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Preparing Colombian coffee production for climate change: Integrated spatial modelling to identify potential robusta coffee (Coffea canephora P.) growing areas

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Abstract
Meeting future demand for coffee under climate change is a challenge. Approaches that can inform where coffee may grow best under current and future climate scenarios are needed. Robusta coffee (*Coffea canephora* P.) is planted in many tropical areas and makes up around 40% of the world's coffee supply. However, as the climate shifts, current robusta areas may become less productive, while in other areas new growing regions for robusta may emerge. Colombia is one of the world's most important Arabica coffee producer, famous for its high-quality coffee. Although robusta coffee is not yet a commercial crop in Colombia, it could be one of the future bastions for robusta coffee in South America contributing to meeting the increasing demand, but this remains unexplored. We aimed to identify areas with highest biophysical and socio-economic potential to grow robusta coffee in Colombia. An integrated modelling approach was used, combining climate suitability and crop-yield modelling for current and future climate scenarios, soil constraints, pest risk assessment and socio-economic constraints to identify the regions with the highest potential productivity and the lowest pest and climate change risks with good market access and low security risks which don't further expand the agricultural frontier. Our results showed that parts of the foothills along the eastern Andean Mountain ranges, the high plains of the Orinoquía region and the wet parts of the Caribbean region are the best candidates for the potential development of robusta coffee plantations in Colombia. The crop-yield model indicated highest yields of green coffee on the foothills of the eastern Andean Mountain range with an estimated average yield of 2.6 t ha^{-1} (under rain-fed conditions) which is projected to occur at elevations below 600 m avoiding interference with the traditional and established Arabica coffee regions in Colombia. Under a 2 °C global warming scenario climate change is projected to have the largest impacts on the Caribbean region. Therefore, larger scale irrigated production system could be an appropriate option in the Caribbean region, while diversified smallholder robusta coffee agroforestry systems are considered more favourable in the Orinoquía region.

Keywords Biogeography · Climate change · Coffee berry borer · Yield · South America · Andean region

Extended author information available on the last page of the article

1 Introduction

As the climate continues to warm and shift in coming decades, maintaining and increasing the global coffee supply faces two key challenges. First, areas suitable to grow Arabica coffee profitably, currently supplying around 60% of the world's coffee, are projected to decrease under climate change (Moat et al. 2017; Grüter et al. 2022; Kath et al. 2022). Coffee quality and growing areas are likely to decline due to increasing temperatures (Bunn et al. 2015a). East Africa is projected to experience large reductions of suitable climate areas in its main Arabica producing regions (Moat et al. 2017). Second, while suitable areas for Arabica are projected to decline, global demand for coffee continues to increase (Torga and Spers 2020). There is, therefore, an urgent need for research to identify ways in which the global coffee industry can maintain and / or increase supply in the face of these two compounding issues.

On a global scale, despite efforts to adapt Arabica coffee to climate change (Vinci et al. 2022), coffee species acclimated to tropical lowlands that are less sensitive to increasing temperature, such as. robusta coffee (*Coffea canephora* Pierre ex A. Froehner), *C. liberica* W. Bull ex Hiern, and C. *stenophylla* G. Don., could be critical to help meet the anticipated shortfalls in coffee supply. Of these, robusta is arguably the most important option, as *C. canephora* can be cultivated in lowlands unsuitable for Arabica, is already supplying 40% of the current global supply and is gaining popularity among coffee growers worldwide (Bunn et al. 2015a; Krishnan et al. 2021; Oberthür et al. 2011). Even so, while robusta has the potential to complement Arabica's consumer markets or create new ones, its expansion, and thus its ability to offset falling global coffee supply, could be compromised if new growing areas are inaccurately assessed.

Furthermore, while robusta may be more productive under higher temperatures than Arabica (but see research on some Arabica genotypes that perform well at high temperatures, i.e., Vinci et al. 2022), it is not entirely insensitive to climatic variability, and robusta coffee regions also suffer from negative effects (Lemma and Megersa 2021). For instance, robusta regions in Mozambique, Uganda, and Tanzania have experienced great impacts on productivity due to climate change (Cassamo et al. 2023; Mulinde et al. 2022). Throughout South-East Asia, where most of the world's robusta coffee is currently grown, higher temperatures have also been linked with lower productivity (Kath et al. 2020). As such, research is needed to map where robusta could be grown under climate change.

Current zoning approaches, which are largely based on species distribution modelling (SDM), rely on a binary assessment of suitability (i.e., if the crop is present the location is deemed 'suitable' if absent then 'unsuitable'). Suitability models, while helping to advance our understanding of the risks that climate change pose to future coffee production (Bunn et al. 2015b; Grüter et al. 2022) could be complemented by other approaches to give a more detailed and refined picture of which areas may be the most promising for future coffee production. The integration of suitability models with productivity models (i.e., models which estimate coffee yield (i.e., yld/ha)) as well as pest risk assessments, along with spatial evaluations of critical socio-economic and environmental factors is one way a more detailed and holistic view of future potential coffee growing areas could be achieved. However, methods and examples on the integration of these various modelling approaches to provide a holistic assessment of where the best future areas may be to grow coffee are absent from the scientific literature.

The zoning of robusta has been carried out in several countries in Latin America, such as Mexico (Aceves et al. 2018), and particularly in Brazil, which is the second-largest producer of robusta in the world after Vietnam (USDA 2022). Since the 1970s, Brazil has generated studies to identify suitable areas for growing coffee (Camargo 1977). Climate variables (rainfall, mean air temperature, and relative air humidity) and soil characteristics (depth, pH, texture, or drainage) have been used to carry out the studies (Evangelista et al. 2002; de Carvalho et al. 2013; Bardales et al. 2018). More recently, as concerns over climate change have increased, studies identifying growing areas for robusta incorporating increasing temperature predictions under global warming have also been undertaken (Andrade et al. 2012; Aceves et al. 2018).

Besides climate, an integrated approach needs to include biological and agricultural variables. Biotic limiting factors on productivity and quality, namely pests and disease presence and severity, are another important aspect that could influence regionalizations identifying the best areas to grow robusta but are not yet commonly accounted for by SDMs on coffee suitability. There are only a few studies that have included pest pressure in SDM studies in the case of coffee (i.e., Magrach and Ghazoul 2015). Pests such as the coffee berry borer (CBB), *Hypothenemus hampei* (Coleoptera: Curculionidae), increase the risks of losing yield and quality under changing conditions (Vega et al. 2009; Kath et al. 2021). This pest has mainly attacked Arabica but there are recent studies showing that it is also affecting robusta crops. As climate is a major driver of the presence of the CBB (Jaramillo et al. 2011), predicting and modelling the factors that affect its distribution in relation to the productivity models and climate change scenarios is likely an important part of any regionalization approach to identify potentially new coffee growing areas.

To advance current regionalization methods that rely solely on coffee presence data (Zhang et al. 2022; Folberth et al. 2012), we propose an integrated model for robusta coffee regionalization in Colombia. While robusta coffee is established in many tropical areas, regions in Colombia have not yet been explored and could hold potential for rural development. Our study aims to identify optimal environmental conditions for robusta cultivation, considering climate change, pest risks, soils, and socioeconomic factors, yet without creating conflicts with the high quality Arabica coffee. Despite limited current cultivation, interest in robusta is rising with changing climates. This approach holds international relevance as other coffee-producing countries likely face the need to consider similar shifts in the types of coffee they grow and where to grow them in a changing climate. The key guiding focus of our research is to identify where the optimal regions for robusta cultivation are and to assess risks associated with a 2-degree Celsius temperature increase and the potential presence of the main coffee pest, coffee berry borer. Soil and socioeconomic factors related to robusta cultivation are also considered in this inquiry.

2 Materials and methods

2.1 Study area

The study took place in continental Colombia. Elevational gradients in Colombia range from 0 to 5656 m above sea level -m.a.s.l-. This is due to the presence of three Andean Mountain ranges (east, west, and central) that cross the country from north to south on the western side of the country. The east of the country is nearly half of the territory and comprises the Orinoco plains and Amazon rain forests (González-Orozco 2021). The latitude of Colombia coincides with the robusta production zone throughout the world's tropical belt.

2.2 Phenological calendar basis for analysis

Although commercial plantations of robusta coffee have not yet been formally established in Colombia, the Colombian Corporation for Agricultural Research (AGROSAVIA) conducted agronomic trials of robusta in four strategic regions of Colombia that were initially identified by experts (Campuzano-Duque et al. 2021). AGROSAVIA has carried out a preliminary analysis of the environmental suitability of key regions for robusta. The analysis included variables such as air temperature (maximum, mean, and minimum), relative humidity, elevation, and solar radiation. Based on these results AGROSAVIA is evaluating different robusta genotypes under four contrasting environments in Colombia: El Mira, Turipaná, Carimagua, and Taluma research stations. These tests have 4 years' worth of phenological data, which were included in the productivity model (see details below). The phenological data were used to guide the extraction of climate data for the productivity model (i.e., for the flowering and growing seasons) to ensure yield estimates considered Colombia's seasonality.

2.3 Soil data and analyses

A soil map of Colombia at 100 k spatial resolution generated by the National Geographical Institute Agustin Codazzi (IGAC 2015), and the ECOCROP database of Crop Constraints and Characteristics (FAO 2021) was used to classify soils for potential robusta growing areas. Cartographical units of IGAC´s soil map for Colombia for robusta regions, showed six ECOCROP soil variables important (Table 1). Data on these six soil variables were extracted and analyzed to generate a new layer of soil quality classes that was relevant for robusta suitability.

All soil variables were weighted as equally important, and spatially analysed assigning presence (value = 1) or absence (value = 0) for each of the cartographical units. Using ArcGIS Pro v.2.9.0 (ESRI 2022), a geoprocessing tool was used to re-classify the results of the categorical units into three soil type categories: Nonoptimal soils with values between 0 and 3; marginal soils with intermediate values of 4; and optimal soils with values between 5 and 6. Finally, the area of coverage and percentage for each soil type class was calculated across all proposed regions.

2.4 Analysis: an integrated modelling approach for robusta (IMAR) regionalization

A summary of the five steps and content of the IMAR model is shown in Fig. 1. Data components and sources of IMAR are summarised in Table 2.

Table 1 Edaphic parameters required for robusta coffee. *Parameters sourced from **ECOCROP** (FAO, 2021)

Variables	Optimal soil parameters for robusta*
Soil pH	Slighty acidic to strongly acidic
Soil fertility	High, moderate and low
Soil depth	Deep to moderate
Soil Natural drainage	Good
Soil texture	Heavy to medium
Soil salinity	Not salty

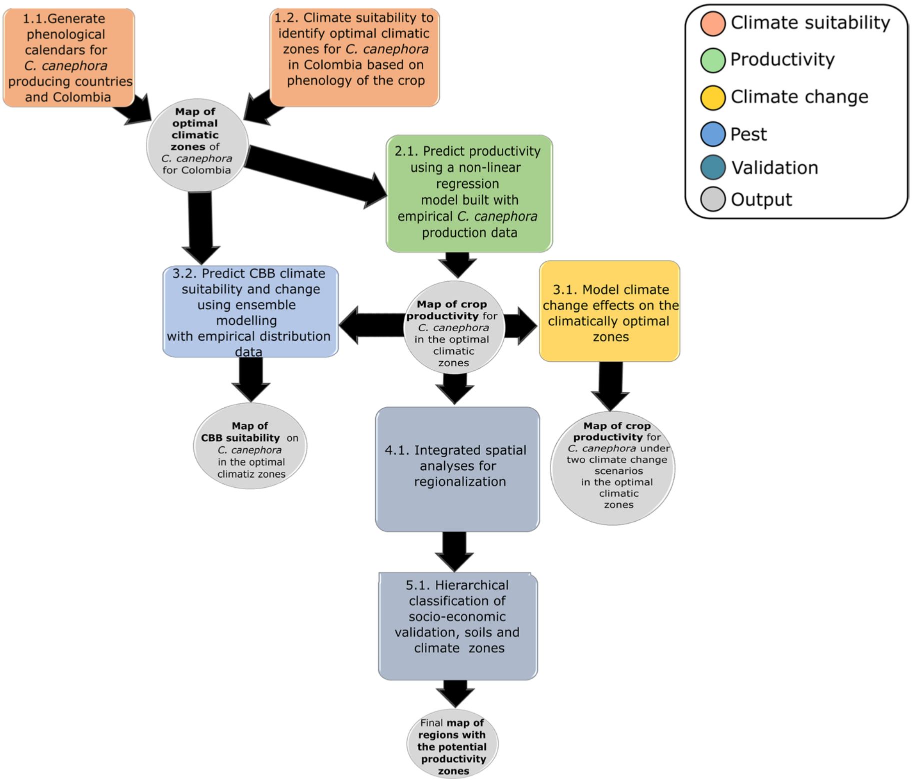

Fig. 1 Summary flowchart of the Integrated Modelling Approach for the robusta coffee regionalization in Colombia. Details on the data sources used for each step are in Table 2

Table 2 Summary table showing the main data type and sources of the proposed framework

Methodological steps	Data type	Source
Phenology	Phenological calendar and sites climate	AGROSAVIA´s field research stations
Soils	Soil quality (ECOCROP)	FAO, 2021
Climate baseline (step 1)	Temperature and precipitation	Abatzoglou et al. 2018
Climate change (step 1)	Scenarios	Qin et al. 2020
Coffee farms (step 1)	robusta occurrences	Bunn et al. 2015b
Productivity (step 2)	robusta yield	Kath et al. 2020
Coffee pests (step 3)	Coffee berry borer occurrences	Multiple papers summarised in Dataset S2
Land Use change (step 4)	Layer of agricultural changes	UPRA 2021
Socio-economic (step 5)	Road networks and conflict	DNP, 2016

2.4.1 Climate data used in analysis

Climate predictors Climate data was from the global historical dataset—TERRAClimate (~4 km spatial resolution and 1985–2015 temporal resolution; Abatzoglou et al. 2018; Qin et al. 2020). We extracted rainfall, minimum temperature, and maximum temperature data for each of the 1297 robusta locations (used in the SDM modelling; Bunn et al. 2015b). This climate data was also extracted for the 798 robusta farms we have ten years of yield data for (Kath et al. 2020), and which was the basis of our productivity model (see below). Climate variables were extracted for the flowering and growing season each year as this is when production is most sensitive to climatic variability (Craparo et al. 2015; Kath et al. 2020). To deal with potential collinearity between climate variables we assessed predictor collinearity using Pearson correlations, setting a threshold of $|r| < 0.70$ (Dormann et al. 2013). (Fig. 1, see Productivity mapping section for details on modelling).).

Climate change scenarios Climate change scenario data was extracted and aggregated as outlined above for the historical climate dataset (i.e. using TERRAClimate data, Abatzoglou et al. 2018; Qin et al. 2020). Climate scenarios corresponded to 2 °C above pre-industrial conditions, as well as a baseline scenario (1985–2015). The TERRAClimate dataset scenarios are derived from 23 CMIP5 climate models and use pattern scaling that superposes climate mean and variability on conditions from 1985–2015. These scenarios—based on policy relevant goals, are highly flexible and allow for the assessment of climate change impacts on coffee production in an interpretable way while accounting for the uncertainty that is implicitly a part of climate model projections and emission scenarios (Qin et al. 2020).

2.4.2 Climate suitability (Step 1)

Occurrences of robusta coffee regions The raw robusta occurrences dataset used to develop a climate suitability model contained 1,297 records (Dataset S1) of sites where the species is planted (Bunn et al. 2015b). The potential spatial sampling biases were rectified by implementing a randomized spatial thinning process using the 'spThin' package (Aiello-Lammens et al. 2015; Alves de Andrade et al. 2020) establishing a thinning distance of 4 km. Finally, a total of 631 robusta occurrences across the ten main growing countries (Ecuador, Côte d'lvoire, Benin, Cameroon, Uganda, India, Thailand, Vietnam, Indonesia, and Philippines) located in the latitudinal belt (-6°Sto 18°N) were used as response variables for the species distribution modelling analysis (Fig. 2). As such, our dataset covers

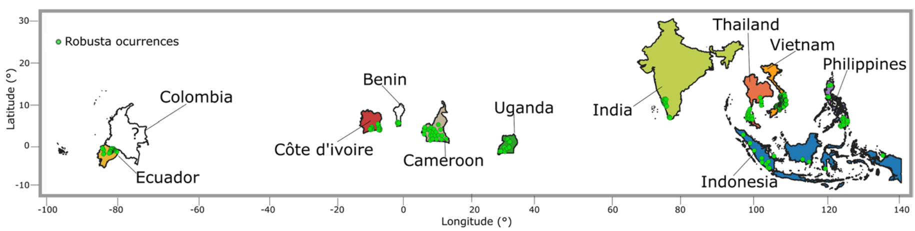

Fig. 2 Robusta occurrences (green dots) across the countries of the tropical latitudinal belt used for the suitability Species Distribution Modelling

major robusta-producing countries globally, making it robust for predicting the ideal climatic conditions in Colombia for all the known climatic range of the crop.

Ensemble modelling The BiodiversityR package was used to conduct the climate ensemble modelling (Kindt and Coe 2005). The ensemble was applied to predict the climate suitability of robusta for the ten producing countries shown in Fig. 2 (González-Orozco et al. 2020). Twenty-two models are contained in the BiodiversityR package (Ranjitkar et al. 2016), among them vector machine learning, random forest, general linear model, neural network, and predictive models.

2.4.3 Productivity mapping (Step 2)

The climate productivity model is based on a non-linear regression trained on a robusta yield dataset consisting of 798 farmers from Vietnam and Indonesia (Kath et al. 2020). This model was extrapolated to Colombia using the climate variables corresponding to flowering and growing seasons of Colombia.

The phenological data sets of Taluma, Turipaná, and El Mira research centers in Colombia were used to create a phenological calendar. Climate variables were adjusted to this phenological calendar and used as input to the regression model of robusta yield response to climate adapted from Kath et al. (2020). That study identified four key climate predictors, (1) minimum growing season temperature, (2) minimum flowering season temperature, (3) total growing season rainfall, and (4) total flowering season rainfall as the key climate predictors of robusta coffee yield in South East Asia, based on the Watanabe-Akaike's Information Criteria (WAIC) and the deviation information criterion (DIC) for model selection (see Kath et al. 2020 for model selection and performance details ofthe productivity model).

In Kath et al. (2020) a Bayesian model using INLA (Rue et al. 2009) was used, but here the response of robusta yield to these four key climate predictors were modelled using a bayesian additive regression model (Wood 2011), which was less computationally intensive and more efficient for the multiple yield projections and mapping we undertake here. INLA and bam model results were congruent in terms of the response to climate predictors and model performance.

All analyses were carried out in R (R Core Team 2021). In the model,

$$y_{ij} = \beta_o + f\left(x_{ij}\right) + s_i\varphi + c_i\varphi + \epsilon_{ij}$$

$$\epsilon_{ij} N(y)$$

$$\varphi N(0, \Gamma)$$

Yields (y) were modelled as a non-linear (f) function of climate predictor variables (x) for each country (i) and year (j) using a gaussian distribution with an identity link. A random effect (ϵ) for each site (si) and country (ci) was included to account for the repeat measurements for each year at the site and country level. Random-effects control for non-independence by constraining non-independent observations to have the same intercept (Harrison et al. 2018). For example, yield observations from a particular country and/or site may be more similar (e.g., higher on average if soils and management techniques are better) relative to yield observations from other areas.

The productivity model we fit, and are extrapolating from, was constrained in two ways. First, we did not fit any interaction terms in the model as under climate change there will be novel climate interactions (i.e., higher temperatures and rainfall conditions) that yield response data is lacking for. This is likely to have a negligible effect though and we checked the difference between models with and without interaction and the model performance is similar, i.e., adjusted $R^2=0.894$, and 0.885, respectively. Second, we constrained predictions to the temperature ranges of those in our dataset for Vietnam and Indonesia. As rainfall conditions are more dissimilar between these countries, containing the model to the exact conditions was not possible. We did however constrain predictions to < 1500 mm in the flowering season (maximum value in our dataset is 1359 mm) and < 3000 mm in the growing season (maximum value in our dataset is 2876 mm). However, given that temperature is the primary driver of spatial differences in robusta coffee yield (Kath et al. 2020) doing this is likely to have negligible implications for our predictions. Our model was developed under rain-fed conditions.

2.4.4 Pest risk mapping (Step 3)

A presence-only dataset of the coffeeberry borer (CBB), *Hypothenemus hampei* (Ferrari), in robusta plantations published in scientific publications was developed for the tropical latitudinal belt under study. A total of 261 occurrences were gathered. Only 37 occurrences were reliable and fulfilled georeferencing criteria to be used in the ensemble modelling of the CBB (Dataset S2). Dataset S2 contains the presence only data of the CBB used for the modelling. This gave us a dataset of the approximate potential distribution of the insect across the environments that cover robusta in tropical regions. The ensemble methodology described above was carried out to generate the CBB suitability predictions (risk map) for Colombia.

2.4.5 Integrated spatial analyses for regionalization (Step 4)

We prioritized potential robusta regions by converting the maximum and minimum values of climate variables, yield, and coffee berry borer (CBB) risk suitability into three quartiles. Mapping the upper 75th percentile onto a GIS map for yield and suitability layers allowed us to identify areas of greatest potential for robusta cultivation. For CBB risk, we mapped the 25th percentile to identify areas with the least predicted risk. Overlaying these areas with the 75th percentile of yield and robusta climate suitability revealed regions with both high potential for robusta and low CBB risk. The selection of 25th and 75th percentiles, while arbitrary, simplifies communication with stakeholders and aligns with thresholds used in other pest risk assessments.

Not all potential regions are considered candidates for cropping due to territorial restrictions. Hence, suitable areas of all three models (yield, ensemble suitability, and pest risk) were trimmed to exclude the traditional arabica coffee regions and municipalities that grow Arabica. Arabica coffee is one of the flagships of Colombian agriculture (Oberthür et al. 2011), therefore, our study excluded Arabica growing regions. We took a conservative approach to minimize the degree of spatial overlap with the current extent of the traditional Arabica coffee regions. This is important, as robusta should not compete with Arabica and the high-quality standards of Colombian Arabica coffee need to be protected.

A national agricultural land use layer (UPRA 2021) was used to identify regions that were legally bound to expand the agricultural frontier. Once the potential areas were narrowed down to these specific zones, additional refinement of potential regions was conducted using biophysical parameters such as elevation, soil type, and socio-economic indicators. Other human induced effects such as agricultural practices were also considered as part of the spatial filtering process.

A two-step integration process was applied to the coffee yields of current and future climate, and CBB risk suitability outputs as part of a validation strategy. The first step consisted of excluding the areas from the modelling outputs that showed spatial congruence with all municipalities of reported arabica coffee growing regions. Based on data from the National Federation of Coffee Growers of Colombia, we developed a list of the municipalities that grew arabica coffee in Colombia as of December 2021.

The following step consisted of using the layer of the national system for planning agronomic development in the rural areas of Colombia UPRA (2021) to trim the outputs of the filtered Arabica municipalities and coffee regions mentioned in the previous step. This level of spatial cleaning allowed us to exclude natural forest regions, protected areas, and zones of agronomical exclusion. This was implemented to protect biodiversity and therefore avoid environmental degradation in the surrounding areas with potential for robusta. These filtered areas are places that only correspond spatially with authorised future agronomical development sites as stated by the government in the UPRA (2021) agronomical planning map.

The next step consisted of crossing the resulting map of the filtered UPRA with the municipalities against the elevational limits of the potential regions. In this way, we were able to list the municipalities per department that are in high or lower elevations which is important to understand potential cropping places. A national map of soil types at a coarse scale (1:100.000) developed by IGAC (2015) was used to cross validate the previous filtered layers with the soil types. A ranked list of the municipalities that were found in good or bad quality soil types was provided. The sites with the best quality soil types across the landscapes were mapped as a final output of the IMAR. The final output was a map and tables of proposed municipalities with potential suitable environmental conditions to grow robusta coffee in Colombia.

2.4.6 Integrating socio-economic information (Step 5)

To understand the socio-economic constraints to robusta coffee farming regionally, access to markets and the presence of armed conflict were considered. This status was determined based on two variables (Table 3). First, distance to the road network, because the greater the distance to the road network, the higher the logistic costs. Second, zones of armed conflict were highlighted. If the security situation is complex, the investments made are put at risk.

The results were divided into three categories of "socioeconomic rank", in order to score each region or sub-region: "Optimal = 3", "Sub-optimal = 2", and "Inadequate = 1". This socioeconomic status serves as an indication for determining whether

Table 3 Variables of socioeconomic analysis

Variables	Source
Distance to highway network	Road map (IGAC, 2019)
Armed conflict zones	Armed Conflict Incidence Rate (IICA) (DNP, 2016)

robusta coffee production is socioeconomically viable. According to the interpretation, the areas where robusta production is most economically feasible are those with the highest yield values, the best socioeconomic possibilities, and the least potential pest risk.

Areas experiencing armed conflict were identified using the National Planning Department's Armed Conflict Incidence Index (IICA) (Table 4). Six variables were used to calculate the index (Table 4). Five previously established categories are used to score the index. Three socio-economic rank groups were standardized because they are used in this study, as can be seen in Table 5.

We conducted a path distance mapping analysis to assess the impact of road network access and proximity to productivity regions in each municipality. Using ESRI software (ESRI 2022), we utilized three variables: the 2019 IGAC road map (including paved and unpaved roads), a 90 m Digital Elevation Model (SRTM 2000 mission adjusted by IGAC in 2012), and a productivity raster per municipality. The distances were reclassified based on biogeographic regions and municipalities, scored according to socio-economic categories. We employed the intervals of equal distances method (max value-min value)/3, identifying path distance factors for each natural region. Optimal values were classified as category 3, while non-optimal values were in category 1. For instance, in the Caribbean, Andean, and Pacific regions, the maximum distance was 90.9 km, and the minimum distance was 0.1 km, resulting in intervals of approximately 30 km. This analysis provides insights into road network accessibility and proximity to enhance decision-making for agricultural development in different regions.

3 Results

3.1 Climate suitability (Step 1)

The results of the climate suitability modeling for robusta regions using the municipality level filtering indicate significant spatial changes in suitability across the country (Fig. 3). Particularly, the spatial patterns of suitability based on baseline climatic conditions (1985–2015) and under a 2 °C climate change scenario according to the phenological stages and their responses to minimum temperatures and maximum temperatures (Fig. 3). For instance, regarding the suitability patterns for flowering stages, the Caribbean region shows high suitability under minimum temperature conditions during its flowering stages, but this suitability decreases under maximum temperature conditions and climate change, leading to a significant loss of these highly suitable areas. In other cases, it is observed that there are areas that maintain their high suitability despite being exposed to variations in maximum and minimum temperatures as projected under a 2 °C global climate change scenario. These areas include the Amazonian foothills and some parts of the Pacific region in Nariño and the inter-Andean valleys of the Magdalena and Cauca rivers.

When we observe the suitability for fruiting stages (Fig. 3), the patterns of response to climatic suitability change. For instance, in the Orinoco region, there are more extensive areas of high suitability compared to the Caribbean region, which is the opposite of the flowering stages. The Pacific region and the Amazonian foothills maintain high suitability in the modeling of both phenological stages.

Table 4 Variables that make up the IICA indicator

Variable	Definition	Source
Armed actions	These are offensive armed actions committed by armed groups within the territory of a State with the aim of attacking and weakening the military structures of the opposing side (Observatory of the Presidential Program for Human Rights and IHL, 2010)	Human Rights (HR) and International Humanitarian Law (IHL) Observatory, General Command of the Armed Forces, Police
Homicide	Violent death caused by any type of weapon, except for those committed in traffic accidents	Police
Kidnapping	It is the action of snatching, subtracting, withholding, or hiding a person for any purpose	Ministry of Defense
Anti-personnel mines	Corresponds to the number of victims of accidents caused by Anti-Personnel Mines (APM)	Directorate for Integral Action against Anti Personnel Mines (DAICMA)
Forced displacement	Action in which a person or community is forced to migrate within the national territory, abandoning their place of residence or usual economic activities (Law 1448 of 2011)	Unit for the Attention and Integral Reparation of Victims (UARIV)
Coca crops	Áreas sembradas con cultivos de coca, componente primario para la producción de cocaína	Integrated Illicit Crop Monitoring System (SIMCI)

Taken From: DANE https://www.dane.gov.co/index.php/servicios-al-ciudadano/servicios-informacion/sipsa

Table 5 Homologation between the second category, "armed conflict zones," and the armed conflict incidence index

Category	Range of deviation	Homologation
Under	<—0,5	Optimal
Medium low	- 0,5—0	
Medium	0—0,5	Sub-optimal
Medium High	0,5—1,5	
High	> 1,5	Inadequate

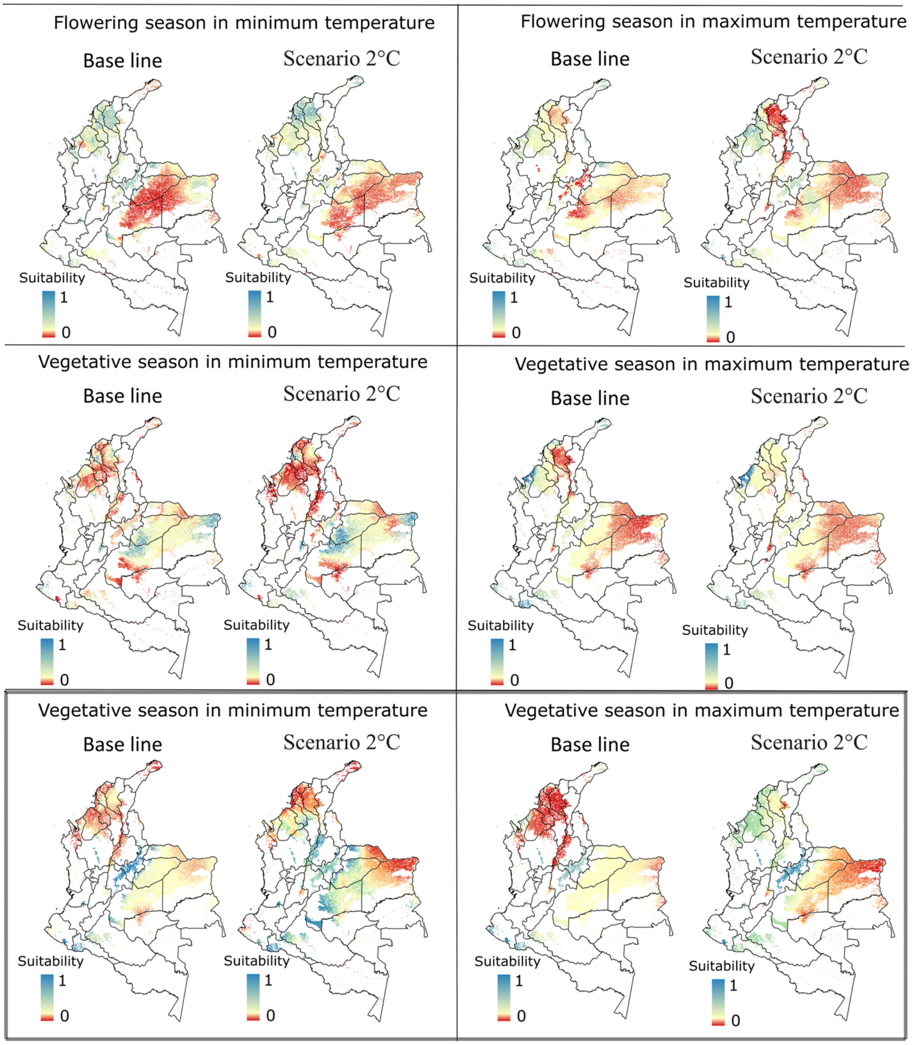

Fig. 3 Climate suitability maps under base line climate (1985 and 2015) and 2 °C climate change scenario for robusta coffee regions in Colombia from **e**nsemble modelling. Maps within the dotted rectangle correspond to the ensemble modelling of CBB pest risk. Colour bars classified as 3er quartiles

3.2 Productivity mapping (Step 2)

The yield and climate change results of the arabica coffee regions filtering are provided in Fig. 4, but not used here as the main regionalization results in this paper. In Fig. 4, we present the results of both of a minimum and maximum temperature-based model, as these two predictors are highly correlated $r > 0.7$ and so were not included in the same

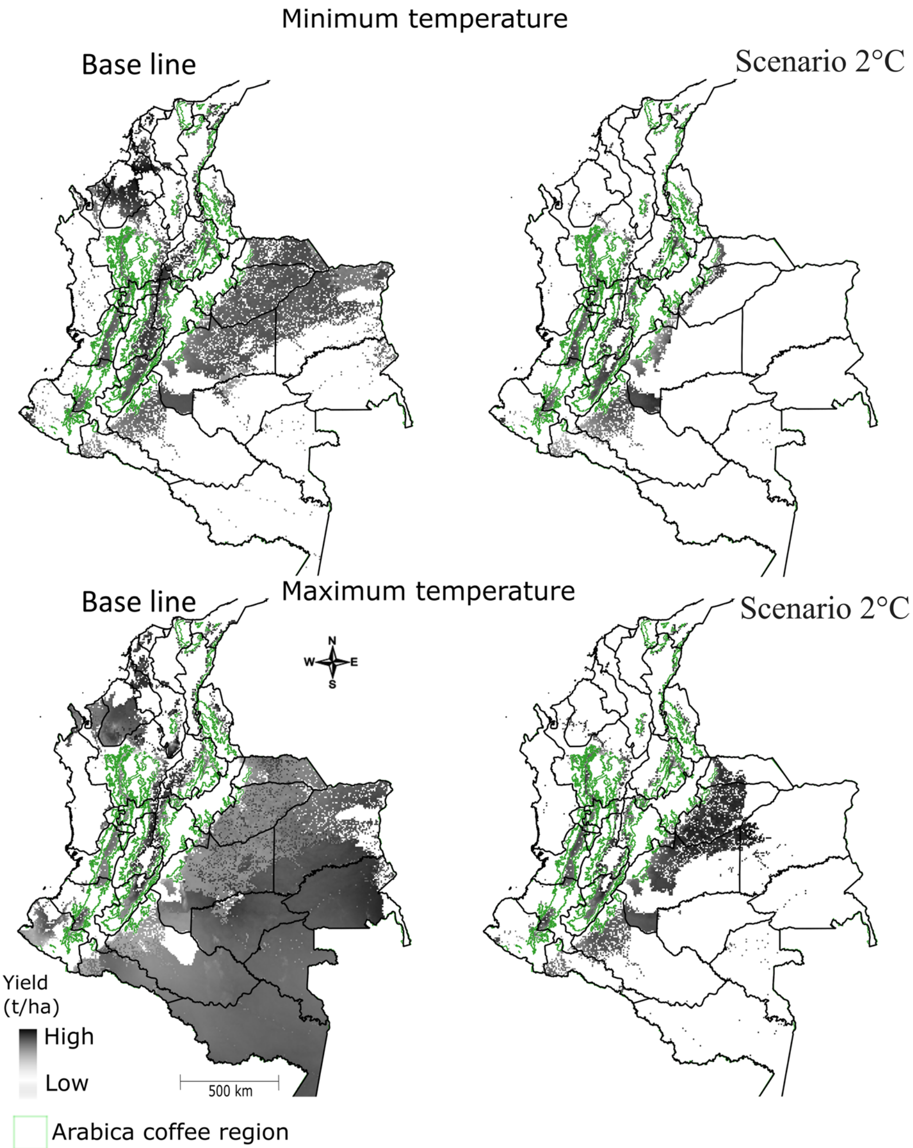

Fig. 4 Maps of predicted robusta yield (prior to filtering and showing Arabica growing areas) under base line climate (1985 and 2015) and under a 2 °C climate change scenario. Maps generated using three Quartiles (75th-25th). For all maps the upper 75th percentile at the municipalities level was used

productivity model and to show that results are largely congruent regardless of the temperature predictor used. Overall, the wet and dry Caribbean regions, central Magdalena and Cauca valleys, southeast amazon foothills, Orinoco foothills, the southwest pacific plains, and the Orinoco high plains show the best modelled productivity. The areas with the least climate change impact for robusta were found in the Cauca river valley, southern part of the Magdalena river valleys and foothills of the Orinoco and Amazonia regions (Fig. 4). We found that maximum and minimum temperature conditions can affect the spatial patterns of potential robusta suitability depending on the phenological seasons. Flooded areas and the high plains of the Orinoquia region show low productivity for the flowering season in conditions of minimum temperatures (Fig. 4).

In contrast, high temperatures conditions corresponding to high modelled yields were observed for the Orinoquia region for the vegetative growing season. Regarding spatial patterns of maximum temperature conditions, modelled yield values were higher on the Orinoquia and Amazon foothills, southwest pacific plains, and the Caribbean regions for the flowering season (Fig. 4). In contrast, some parts of the Caribbean and Orinoquia regions show low values for the vegetative growth season. Some areas in the wet Caribbean, Orinoquia and Amazon foothills, central Magdalena valley and the southwest Pacific plains remained stable regardless of the phenological season.

Based on the municipality filtering results, the highest values of yield (2.2 to 2.6 t ha^{-1}) for the baseline climate occurred on the foothills of the eastern mountain range facing the Amazon and Orinoquia regions (Fig. 5). These areas cover approximately 600 km from north to south in the Orinoquia and Amazon regions. The most affected regions under a 2 °C global climate change scenario are inter-Andean valleys, and the Caribbean and Pacific regions (Fig. 5). However, under a 2 °C global climate change scenario our results suggest that areas of moderate to high modelled yield in the Caribbean regions 1 and 2 will disappear if emissions continue at the present rate. The ensemble suitability modelling results are supportive of the regionalization presented under the base line climate (Fig. 5).

In both the flowering and growing seasons, maximum temperature predictors influence the robusta coffee yield the most across Colombia with larger areas of high yields (Table S1). In contrast, minimum temperature predictors indicate a more limiting influence on robusta coffee yield with areas of smaller extent than for maximum temperature (Table S2). The Orinoquia and Amazon regions 3 and 4 remained with moderate to high yields under the maximum and minimum temperature predictors. The areas of the Caribbean and Pacific regions 1, 2, 6B, as well as the Andean region 5B showed low to moderate yields under the maximum and minimum temperature predictors.

3.3 Pest risk mapping (Step 3)

The CBB risk is higher in the Caribbean and Magdalena valley, whereas the Orinoquia region remains more stable under any temperature conditions. The CBB risk for the southwestern Pacific plains and the southeast Amazon foothills is the lowest of all regions (Fig. 3). CBB risks are greatest in the same regions where the climate change scenario predicted yield to be most affected (Fig. 3). Tables S1 and S2 contain a list of municipalities potentially affected by CBB. The effects of those predictors are spatially differential. For instance, we found more municipalities when using the maximum temperature predictors and fewer numbers under the minimum temperature predictors. This result indicates that increasing minimum temperatures are potentially a greater threat to the robusta regions because the yield area is smaller than the areas under maximum temperatures.

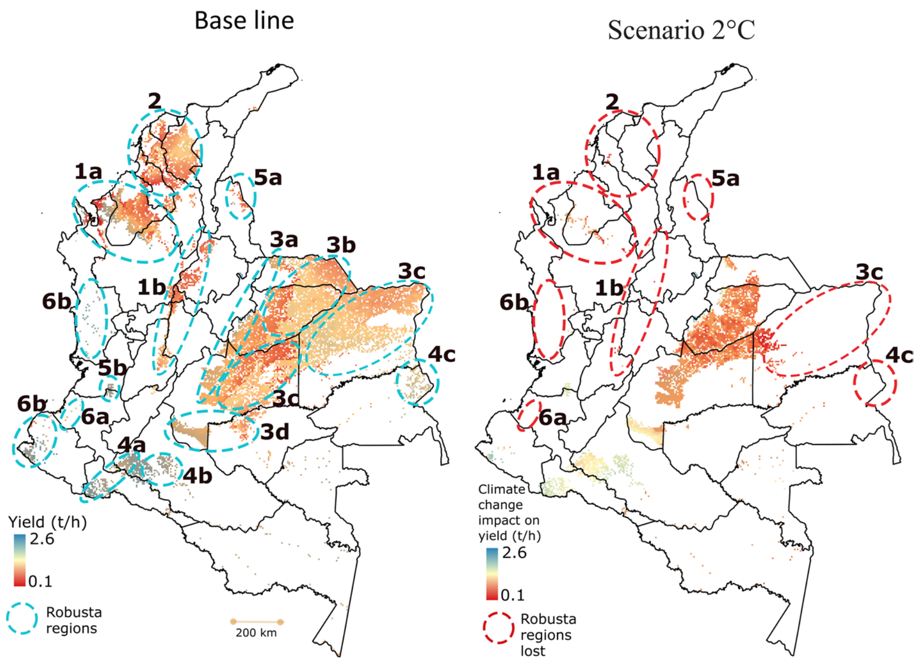

Fig. 5 Regionalization for robusta coffee in Colombia under baseline (1985–2015) climatic conditions and a 2 °C climate change scenario. The regions and sub-regions are numbered 1 to 6. To see details about each region and sub-region see text shown in tables S1 (maximum temperature) and S2 (minimum temperature) where each of them are described and explained. Regions numbered as listed and described in Tables S1 and S2. Maps generated using three Quartiles (75th-25th)

3.4 Regionalization and climate change (Step 4)

A regionalization composed of six major regions for robusta production is proposed (Fig. 5). They correspond to the main biogeographical regions of Colombia (González-Orozco 2021). The regions shown in Fig. 5 are: (1–2) Caribbean wet and dry; (3) Orinoquia and transitional; (4) Amazon; (5) Andean, and (6) Pacific. The regions are subdivided into thirteen sub-regions. The Caribbean region is composed of two sub-regions: wet and dry. The Caribbean Magdalena plains are characterised by wetlands and fertile valleys with a wealth of water for agriculture (1a in Fig. 5). Further south-east, another sub-region is formed along the middle catchment of the iconic Magdalena River (1b in Fig. 5). The dry sub-region at the top end of Colombia covers ecosystems of dry forests part of the Caribbean Guajira region (2 in Fig. 5). The Orinoquia is the largest of all regions, and it is subdivided into four sub-regions: foothills, flooded savannas, high plains, and a transitional zone into the Amazonian region (3a-d Fig. 5). The amazon region is subdivided into three sub-regions: foothills, midlands, and lowlands (5a-c in Fig. 5). The Andean region is subdivided into two subregions: Catatumbo in the northeast and Cauca valley in the southwest of Colombia (5a-b in Fig. 5). This region is representative of interandean valleys rather than high elevations in the Andean Mountain ranges. The final region is on the Pacific Ocean side, which is subdivided into foothills and lowland plains on the coastal areas (6a-b in Fig. 5).

Tables S1 and S2 show that 98% of the elevational ranges of the proposed robusta regions in Fig. 5 are below 1.000 m above sea level with a few exceptions of maximum elevations of 1400–1600 m. The elevation range for the areas with the highest predicted robusta yield is between 600 and 750 m, which is lower than most Arabica regions.

Figure 6 illustrates the specific patterns underlying the regionalization shown in Fig. 5, depicting the minimum and maximum temperature using a baseline climate and 2 °C climate change scenarios for robusta regions. We present the results of both of a minimum and maximum temperature-based model, as these two predictors are highly correlated $r > 0.7$ and so were not included in the same productivity model and to show that results are largely congruent regardless of the temperature predictor used. It is evident that regions with high yield are limited regardless of the predictors. However, the Orinoquia eastern plains and foothills, as well as the amazon foothills and some interandean valleys, are areas with high and moderate yield. Under a climate change scenario, the Caribbean region and interandean river valleys are expected to experience a greater loss of yield compared to other regions.

3.5 Soils and socio-economic filtering (Step 5)

Analysis of soil types showed that 54.1% of the productive robusta regions have optimal soils, 24.2% present a marginal value and 21.7% were not suitable (Fig. 7). Regions 3 and 4 have the largest amount of optimal soils. However, the flooding savannas in the Orinoquia region or in the wet Caribbean regions showed nonoptimal soils for robusta. These areas are important for conservation because they provide water ecosystem services for people and biodiversity. The regions with optimal soil types showed spatial congruence with the regions of highest yield levels.

The socioeconomic status for each region shows that the modelled productivity, and hence possible profitability of robusta coffee production varies according to the temperature prediction. This is related to the fluctuation in the number and characteristics of municipalities with potential for growing robusta under a high and low temperature prediction. There are 163 municipalities with productive potential when using maximum temperature-based prediction and 116 when using a model based on minimum temperature. The difference is 47 municipalities, decreasing its potential in municipalities located in the Caribbean regions mainly in the Guajira subregion. Despite the decrease in the number of municipalities, there was a slight increase in the number of municipalities in the Orinoquia and Pacific regions.

Figure 8 shows that road access is a major determinant affecting the potential socioeconomic development of robusta in Colombia. The lowlands in the wet Caribbean, Orinoquia, and some smaller areas in the Pacific and amazon regions provide the closest distances to high productivity regions and sub-regions. The proximity distance to productivity regions ranges between 0 and 394 km along the existing road network. The results of the equal interval distance categorical analysis show that the access distances from the municipalities to the production areas for the Caribbean, Andean, and Pacific regions are shorter: Category 3 [< 30 km]; Category 2 [30 – 60 km]; and Category 1 [> 60 km]. In contrast, longer distances were found for the municipalities in the Orionoquia and Amazon regions: Category 3 [< 128 km]; Category 2 [128 – 255 km]; and Category 1 [> 255 km]. Category 3 suggests the optimal scenario.

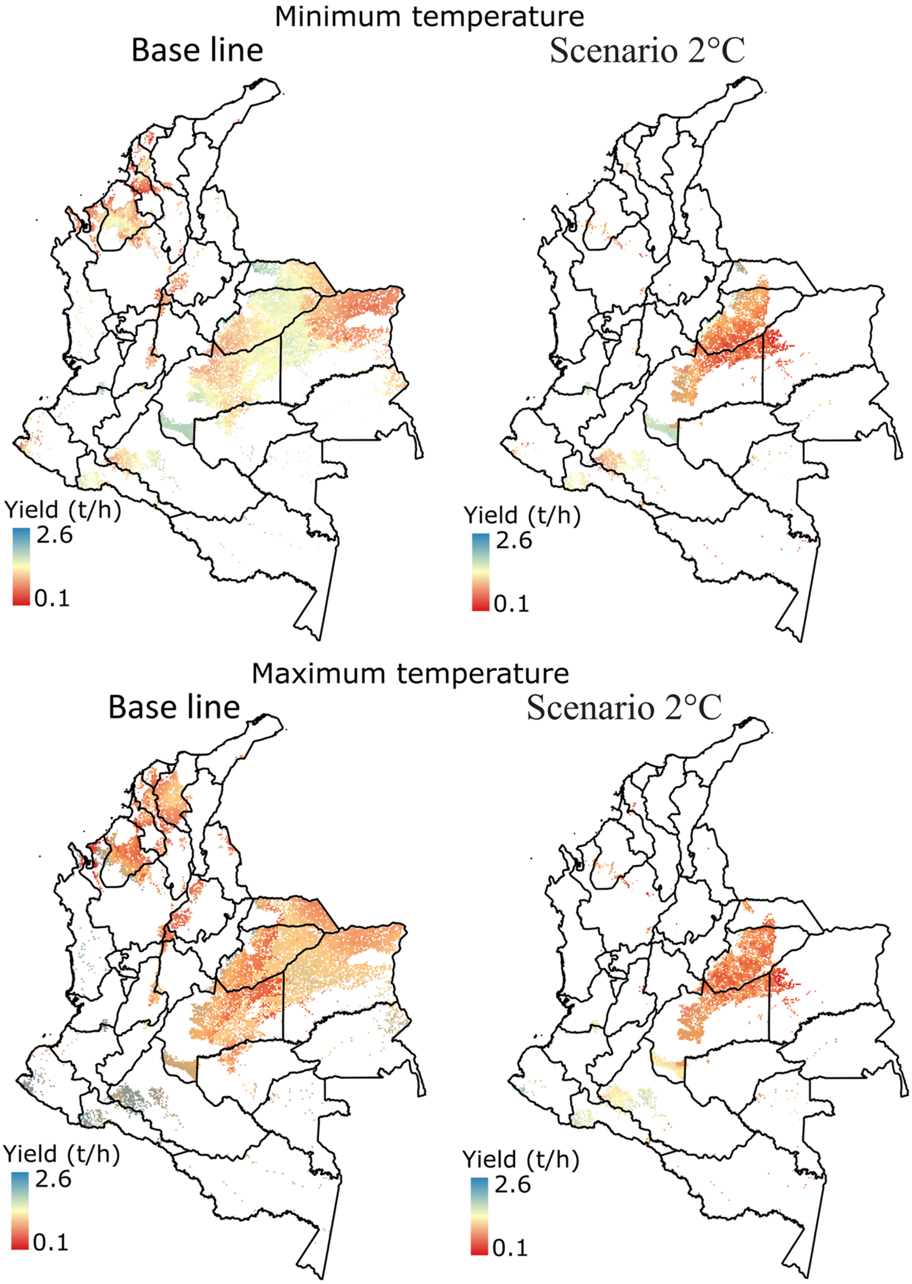

Fig. 6 Maps of predicted robusta yield using minimum and maximum temperature in the yield model under baseline climate conditions (1985–2015) and under a 2 °C climate change scenario. Maps generated using three Quartiles (75th-25th). For all maps the upper 75th percentile at the municipalities level was used

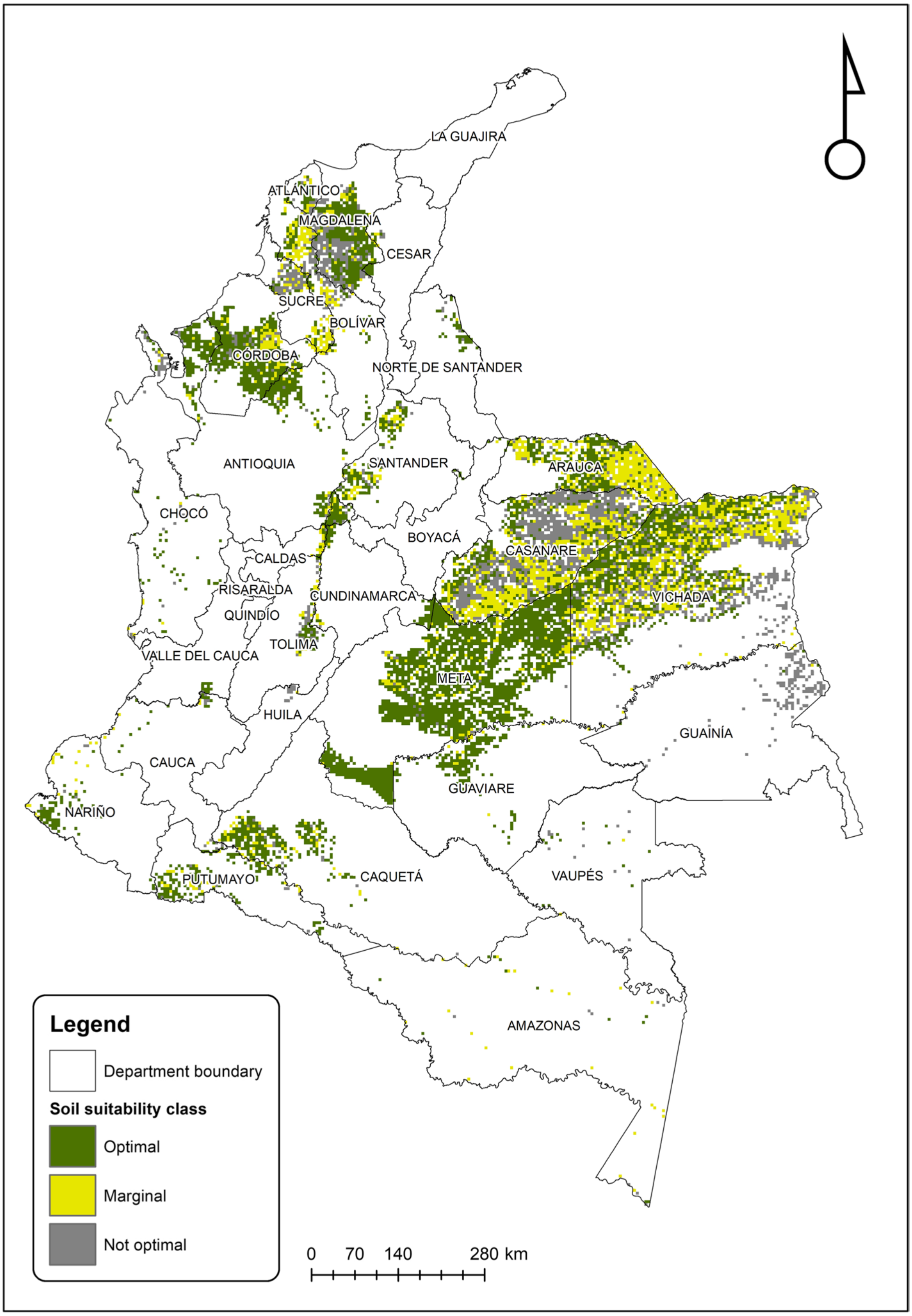

Fig. 7 Soil quality types map for robusta coffee in Colombia

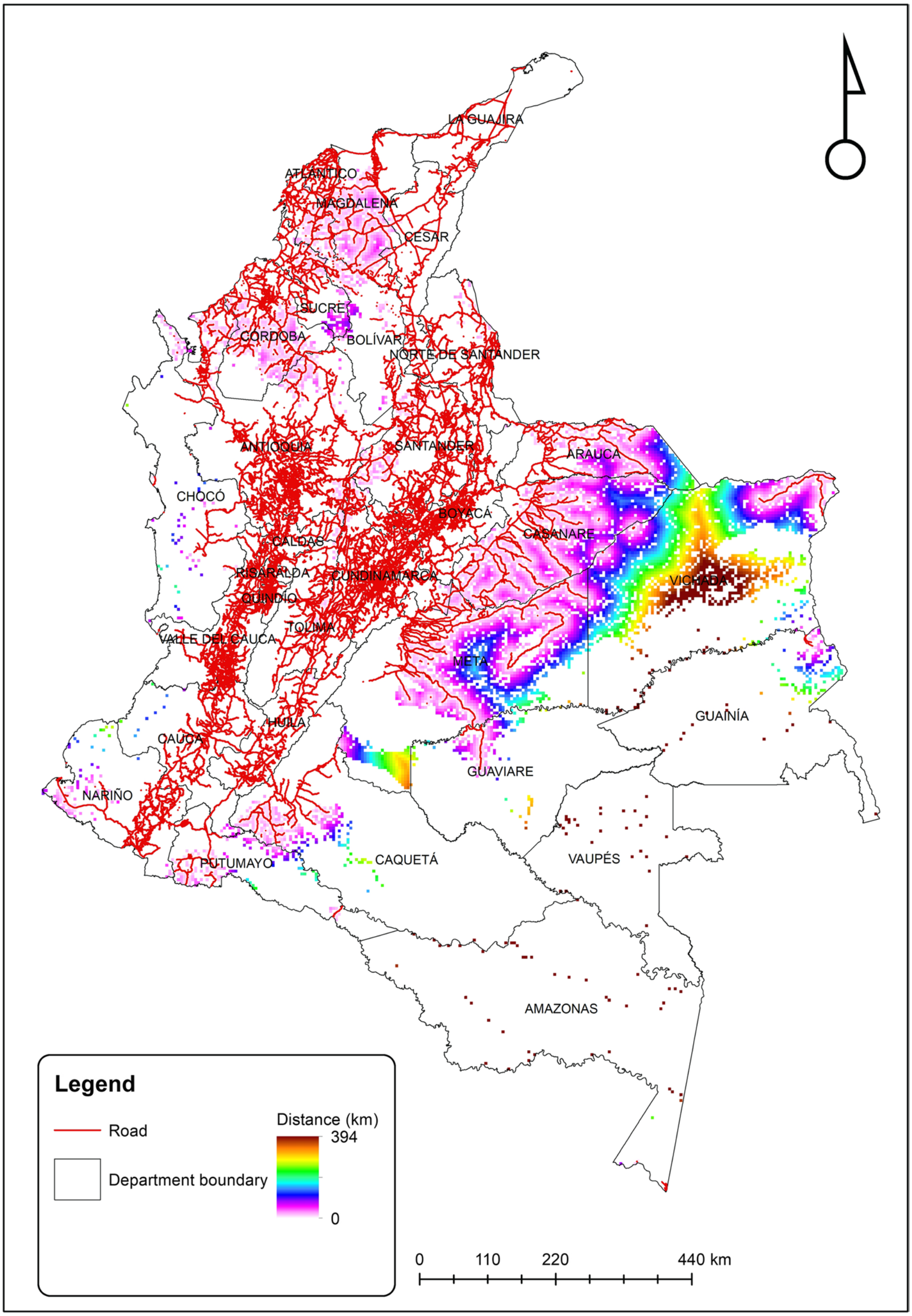

Fig. 8 Analysis of path distance using access to the roads network and productivity regions and sub-regions per municipalities

4 Discussion

4.1 Climate suitability and productivity mapping

The climate of coffee growing areas is changing globally, posing a significant challenge to governments, industry, and farmers. In our study the challenge of identifying potential robusta growing areas in Colombia provided an opportunity to explore an integrated approach which can be adapted to other tropical coffee countries globally. By integrating climate suitability modelling with a statistical crop yield model, pest risk assessment and socio-economic constraints we achieved a more complete understanding of potential robusta growing areas. This provides a more informative spatial prioritization than when only considering the climate suitability of a specific crop. For instance, we observed that regions of hotter and drier conditions such as the Orinoco plains, while having lower yields, were less likely to be affected by the CBB. In contrast, regions of high humidity closer proximity to the foothills of the Andean ranges or wet lowlands in the Caribbean presented higher suitability of the CBB. Below we discuss the key components of our integrated modelling approach, highlighting key areas for future research.

4.2 Pest coffee berry borer (CBB) risk mapping

The presence of pests is increasing in the tropics due to rising temperatures (Cilas et al. 2016). Although there might be risks from other pests and diseases, this study only considered the CBB, widely recognized as the key pest risk to coffee. In this study, we found that CBB risk is higher in regions nearest to the existing Arabica coffee suitability zones. These areas are predisposed to the incremental dissemination of the pest, owing to its historical prevalence within the Arabica coffee cultivation in the country (Cure et al. 2020). A clear example is the influence zone of the Magdalena Valley in the Santander department, wherein a CBB climate suitability is observed under existing climatic conditions and remains consistent in a climate change scenario.

It is also interesting to note that under low-temperature modeling, there are larger areas of CBB presence probability, while under high temperatures, the probability areas decrease along the main identified potential zones such as the Orinoco and Caribbean plains. Under climate change, the suitability areas identified are in line with those observed for the CBB in Colombia by Magrach and Ghazoul (2015). Suitability decreases in the Orinoco plains and increases in the Caribbean and the foothills along the eastern Andean ranges, potentially affecting some areas of high robusta yield in the future.

4.3 Regionalization and climate change: potential planting regions of robusta in Colombia

The future implementation of robusta coffee in Colombia raises the question of where the plantations might expand in coming years. We identified 163 political units ¨municipalities¨ with potential for robusta in Colombia (Fig. 5; Tables S1-2). Sites for cultivation need to be carefully selected across the territory considering socio-economic variables such as type of farmers. Because most farmers in Colombia are smallholders, we proposed a regional-scale strategy for cultivating robusta coffee. Smallholders (< 2 hectares) and even medium-sized holders (> 10 hectares) in the eastern part of the country, particularly in the Orinoquia and Amazon regions, could adopt robusta coffee cropping as an economic alternative, replacing illicit crops. This strategy, implemented at a small-regional scale, may involve agroforestry systems, non-mechanized harvesting, and non-irrigated robusta coffee agriculture. Introducing robusta alongside cultivated cacao or native cacao species in agroforestry systems, as seen in the Amazon of Brazil, could be a profitable option (Gama-Rodrigues et al. 2021). Considering Colombia's socio-political situation and climate change impacts, this model could be viable in post-conflict regions like Orinoquia and Amazonia. For successful implementation, government support is essential to establish farmer networks, commercial hubs, and ensure fair product payment for denominations of origin. Colombia, known for high-quality Arabica coffee, could also specialize in premium robusta. The distinct market potential of well-processed robusta coffee, with higher caffeine content, offers an opportunity for Colombia to leverage its reputation for quality coffee (Campuzano-Duque et al. 2021). There is an increasing consumer interest in specialty robusta coffee with Q robusta grader programs now established by the Coffee Quality Institute.

Large scale robusta farmers (> 50 hectares) on the other hand could benefit the most from implementing plantations in the Caribbean regions 1 and 2 because there is better access to secondary and tertiary roads. This model could be adopted by well-established agro-industrial groups that can afford large scale irrigated, mechanized production systems and hence will likely provide a better socio-economic stability keeping in mind that such regions suffer the largest losses of potential areas under climate change. Besides productivity, it is important to mention that our filtering strategy was based on the idea that sustainability must be a key aspect in future robusta plantations. Biodiversity of native forests and water resources cannot be compromised under any circumstances. This is a strong reason to clarify that our regionalization proposes areas that were prioritized by the government as future agricultural frontier under the current land use legislation (UPRA 2021). We also emphasize that future research assessing environmental sustainability and biodiversity impacts at multiple scales (i.e., from the farm level to regional scales) is needed.

The maximum value of yield found in our regionalization is 2.6 t ha^{-1}. In areas of similar climates, such as Vietnam, where irrigation and high nutrient inputs are common, yields of up to 5 t ha^{-1} are achieved (Byrareddy et al. 2020; 2021). Considering that management is not part of the modelling, the obtained estimates of yield represent average yield values, but could potentially be increased if well managed and high yielding well adapted robusta genotypes are used. The experimental trials comparing the performance of different robusta genotypes currently conducted by AGROSAVIA in different agro ecological conditions of Colombia, will provide more insights in the coming years.

4.4 Soils

We found that the eastern plains of the Orinoquia region is the largest area with high modelled yield for robusta. The analysis focusing on the finer spatial resolution soil conditions within the Orinoquia region, one of the regions with the greatest suitability for growing *C. canephora,* revealed that these areas correspond to the non-flooding Eastern Plains, an area which has rapidly transitioned from a semi-natural savanna dedicated to extensive cattle ranching, and low-input traditional agriculture, to highly intensified commercial farming (Lavelle et al. 2014). According to Amézquita et al. (2004), soils in this region are inherently acidic (pH range of 3–5) and compact (bulk density in the range of 1.4–1.6 g cm^{-3}), therefore, these require the formation of an arable soil layer via deep tillage to de-compact them, along with substantial applications of lime to increase soil pH.

4.5 Socio economic implications, future perspectives, and limitations

Preparing Colombia for the shift from Arabica to robusta requires a comprehensive understanding of climate change impacts on suitability, productivity, and pest distribution. Identifying potential robusta regions is an ongoing process, recently acknowledged by the Colombian government. Research institutions like AGROSAVIA, planning agencies like UPRA, and international collaborators such as Nestle are discussing options for robusta introduction. The CEO of the national coffee fund emphasizes that robusta coffee might be an option for the country. However, prioritizing potential robusta regions should consider Colombia´s high quality Arabica coffee heritage over market pressures. Our study follows this advice by excluding the current Arabica coffee growing zones from the analysis. It successfully identifies potential robusta regions under current and future climate change and risks like CBB. Climate change affects suitability differentially, crucial information for future decisions on agronomic trials, especially in critical regions highlighted in our regionalization.

This research is vital for agronomic planning, especially in introducing new crops like robusta coffee in Colombia. However, questions arise about the preparedness of Colombia's coffee industry for such a transition. Shifting to robusta in non-Arabica areas demands an advanced support system for coffee growers, who have long focused on quality Arabica coffees. Our study outlines optimal areas for robusta introduction, providing initial recommendations to industry, government, and coffee farmers to prevent overlap with traditional Arabica cultivation zones, addressing the challenges posed by significant climate changes and associated risks.

Climate change will likely make some Arabica coffee growing areas unsuitable for future production (Läderach et al. 2017). Coffee farmers in Colombia already struggle to adapt to changing climate and decision makers often lack sufficient spatial information needed for providing targeted recommendations (Eise and White 2018; Eise 2022). Alongside the loss of current growing areas, climate change may also make unsuitable areas more suitable for growing other crops. Our study suggests that robusta coffee is a crop that can provide new opportunities for several areas throughout Colombia.

In addition to climate change, the economic and social implications of a change in coffee species in Colombia could lead to significant environmental shifts. For example, lowland areas suitable for robusta cultivation are surrounded by valuable forested areas that should not be disturbed by agricultural activity. There is also a risk of general ecosystem degradation due to the industrialization of these optimal regions. These, among other factors, are uncertainties that the country needs to address through well-informed, research-based decisions.

Despite the challenge of limited nationwide information on potential robusta growing areas in Colombia, our innovative methods, incorporating data from robusta cultivation sites worldwide and numerous modelling techniques, facilitated to propose an initial regionalization. To advance, further research on robusta's physiology and agronomic adaptation in potentially suitable regions and those vulnerable to climate change and CBB is crucial. Sociocultural factors, including social and economic resistance to transitioning from the quintessential Colombian Arabica coffee, also pose genuine constraints that need to be investigated. Future research efforts should explore areas affected by climate change that are bordering traditional Arabica zones, assessing acceptance and resistance to a paradigm shift in coffee cultivation.

5 Conclusion

The eastern Andean Mountain foothills, Orinoquia high plains, wet Caribbean areas, and parts of the Pacific and Magdalena/Cauca River valleys constitute potential areas for robusta coffee plantations, with elevations between 200 and 600 m.a.s.l showing the highest modelled yields at 2.6 t ha^{-1}. Climate change will greatly impact the Caribbean, Pacific, and Inter Andean valleys. CBB will affect productive areas, particularly Andean foothills, and interandean valleys. Temperature plays a key role for flowering and growing seasons in identified lowlands suitability for robusta coffee, with rainfall playing a secondary role as a predictor in the yield model. However, we found that some of the regions with high yield were in areas of predominantly high annual precipitation. Our integrated modelling approach was effective to identify potential robusta regions. However, future research should focus on a region-based zonification strategy considering finer spatial scale for selecting robusta coffee trial sites.

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Data availability The species occurrences datasets (Data S1-S2) are directly available in the supplementary information. Other data are available under specific requests.

Declarations

Conflict of interests The authors declare that there is no conflict of interests. No financial interest to disclosure.

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