol. 207, 1–10. https://doi.org/10.1016/j.agrformet.2015.03.005.

DaMatta, F.M., Ramalho, J.D.C., 2006. Impacts of drought and temperature stress on coffee physiology and production: A review. Braz. J. Plant Physiol. 18 (1), 55–81. https://doi.org/10.1590/S1677-04202006000100006.

Davis, A.P., Gole, T.W., Baena, S., Moat, J., 2012. The impact of climate change on indigenous Arabica coffee (Coffea arabica): predicting future trends and identifying priorities. PLoS One 7 (11), e47981. https://doi.org/10.1371/journal.pone.0047981.

Di Cola, V., Broennimann, O., Petitpierre, B., Breiner, F.T., D'Amen, M., Randin, C., Engler, R., Pottier, J., Pio, D., Dubuis, A., Pellissier, L., Mateo, R.G., Hordijk, W., Salamin, N., Guisan, A., 2017. Ecospat: an R package to support spatial analyses and modeling of species niches and distributions. Ecography 40 (6), 774–787. https://doi.org/10.1111/ecog.02671.

Dormann, C.F., Schymanski, S.J., Cabral, J., Chuine, I., Graham, C., Hartig, F., Kearney, M., Morin, X., Römermann, C., Schröder, B., Singer, A., 2012. Correlation and process in species distribution models: bridging a dichotomy. J. Biogeogr. 39 (12), 2119–2131. https://doi.org/10.1111/j.1365-2699.2011.02659.x.

Elith, J., Graham, C.H., 2009. Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models. Ecography 32 (1), 66–77. https://doi.org/10.1111/j.1600-0587.2008.05505.x.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40 (1), 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159.

European Commission. Joint Research Centre, 2024. Mapping Global Forest Cover of the Year 2020 to Support the EU Regulation on Deforestation-Free Supply Chains. Publications Office. https://data.europa.eu/doi/10.2760/262532.

FAO, 2015. FAO Statistical Pocketbook: Coffee 2015. Food and Agriculture Organization of the United Nations.

FAO, UNDP, 2020. The state of the world's forests 2020. FAO and UNEP. https://doi.org/10.4060/ca8642en.

Fashing, P.J., Nguyen, N., Demissew, S., Gizaw, A., Atickem, A., Mekonnen, A., Nurmi, N. O., Kerby, J.T., Stenseth, N.Chr., 2022. Ecology, evolution, and conservation of Ethiopia's biodiversity. Proc. Natl. Acad. Sci. USA 119 (50), e2206635119. https://doi.org/10.1073/pnas.2206635119.

Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environ. Conserv. 24 (1), 38–49. https://doi.org/10.1017/S0376892997000088.

Forest Observatory, 2023. Global Map of Forest Cover Change. European Union, Brussels. https://forest-observatory.ec.europa.eu/forest/ghm.

Gallemore, C., Berecha, G., Eneyew, A., Grabs, J., Jespersen, K., Kasongi, N.'Gwinamila, Mamuye, M., Maskell, G., Mathe, A., Mwalutolo, D., Niehues, I., Terry, S., Yamungu, N., 2025. Avoiding access inequity due to classification errors in zero-deforestation value chains: coffee and the European union deforestation regulation. Land Use Policy 157, 107609. https://doi.org/10.1016/j.landusepol.2025.107609.

Gebisa, B.T., Dibaba, W.T., Kabeta, A., 2023. Evaluation of historical CMIP6 model simulations and future climate change projections in the Baro River basin. J. Water Clim. Chang. 14 (8), 2680–2705. https://doi.org/10.2166/wcc.2023.032.

Gebremichael, G., Hundera, K., De Decker, L., Aerts, R., Lens, L., Atickem, A., 2022. Bird community composition and functional guilds response to vegetation structure in Southwest Ethiopia. Forests 13 (12), 2068. https://doi.org/10.3390/f13122068.

Getachew, M., Tolassa, K., De Frenne, P., Verheyen, K., Tack, A.J.M., Hylander, K., Ayalew, B., Boeckx, P., 2022. The relationship between elevation, soil temperatures, soil chemical characteristics, and green coffee bean quality and biochemistry in Southwest Ethiopia. Agron. Sustain. Dev. 42 (4), 61. https://doi.org/10.1007/s13593-022-00801-8.

Grüter, R., Trachsel, T., Laube, P., Jaisli, I., 2022. Expected global suitability of coffee, cashew and avocado due to climate change. PLoS One 17 (1), e0261976. https://doi.org/10.1371/journal.pone.0261976.

Guisan, A., Thuiller, W., Zimmermann, N.E., 2017. Habitat Suitability and Distribution Models with Applications in R. Cambridge University Press.

Guo, Q., Kelly, M., Graham, C.H., 2005. Support vector machines for predicting distribution of sudden oak death in California. Ecol. Model. 182 (1), 75–90. https://doi.org/10.1016/j.ecolmodel.2004.07.012.

Harris, J., Pirtle, J.L., Laman, E.A., Siple, M.C., Thorson, J.T., 2024. An ensemble approach to species distribution modelling reconciles systematic differences in estimates of habitat utilization and range area. J. Appl. Ecol. 61 (2), 351–364. https://doi.org/10.1111/1365-2664.14559.

Hengl, T., de Jesus, J.M., MacMillan, R.A., Batjes, N.H., Heuvelink, G.B.M., Ribeiro, E., Samuel-Rosa, A., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Gonzalez, M.R., 2014. SoilGrids1km—global soil information based on automated mapping. PLoS One 9 (8), e105992. https://doi.org/10.1371/journal.pone.0105992.

Hijmans, R., 2024. *Terra: Spatial Data Analysis. R package version 1.7-82* [computer software]. https://rspatial.github.io/terra/. https://rspatial.org/.

Hirons, M., Mehrabi, Z., Gonfa, T.A., Morel, A., Gole, T.W., McDermott, C., Boyd, E., Robinson, E., Sheleme, D., Malhi, Y., Mason, J., Norris, K., 2018. Pursuing climate resilient coffee in Ethiopia – A critical review. Geoforum 91, 108–116. https://doi.org/10.1016/j.geoforum.2018.02.032.

Huettmann, F., Arhonditsis, G., 2023. Towards an ecological informatics scholarship that is reflective, repeatable, transparent, and sharable! Eco. Inform. 76, 102132. https://doi.org/10.1016/j.ecoinf.2023.102132.

Hylander, K., Nemomissa, S., Fischer, J., Zewdie, B., Ayalew, B., Tack, A.J.M., 2024. Lessons from Ethiopian coffee landscapes for global conservation in a post-wild world. Commun. Biol. 7 (1), 714. https://doi.org/10.1038/s42003-024-06381-5.

ICO, 2023. COFFEE REPORT AND OUTLOOK: International coffee organization.

IPCC, 2021. Climate change 2021: the physical science basis. In: Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press (In Press).

Jaramillo, J., Muchugu, E., Vega, F.E., Davis, A., Borgemeister, C., Chabi-Olaye, A., 2011. Some like it hot: the influence and implications of climate change on coffee berry borer (Hypothenemus hampei) and coffee production in East Africa. PLoS One 6 (9), e24528. https://doi.org/10.1371/journal.pone.0024528.

Jiménez-Valverde, A., 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling. Global Ecology and Biogeography 21 (4), 498–507. https://doi.org/10.1111/j.1466-8238.2011.00683.x.

Kaky, E., Nolan, V., Alatawi, A., Gilbert, F., 2020. A comparison between ensemble and MaxEnt species distribution modelling approaches for conservation: A case study with Egyptian medicinal plants. Eco. Inform. 60, 101150. https://doi.org/10.1016/j.ecoinf.2020.101150.

Kasongi, N., Yamungu, N., Gallemore, C., Jespersen, K., 2024. Projected rising temperatures and vapour pressure deficit threaten Arabica coffee production Tanzania's burgeoning coffee region: empirical insight from Mbinga district, Tanzania. Environ. Challenges 16, 100974. https://doi.org/10.1016/j.envc.2024.100974.

Keane, J., Agarwal, P., Mendez-Parra, M., Debowicz, D., 2024. Avoiding a 'green squeeze': Supporting Least Developed Countries navigate new greening trade measures. In: London: ODI (https://odi.org/en/publications/avoiding a-green-squeeze-supporting-least-developed-countries-navigate new-greening-trade-measures).

Kharel, B., Ayer, S., Kafle, S., Timilsina, S., Bhatta, K.P., Gautam, J., Acharya, A.K., Lamichhane, P., Airee, J., 2024. Current and future habitat suitability modelling of Bambusa teres outside forest areas in Nepal under climate change scenarios. Adv. Bamboo Sci. 9, 100112. https://doi.org/10.1016/j.bamboo.2024.100112.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J.D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A.K., Augeri, D.M., Cheyne, S.M., Hearn, A.J., Ross, J., Macdonald, D.W., Mathai, J., Eaton, J., Marshall, A.J., Semiadi, G., Rustam, R., Wilting, A., 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. Divers. Distrib. 19 (11), 1366–1379. https://doi.org/10.1111/ddi.12096.

Kufa, T., 2011. Chemical properties of wild coffee forest soils in Ethiopia and management implications. Agric. Sci. 02 (04), 443–450. https://doi.org/10.4236/as.2011.24057.

Labouisse, J.-P., Bellachew, B., Kotecha, S., Bertrand, B., 2008. Current status of coffee (Coffea arabica L.) genetic resources in Ethiopia: implications for conservation. Genet. Resour. Crop. Evol. 55 (7), 1079–1093. https://doi.org/10.1007/s10722-008-9361-7.

Laderach, P., Lundy, M., Jarvis, A., Ramirez, J., Portilla, E.P., Schepp, K., Eitzinger, A., 2011. Predicted impact of climate change on coffee supply chains. In: Leal Filho, W., FilhoW., Leal (Eds.), The Economic, Social and Political Elements of Climate Change. Springer Berlin Heidelberg, pp. 703–723. https://doi.org/10.1007/978-3-642-14776-0_42.

Läderach, P., Ramirez–Villegas, J., Navarro-Racines, C., Zelaya, C., Martinez–Valle, A., Jarvis, A., 2017. Climate change adaptation of coffee production in space and time. Clim. Chang. 141 (1), 47–62. https://doi.org/10.1007/s10584-016-1788-9.

Laekemariam, F., 2020. Carbon stock, sequestration and soil properties among fields in smallholder farms in southern Ethiopia. Environ. Syst. Res. 9 (1), 16. https://doi.org/10.1186/s40068-020-00176-3.

Lambin, E.F., Furumo, P.R., 2023. Deforestation-free commodity supply chains: myth or reality? Annu. Rev. Environ. Resour. 48 (1), 237–261. https://doi.org/10.1146/annurev-environ-112321-121436.

Lara Estrada, L., Rasche, L., Schneider, U.A., 2017. Modeling land suitability for Coffea arabica L. in Central America. Environ. Model Softw. 95, 196–209. https://doi.org/10.1016/j.envsoft.2017.06.028.

Li, X., Wang, Z., Wang, S., Qian, Z., 2024. Maxent and Marxan modeling to predict the potential habitat and priority planting areas of *Coffea arabica* in Yunnan, China under climate change scenario. Front. Plant Sci. 15, 1471653. https://doi.org/10.3389/fpls.2024.1471653.

Magrach, A., Ghazoul, J., 2015. Climate and pest-driven geographic shifts in global coffee production: implications for forest cover, biodiversity and carbon storage. PLoS One 10 (7), e0133071. https://doi.org/10.1371/journal.pone.0133071.

Mamuye, M., Gallemore, C., Jespersen, K., Kasongi, N., Berecha, G., 2024. Changing rainfall and temperature trends and variability at different spatiotemporal scales threaten coffee production in certain elevations. Environ. Challenges 15, 100950. https://doi.org/10.1016/j.envc.2024.100950.

Manson, S., Nekaris, K.A.I., Nijman, V., Campera, M., 2024. Effect of shade on biodiversity within coffee farms: A meta-analysis. Sci. Total Environ. 914, 169882. https://doi.org/10.1016/j.scitotenv.2024.169882.

Maurya, S., Abraham, J.S., Somasundaram, S., Toteja, R., Gupta, R., Makhija, S., 2020. Indicators for assessment of soil quality: A mini-review. Environ. Monit. Assess. 192 (9), 604. https://doi.org/10.1007/s10661-020-08556-z.

Meyer, C., Weigelt, P., Kreft, H., 2016. Multidimensional biases, gaps and uncertainties in global plant occurrence information. Ecol. Lett. 19 (8), 992–1006. https://doi.org/10.1111/ele.12624.

Moat, J., Williams, J., Baena, S., Wilkinson, T., Gole, T.W., Challa, Z.K., Demissew, S., Davis, A.P., 2017. Resilience potential of the Ethiopian coffee sector under climate change. Nat Plants 3 (7), 17081. https://doi.org/10.1038/nplants.2017.81.

Muradian, R., Cahyafitri, R., Ferrando, T., Grottera, C., Jardim-Wanderley, L., Krause, T., Kurniawan, N.I., Loft, L., Nurshafira, T., Prabawati-Suwito, D., Prasongko, D., Sanchez-Garcia, P.A., Schröter, B., Vela-Almeida, D., 2024. Will the EU deforestation-free products regulation (EUDR) reduce tropical forest loss? Insights from three producer countries. Ecol. Econ. 227, 108389. https://doi.org/10.1016/j.ecolecon.2024.108389.

Naimi, B., Araújo, M.B., 2016. Sdm: A reproducible and extensible R platform for species distribution modelling. Ecography 39 (4), 368–375. https://doi.org/10.1111/ecog.01881.

Naimi, B., Hamm, N.A.S., Groen, T.A., Skidmore, A.K., Toxopeus, A.G., 2014. Where is positional uncertainty a problem for species distribution modelling? Ecography 37 (2), 191–203. https://doi.org/10.1111/j.1600-0587.2013.00205.x.

Nair, K.P.P., 2014. The Agronomy and Economy of Important Tree Crops of the Developing World. Elsevier Science. http://qut.eblib.com.au/patron/FullRecord.aspx?p=630047.

Navarro-Racines, C., Tarapues, J., Thornton, P., Jarvis, A., Ramirez-Villegas, J., 2020. High-resolution and bias-corrected CMIP5 projections for climate change impact assessments. Sci Data 7 (1), 7. https://doi.org/10.1038/s41597-019-0343-8.

Ni, M., Vellend, M., 2022. Soil Properties Constrain Forest Understory Plant Distributions along a Climatic Elevational Gradient. https://doi.org/10.13140/RG.2.2.36160.61445.

Olana Jawo, T., Teutscherová, N., Negash, M., Sahle, K., Lojka, B., 2023. Smallholder coffee-based farmers' perception and their adaptation strategies of climate change and variability in south-eastern Ethiopia. Int. J. Sustain. Dev. World Ecol. 30 (5), 533–547. https://doi.org/10.1080/13504509.2023.2167241.

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Chang. 122 (3), 387–400. https://doi.org/10.1007/s10584-013-0905-2.

Ongoma, V., Chen, H., Gao, C., Nyongesa, A.M., Polong, F., 2018. Future changes in climate extremes over equatorial East Africa based on CMIP5 multimodel ensemble. Nat. Hazards 90 (2), 901–920. https://doi.org/10.1007/s11069-017-3079-9.

Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., Schroth, G., 2015. Projected shifts in Coffea arabica suitability among major global producing regions due to climate change. PLoS One 10 (4), e0124155. https://doi.org/10.1371/journal.pone.0124155.

Pebesma, E., 2016. *sf: Simple Features for R* (p. 1.0–18) [Dataset]. https://doi.org/10.32614/CRAN.package.sf.

Pham, Y., Reardon-Smith, K., Mushtaq, S., Cockfield, G., 2019. The impact of climate change and variability on coffee production: a systematic review. Clim. Chang. 156 (4), 609–630. https://doi.org/10.1007/s10584-019-02538-y.

Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31 (2), 161–175. https://doi.org/10.1111/j.0906-7590.2008.5203.x.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190 (3–4), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.

Pourghasemi, H.R., Yousefi, S., Kornejady, A., Cerdà, A., 2017. Performance assessment of individual and ensemble data-mining techniques for gully erosion modeling. Sci. Total Environ. 609, 764–775. https://doi.org/10.1016/j.scitotenv.2017.07.198.

R Core Team, 2023. *R: A language and environment for statistical computing (Version 4.3.2). R Foundation for Statistical Computing.* [Computer software]. https://www.R-project.org.

Regulation (EU), 2023. Regulation (EU) 2023/1115 of the European Parliament and of the Council of 31 May 2023 on the making available on the Union market and the export from the Union of certain commodities and products associated with deforestation and forest degradation and repealing Regulation (EU) No 995/2010. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32023R1115.

Rettie, F.M., Gayler, S., Weber, T.K.D., et al., 2023. High-resolution CMIP6 climate projections for Ethiopia using the gridded statistical downscaling method. Sci. Data 10, 442. https://doi.org/10.1038/s41597-023-02337-2.

Salas López, R., Gómez Fernández, D., Silva López, Rojas Briceño, Oliva, M., Terrones Murga, Iliquín Trigoso, D., Barboza Castillo, E., Barrena Gurbillón, 2020. Land Suitability for Coffee (Coffea arabica) Growing in Amazonas, Peru: Integrated Use of AHP. GIS and RS. ISPRS Intern. J. Geo-Inform. 9 (11), 673. https://doi.org/10.3390/ijgi9110673.

Samuel, D., Erko, B., Mesay, Y., 2019. Cost of Production of Coffee in Jimma Zone, Southwest Ethiopia, 29 (3). https://www.researchgate.net/publication/336133924_Cost_of_Production_of_Coffee_in_Jimma_Zone_Southwest_Ethiopia?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6Il9kaXJlY3QiLCJwYWdlIjoicHVibGljYXRpb24iLCJwcmV2aW91c1BhZ2UiOiJfZGlyZWN0In19.

Sánchez-Reinoso, A.D., Ávila-Pedraza, E.Á., Lombardini, L., et al., 2023. The Application of Coffee Pulp Biochar Improves the Physical, Chemical, and Biological Characteristics of Soil for Coffee Cultivation. J. Soil Sci. Plant. Nutr. 23, 2512–2524. https://doi.org/10.1007/s42729-023-01208-4.

Santini, L., Benítez-López, A., Maiorano, L., Čengić, M., Huijbregts, M.A.J., 2021. Assessing the reliability of species distribution projections in climate change research. Divers. Distrib. 27 (6), 1035–1050. https://doi.org/10.1111/ddi.13252.

Sayed, O.H., Masrahi, Y.S., Remesh, M., Al-Ammari, B.S., 2019. Coffee production in southern Saudi Arabian highlands: current status and water conservation. Saudi J. Biol. Sci. 26 (7), 1911–1914. https://doi.org/10.1016/j.sjbs.2019.03.002.

Scholz, M.B.D.S., Kitzberger, C.S.G., Prudencio, S.H., Silva, R.S.D.S.F.D., 2018. The typicity of coffees from different terroirs determined by groups of physico-chemical and sensory variables and multiple factor analysis. Food Res. Int. 114, 72–80. https://doi.org/10.1016/j.foodres.2018.07.058.

Sime, C.H., Dibaba, W.T., 2023. Evaluation of CMIP6 model performance and extreme precipitation prediction in the awash basin. Heliyon 9 (11), e21578. https://doi.org/10.1016/j.heliyon.2023.e21578.

Sisay, B.T., 2018. Coffee production and climate change in Ethiopia. In: Lichtfouse, E. (Ed.), Sustainable Agriculture Reviews 33 (Vol. 33, pp. 99–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-99076-7_3.

Srivastava, V., Lafond, V., Griess, V.C., 2019. Species distribution models (SDM): applications, benefits and challenges in invasive species management. CABI Rev. 1–13. https://doi.org/10.1079/PAVSNNR201914020.

Steen, V.A., Tingley, M.W., Paton, P.W.C., Elphick, C.S., 2021. Spatial thinning and class balancing: key choices lead to variation in the performance of species distribution models with citizen science data. Methods Ecol. Evol. 12 (2), 216–226. https://doi.org/10.1111/2041-210X.13525.

Steinhart, H., 2005. Coffee: growing, processing, sustainable production—a guidebook for growers, processors, traders, and researchers. Jean Nicolas Wintgens (Ed). Wiley-VCH Verlag, Weinheim, 2004. 976 pp, ISBN 3-527-30731-1. J. Sci. Food Agric. 85 (11). https://doi.org/10.1002/jsfa.2234, 1966-1966.

Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240 (4857), 1285–1293. https://doi.org/10.1126/science.3287615.

Tebekew, F.A., Tadesse, T.B., Alemu, D.A., Ayalew, A.A., 2024. Soil physicochemical properties variation under annual crop and coffee Landuse in the Chentale watershed, upper Blue Nile Basin, Ethiopia. Appl. Environ. Soil Sci. 2024, 1–11. https://doi.org/10.1155/2024/2921614.

Tegegne, G., Melesse, A.M., Worqlul, A.W., 2020. Development of multi-model ensemble approach for enhanced assessment of impacts of climate change on climate extremes. Sci. Total Environ. 704, 135357. https://doi.org/10.1016/j.scitotenv.2019.135357.

Teketay, D., 1999. History, botany and ecological requirements of coffee, pp. 28–50.

Tesfay, F., Moges, Y., Asfaw, Z., 2022. Woody species composition, structure, and carbon stock of coffee-based agroforestry system along an elevation gradient in the moist mid-highlands of southern Ethiopia. Int. J. Forest. Res. 2022, 1–12. https://doi.org/10.1155/2022/4729336.

Vapnik, V.N., 2000. The nature of statistical learning theory. Springer, New York. https://doi.org/10.1007/978-1-4757-3264-1.

Warren, D.L., 2012. In defense of 'niche modeling'. Trends Ecol. Evol. 27 (9), 497–500. https://doi.org/10.1016/j.tree.2012.03.010.

Wiens, J.A., Stralberg, D., Jongsomjit, D., Howell, C.A., Snyder, M.A., 2009. Niches, models, and climate change: assessing the assumptions and uncertainties. Proc. Natl. Acad. Sci. 106 (supplement_2), 19729–19736. https://doi.org/10.1073/pnas.0901639106.

Wintgens, J.N. (Ed.), 2012. Coffee: Growing, Processing, Sustainable Production: A Guidebook for Growers, Processors, Traders, and Researchers, 1st ed. Wiley. https://doi.org/10.1002/9783527619627.

Worku, T., Khare, D., Tripathi, S.K., 2019. Spatiotemporal trend analysis of rainfall and temperature, and its implications for crop production. J. Water Clim. Chang. 10 (4), 799–817. https://doi.org/10.2166/wcc.2018.064.

Yackulic, C.B., Chandler, R., Zipkin, E.F., Royle, J.A., Nichols, J.D., Campbell Grant, E.H., Veran, S., 2013. Presence-only modelling using MAXENT: when can we trust the inferences? Methods Ecol. Evol. 4 (3), 236–243. https://doi.org/10.1111/2041-210x.12004.

Yang, M., Wang, G., Ahmed, K.F., Adugna, B., Eggen, M., Atsbeha, E., You, L., Koo, J., Anagnostou, E., 2020. The role of climate in the trend and variability of Ethiopia's cereal crop yields. Sci. Total Environ. 723, 137893. https://doi.org/10.1016/j.scitotenv.2020.137893.

Yang, Q., Bader, M.Y., Feng, G., Li, J., Zhang, D., Long, W., 2023. Mapping species assemblages of tropical forests at different hierarchical levels based on multivariate regression trees. Forest Ecosyst. 10, 100120. https://doi.org/10.1016/j.fecs.2023.100120.

Zhao, Y., Yin, X., Fu, Y., Yue, T., 2022. A comparative mapping of plant species diversity using ensemble learning algorithms combined with high accuracy surface modeling. Environ. Sci. Pollut. Res. 29 (12), 17878–17891. https://doi.org/10.1007/s11356-021-16973-x.

Zhou, H., Feng, L., Fu, L., Sharma, R.P., Zhou, X., Zhao, X., 2023. Modelling the effects of topographic heterogeneity on distribution of Nitraria tangutorum Bobr. Species in deserts using LiDAR-data. Sci. Rep. 13 (1), 13673. https://doi.org/10.1038/s41598-023-40678-5.

Zhunusova, E., Ahimbisibwe, V., Sen, L.T.H., Sadeghi, A., Toledo-Aceves, T., Kabwe, G., Günter, S., 2022. Potential impacts of the proposed EU regulation on deforestation-free supply chains on smallholders, indigenous peoples, and local communities in producer countries outside the EU. Forest Policy Econ. 143, 102817. https://doi.org/10.1016/j.forpol.2022.102817.