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Research Paper

Projecting trends of arabica coffee yield under climate change: A process-based modelling study at continental scale

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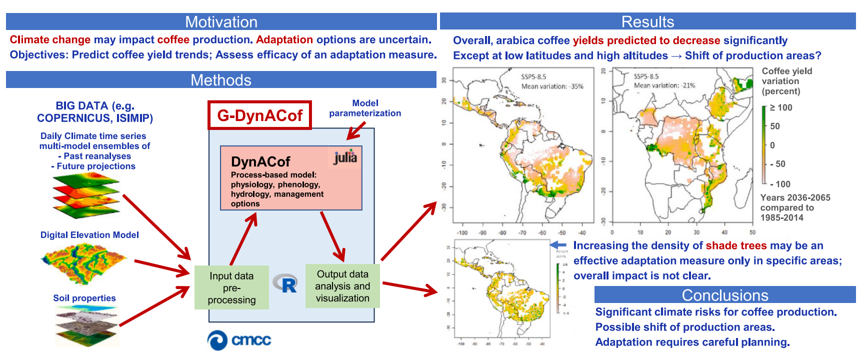
HIGHLIGHTS

- Arabica yields likely to decrease by 23–35 % in Latin America and 16–21 % in Africa.
- Production could shift to less impacted high-altitude and low-latitude areas.
- Adaptation potential of increased shading under agroforestry unclear, likely limited.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Climate change may lead to negative impacts on coffee production, such as reduced yields. Addressing this issue requires identifying climate risks and assessing the adaptation potential of agronomic practices across spatial and environmental gradients.

OBJECTIVE: This study aimed to evaluate climate change impacts on arabica coffee yields at continental scale and evaluate a specific adaptation measure, i.e. increasing shade tree density in agroforestry settings, by simulating the physiological links between coffee growth, climatic factors and agronomic management.

METHODS: After evaluating the performance of the process-based model DynACof in simulating arabica yields (using data from previous studies), we developed a new tool called G-DynACof, a modelling framework for spatializing DynACof on a regional scale using extensive climate projections and soil geodata. We used G-DynACof to simulate trends of potential coffee yields in Latin America and Africa using an ensemble of downscaled and bias-corrected climate projections for the period 2036–2065 compared to a historical period 1985–2014.

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RESULTS AND CONCLUSIONS: Despite considerable uncertainties due to the scarcity of information on agronomic management at the regional scale, our results indicate that potential yields could decrease between 23 % and 35 % in Latin America and between 16 % and 21 % in Africa, depending on the Shared Socioeconomic Pathway (SSP) considered (SSP1–2.6 and SSP5–8.5, respectively). Yield variations were very heterogeneous in space, with yields increasing at high altitudes and low latitudes, indicating a possible future shift of production areas. In our simulations, the effect of increased shade tree density on productivity was also spatially variable, and its potential for adaptation to climate change remains uncertain, requiring further investigation.

SIGNIFICANCE: Impact analyses and adaptation modelling of coffee agrosystems, together with socio-economic indicators, can delineate realistic, comprehensive, integrated risk assessments and support effective adaptation recommendations.

1. Introduction

Climate change poses substantial challenges to agricultural systems and ecosystem services (Lesk et al., 2016). Compared to 1850–1900, global surface temperature averaged over 2081–2100 is very likely to be higher by 1.0 °C to 1.8 °C for the most optimistic scenario, and by 3.3 °C to 5.7 °C for the most pessimistic scenario (IPCC, 2007, 2021). Extreme events such as heat waves, longer and harsher droughts, unpredictable rainfalls, etc. are becoming more frequent and severe (IPCC, 2021). The implications for agriculture systems are profound, as climate change may likely lead to a reduction in crop yield, yield quality, and suitable agricultural areas (IPCC, 2007, 2021).

Coffee production spreads over 80 tropical countries from Central and South America to Africa and Southeast Asia (Damatta et al., 2018). A total of 130 coffee species have been identified, of which two commercial species cover almost 99 % of total production: arabica coffee (*Coffea arabica*) covers around 70 %, while most of the remaining production is by robusta coffee (*C. canephora*) (Damatta et al., 2018; Davis and Rakotonasolo, 2021). There are about 100–125 million people involved directly and indirectly through its production chain. Coffee is a popular beverage consumed by one-third of the global population, with an estimated consumption of 400 billion cups each year (Krishnan et al., 2021; Mishra, 2020). Approximately 20–25 million farmers cultivate coffee, of which 60 % are small landholders with low-income status (DaMatta et al., 2019). Between 2021 and 2022, coffee consumption has increased by 3.3 %, while its production dropped by 2.1 % globally. Production in South America has been particularly affected compared to Africa, with a decrease of 7.6 % and 0.3 % respectively (International Coffee Organisation (ICO), 2023). Severe frost swept Brazil's coffee belt in July 2021, leading to a spike of global coffee price by 13 % (Figueiredo and Teixeira, 2021). Similarly, recent droughts with maximum temperatures well above average have been disastrous across Brazil coffee producing areas, causing dry berries and virtually empty husks. A decrease in coffee production due to adverse weather conditions has, in turn, an impact on world market prices.

According to several statistical studies based on climate change projections, arabica production could suffer significant sensitivity and face a decline in productivity (Bilen et al., 2022; Ovalle-Rivera et al., 2015). The expected drop in production would be mostly due to climate variability, particularly to extreme temperatures and water deficit (DaMatta and Cochicho Ramalho, 2006; Filipe dos Santos et al., 2015), and increasing infestations and distribution of insect pests and diseases that reduce coffee berry quality and yield (Bilen et al., 2022). Moreover, climate change is expected to alter and displace suitable land for coffee growth, besides reducing overall coffee yield (Bunn et al., 2015; Craparo et al., 2015; Läderach et al., 2017). Optimal temperatures for arabica are identified between 18 and 21 °C with little seasonal variation, although it can tolerate as low as 15 °C and up to 25 °C (Barros et al., 1997; Adhikari et al., 2020). Mean air temperature above 23 °C could accelerate fruit ripening of arabica cultivar but also lead to loss of bean quality. Similarly, floral initiation has been reported to decline due to high seasonal temperature above 33 °C and dryer season (Oliveira et al., 2020; Drinnan and Menzel, 1995; Martins et al., 2014). Overall, climate suitability for arabica coffee is predicted to decline globally by 2050 (Faraz et al., 2023). This is especially true in some growing regions of Latin America, including Brazil (Gomes et al., 2020), and Colombia (Ceballos-Sierra and Dall'Erba, 2021). Similar results have been obtained for African countries, such as Ethiopia (Purba et al., 2019; Moat et al., 2019), Tanzania (Craparo et al., 2015), Uganda (Mulinde et al., 2022), and Zimbabwe (Chemura et al., 2016).

Climate resilience of coffee agroecosystems involves adaptation measures such as shade cultivation or mulching to reduce the effects of rising temperatures and maintain soil moisture. Specifically, agroforestry systems involve coffee plantations with shade trees, resulting in a favourable microclimate that improves the supply of nutrients, carbon sink, and biodiversity (Bhagwat et al., 2008; Duarte et al., 2013; Koutouleas et al., 2022). In comparison to monoculture systems, this approach maintains higher soil moisture and lower air temperature (Lin, 2010; Moreira et al., 2018). However, increased shading affects the coffee plant physiology, stimulating vegetative rather than reproductive growth, ultimately leading to a reduction of flower buds and coffee yield (Moreira et al., 2018). Conversely, in full-sun systems, coffee plants exhibit significant fluctuations in flowering, leading to a biennial production pattern with alternating years of high and low productivity (DaMatta, 2004). These fluctuations not only shorten the coffee plant's lifespan but also create income uncertainty for farmers. In contrast, agroforestry systems favour more stable and sustainable conditions compared to unshaded systems (DaMatta, 2004). Several studies have demonstrated a positive impact of agroforestry practices on coffee production. For instance, research conducted in Brazil revealed that agroforestry systems have the potential to partially mitigate the impact of climate change on coffee suitability (Gomes et al., 2020). The decrease in coffee yield due to climate change at two Ethiopian sites was predicted to be lower in agroforestry systems than in monoculture systems (Gidey et al., 2020). Optimal shade management in two locations in Tanzania and Uganda could lead to a maximum yield gain between 10 and 18 % (Rahn et al., 2018).

Dynamic, process-based crop models simulate the physiology and developmental stages of crops and allow extrapolation of predictions considering changes in climate, soil, management and competition among species. A few process-based crop models documented in literature have been applied at local scale to assess coffee yields and evaluate adaptation options under changing climate scenarios. The model developed by Rodríguez et al. (2011) has investigated monoculture systems to evaluate phenology and physiological processes using branch-level cohorts of flowers and fruits for the entire two-year reproductive cycle. However, this model was not developed for large plots, long rotations or agroforestry systems. On the contrary, the CAF (Coffee Agro-Forestry) model (van Oijen et al., 2010; Rahn et al., 2018; Ovalle-Rivera et al., 2020) was specifically developed to simulate agroforestry systems. It incorporates many shading species and can assess ecosystem services, such as carbon and nitrogen cycles. However, it has some limitations in the representation of physiological processes, in particular it does not fully consider microclimate conditions nor continuous light distribution under shade trees as described by Charbonnier et al. (2017).

The DynACof (Dynamic Agroforestry Coffee Crop) model (Vezy et al., 2018, 2020) was developed specifically to overcome such limitations, being capable of simulating microclimate conditions under agroforestry using metamodels obtained from the MAESPA model (Duursma and Medlyn, 2012; Medlyn, 2004; Wang and Jarvis, 1990), a 3-dimensional model of forest canopy radiation absorption, photosynthesis and water balance. Another significant advantage of the DynACof model lies in its approach to simulating shading trees, which allows for fine parameterisation (Vezy et al., 2020).

To our knowledge, process-based coffee crop models have never been employed to evaluate climate change impact on coffee productivity at continental and pantropical scales. At these scales, only statistical approaches have been used so far (e.g. Bunn et al., 2015; Ovalle-Rivera et al., 2015; Magrach and Ghazoul, 2015; Grüter et al., 2022). Estimates from process-based models may be more accurate in depicting non-linear responses to changing climate, taking into account the more complex interactions of phenological and physiological processes, and allowing the evaluation of possible adaptation measures. However, the use of process-based models at continental scale poses significant challenges related to the availability and reliability of data, especially concerning the management of coffee agroecosystems.

To help fill this research gap, we set as our first goal to develop a continental-scale modelling tool built around the process-based model DynACof, so that it could simulate the interactions between climate, soil and coffee growth in space and time. As a necessary preliminary step, we aimed to evaluate the accuracy of the DynACof model to simulate coffee yields at various sites with contrasting characteristics and to assess its sensitivity to environmental variables. The second objective was to test the capability of the new tool in providing a first estimate of the impacts of future climate change on potential coffee yields in Latin America and Africa. We assumed no nutrient limitations, nor impacts from pests and diseases, as our goal was to isolate the effect of climate. The third objective was to demonstrate the possibility of using the new tool to perform preliminary evaluations of potential adaptation strategies; in particular, to evaluate the effects of increased shading within an agroforestry approach. We are fully aware of the challenges posed by these objectives; this study should be considered a first attempt to apply a process-based coffee agroecosystem model at continental scale.

2. The model

2.1. G-DynACof - regional modelling tool

One of our main objectives was to extend the applicability of the plot-scale model DynACof to whole regions, up to the continental and pantropical scales. In order to do that, we developed a tool consisting of a series of scripts in R (version 4.3.0; R Core Team, 2023) that handle the input data, run the model iteratively, and organize the results in tables, graphs, and maps. We named this new tool "G-DynACof" where G highlights its geospatial implementation. Fig. 1 shows the workflow inside G-DynACof. Required data is reported in Table 1 and discussed in section 3.4.2.

2.2. Coffee model DynACof

DynACof (Vezy et al., 2020) is a daily timestep, plot scale crop model with two layers of vegetation (shade trees and coffee plants) and three soil layers. It was developed to simulate the growth and yield of coffee plantations under various management options, either in monoculture or in agroforestry systems (Fig. 2). The advantage of this model over other available coffee models is that variables with high intra-plot variability, i.e., light absorption, light use efficiency, transpiration, plant sensible heat flux, and soil net radiation are computed using metamodels obtained from a 3D explicit process-based model called MAESPA (Duursma and Medlyn, 2012). A metamodel is a simplified version of an actual model, usually developed to reduce complexity and computational requirements. MAESPA is particularly well suited to simulate agroforestry system fluxes because it computes a fine estimation of the light interception, energy, water, and carbon fluxes of each plant in the forest and of the soil, while taking the spatial heterogeneity of the canopy into account. It was calibrated, used and validated on the same agroforestry system used to parameterize DynACof (Charbonnier et al., 2017; Vezy et al., 2018). Metamodels were fitted using multilinear regressions selected according to a trade-off between the number of explanatory variables, their genericity and range of application, and their accuracy obtained using different statistics (Vezy et al., 2020).

DynACof accounts for potential competition for light acquisition and water availability between plant and soil layers. The current version of the model does not consider nutrients as a limiting factor. Water competition is simulated virtually from the day-to-day fluctuations in

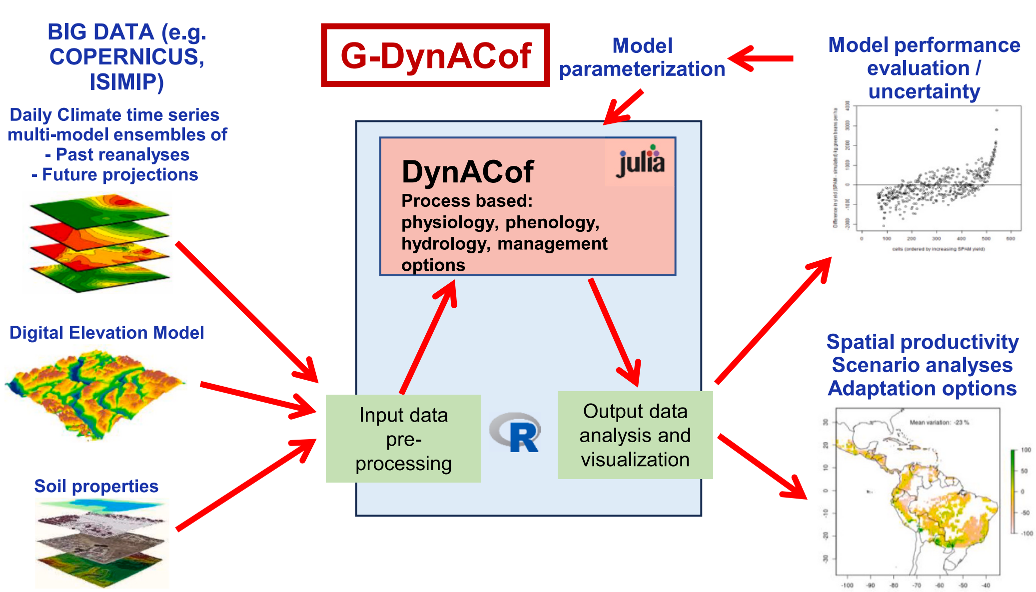

Fig. 1. Schematic representation of the workflow within our tool G-DynACof.

Table 1
Global geospatial datasets used for the regional simulations.

Dataset name and reference	Description	Data utilized
GTOPO30 (USGS, 1996)	Digital elevation model for the world, developed by United States Geological Survey (USGS). It has a 30-arc *sec* resolution (approximately 1 km).	Latitude (°) Longitude (°) Elevation (m asl).
SoilGrids (ISRIC, 2020)	System for global digital soil mapping, developed by ISRIC, that maps the spatial distribution of soil properties across the globe, at six standard depth intervals (0–5, 5–15, 15–30, 30–60, 60–100, 100–200 cm) at a spatial resolution of 250 m (data was downloaded at a resolution of 5 km).	Volumetric water content at −33 kP (field capacity) Volumetric water content at −1500 kP (wilting point)
ISIMIP - MPI, IPSL, GFDL (Lange and Büchner, 2021)	Daily climatic projections at a resolution of 0.5° from three different climatic models: MPI (Max Plank Institute), IPSL (Institute Pierre Simon Laplace), and GFDL (Geophysical Fluid Dynamics Laboratory). Made available by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) under the ISIMIP-3b protocol. Historical data series (1985–2014) and projections (2036–2065) for two different Shared Socioeconomic Pathways (SSPs) and expected level of radiative forcing up to the year 2100, depending on the level of GHG emissions: SSP1–2.6 (Sustainability) with low GHG emissions (expected radiative forcing of 2.6 W/m^2) SSP5–8.5 (Fossil-fuelled Development) with very high GHG emissions (expected radiative forcing of 8.5 W/m^2)	Min Temperature (°C) Max temperature (°C) Radiation (MJ /m^2 day) Rain (mm/day) Wind speed (m/s) Relative humidity (%)
ERA5 (ECMWF, 2022)	Daily surface meteorological data set, based on ERA5, the fifth generation atmospheric reanalyses of the global climate form ECMWF (European Centre for Medium Range Weather Forecast). Data was downloaded for the period 2000–2020 at a resolution of 0.10 from Climate data storage of Copernicus.	Min Temperature (°C) Max temperature (°C) Radiation (MJ /m^2 day) Rain (mm/day) Wind speed (m/s) Relative humidity (%)
ISIMIP CO_2 (Büchner and Reyer, 2017)	CO_2 concentration in the atmosphere, historic and projections up to 2100 (SSP1–2.6 and SSP5–8.5) available from the Inter-Sectoral Impact Model Intercomparison Project.	Atmospheric CO_2 concentration
SPAM (*IFPRI (International Food Policy Research Institute),* 2019)	Spatial Production Allocation Model. Using a variety of inputs, SPAM uses a cross-entropy approach to make plausible estimates of crop distribution within disaggregated units, at global scale, for 42 crops and 4 production systems (irrigated/rainfed, high/low inputs). It includes Arabica coffee and Robusta coffee as different crops. Resolution is 5 arc-minute. At the moment we are using the release 2010 version 2.0. SPAM returns *physical area, area harvested, yield* and *production* for each crop and production system in each pixel. Harvested area, production, and yield are modified to conform after aggregation to country level with FAO's national values for the average over 2004–2006.	Harvested area: SPAM returns the physical area for each crop and production system in each pixel. For our simulations, we use HARVESTED AREA, which is at least as large as physical area, but sometimes more, since it also accounts for multiple harvests of a crop on the same plot. Arabica coffee harvested area (ha) Yield: Yield data contained in the SPAM database is the result of a big effort of global and regional data collection and fusion. The values in SPAM are an average for the period 2004–2006. Arabica coffee yield (kg ha^{-1})

water content in each shared soil layer, which can be reduced by drainage and evapotranspiration or increased by precipitation through throughfall.

DynACof was designed to run at plot scale and was parameterized and evaluated using a highly comprehensive database on a coffee agroforestry experimental site in Costa Rica. The fluxes simulated by the model were close to the measurements over a 5-year period (nRMSE = 26.27 for gross primary productivity; 28.22 for actual evapotranspiration, 53.91 for sensible heat flux and 15.26 for net radiation), and DynACof satisfactorily simulated the yield, NPP, mortality and carbon stock for each coffee organ type over a 35-year rotation.

DynACof has many parameters, but the basic input data set needed to run the model is relatively small. It consists of daily values of main meteorological variables for the desired time period and basic site characteristics (elevation, latitude, and longitude). Other variables can be provided if available, particularly soil characteristics and coffee plantation characteristics and management.

The model generates a number of output variables related to coffee plant growth, such as net primary productivity, distribution of biomass in different organs, bud initiation and dormancy break, and many others. For our purposes, we chose the yield of coffee green beans as the target output. In the model, this corresponds to the output variable "Yield_green" (kg green beans ha^{-1}). We focused our continental-scale analyses on *Coffea arabica*, on which the DynACof model was parameterized.

3. Materials and methods

3.1. Sensitivity analysis

A direct manual sensitivity analysis of the model was carried out to identify the input data that are most influential on the target output, i.e. coffee yield. We performed it only on input variables, and not on model parameters (such as those governing plant growth, which were calibrated during the model development). The method used is very simple. Each variable was varied independently from the others, one at a time, within plausible ranges or according to the available data range. By altering one variable at a time, and keeping all the other fixed, we obtained a useful indication of sensitivity, although we did not reflect all the possible interactions for all inputs varying independently. This analysis was important in order to improve our knowledge of the model behaviour, firstly to assess if the model behaves in a plausible manner, i.

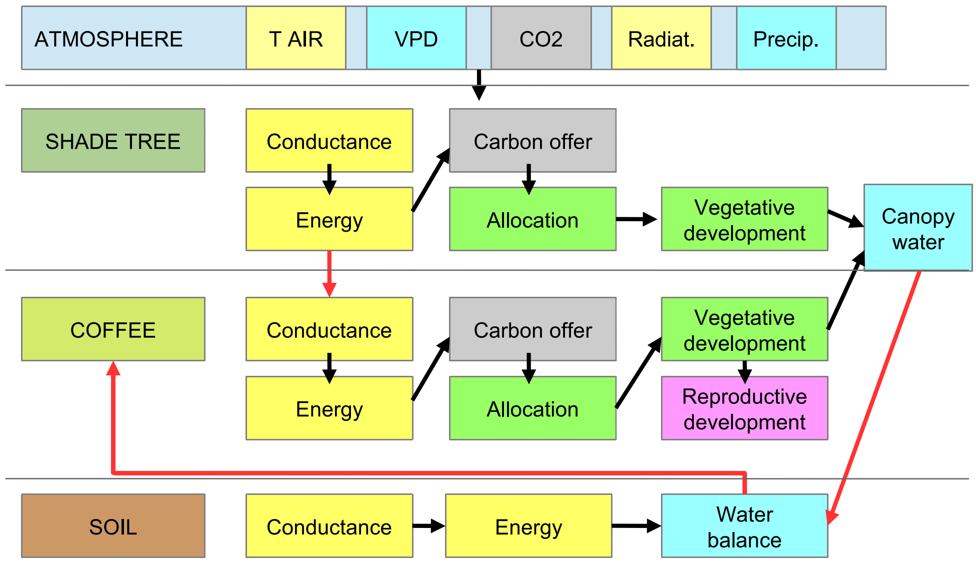

Fig. 2. Schematic representation of the model DynACof. T AIR: Air temperature. VPD: Vapour Pressure Deficit. CO2: Carbon Dioxide. Radiat.: Solar Radiation. Precip.: Precipitations.

e., in line with what is reported in the literature, and secondly to know which are the most influential input variables, on which concentrate the effort to obtain reliable data.

For what concerns climate, soil and topography variables, we performed the sensitivity analysis on a study area composed of four southwestern Brazilian states: Minas Gerais, Espirito Santo, Sao Paolo, Rio de Janeiro. The reason for this choice is that Brazil is the biggest producer of coffee worldwide (FAOSTAT, 2024), and around 80 % of Brazilian coffee production takes place in the southwestern part of the nation (IBGE, 2023). Moreover, this area encompasses a wide variety of topography, soils, and climate conditions, thus rendering our sensitivity analysis valid for a wide spectrum of situations. The data used for this analysis is the same as described in section 3.4.1 for Brazil.

On the other hand, to analyse model sensitivity to management variables (e.g., density of coffee plants and shade trees) we took as a starting point the data used to calibrate the model, i.e., data collected in the Aquiares site in Costa Rica. In this case, baseline values were 5580 coffee plants per hectare and 250 shade trees (*Erythrina poeppigiana*) per hectare. We modified these values and varied them within plausible ranges according to the literature and expert knowledge.

3.2. Model validation and uncertainty estimation

In order for a modelling tool to produce reliable predictions and scenario analyses with an estimation of uncertainty attached to them, the underlying model must be tested and validated at several sites with contrasting climate, soil, and management features. We evaluated the model performance at three different scales: plot scale (3 sites located in Mexico, Costa Rica, and Ethiopia), small regional scale (Rwanda), and wide regional scale (South-eastern Brazil). Data for this validation effort is described in section 3.4.1. Model performance was evaluated using Root Mean Square Error (RMSE) and Normalized RMSE (NRMSE, normalized by the mean of observations). For the Brazilian area, we also used the Willmott Index d (Willmott et al., 1985), defined as:

$$d = 1 - \frac{\sum (O_i - P_i)^2}{\sum \left(|O_i - \overline{P}| + |P_i - \overline{O}|\right)^2}$$

where O_i are observed values and P_i are predicted values. The d index ranges between 0 and 1, with a value of 1 indicating perfect agreement between the predicted and observed values. A value of 0 indicates that the predicted values are no better than predicting the mean of the observed values.

3.3. Experimental design

The main experiments were designed to (i) estimate the effect of future climate changes on potential coffee yields in Latin America and Africa and (ii) assess the efficacy of adaptation measures in addressing the possible negative effects of climate change.

3.3.1. Climate change impact on potential coffee yield

Regarding the first experiment, we simulated coffee growth in Latin America and Africa, where arabica production is more prominent than in Asia. In both regions, we estimated potential yields driven by an ensemble of CMIP6 (Coupled Model Intercomparison Project Phase 6) climate projections from three different Earth System Models: MPI (Max Plank Institute), IPSL (Institute Pierre Simon Laplace), and GFDL (Geophysical Fluid Dynamics Laboratory). Projections were made available by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) under the ISIMIP-3b protocol (Lange and Büchner, 2021). The ISIMIP project established a consistent protocol to define and compare the impacts of climate change across affected sectors and spatial scales, and it represents a harmonized framework for global assessment evaluations (e.g. IPCC report). The ISIMIP framework includes a predefined set of bias-adjusted and downscaled global climate data projections on a 0.5° x 0.5° grid and at daily time steps.

In order to assess how yields might change in the future (around the year 2050) compared with a reference period, simulations were carried out for both a historical 1986–2015 and future 2036–2065 timeframes under two different scenarios: SSP1–2.6 (Sustainability) with low GHG emissions and expected radiative forcing at 2.6 Wm^{-2}, and SSP5–8.5 (Fossil-fuelled Development) with very high GHG emissions and expected radiative forcing at 8.5 Wm^{-2}. To evaluate the effect of CO_2 as atmospheric fertilization on the physiology and productivity of coffee trees, simulations were always performed twice: with constant CO_2 concentration, and with predicted CO_2 concentration change for the two scenarios (further details in the Supplementary Material).

3.3.2. Assessment of an adaptation measure

Regarding the second experiment, we tested the efficacy of increasing shade tree density on mitigating the negative effects of climate change on coffee yield. According to the literature, in some cases, shade trees contribute to creating a microclimate that helps mitigate extreme temperature oscillations and stabilise relative air humidity, ultimately helping coffee plants cope with climate change risks, such as increasing temperatures or decreasing precipitations (Koutouleas et al., 2022). Moreover, depending on the tree species used, there may be other additional services, such as firewood, fruits, the creation of habitats with a consequent increase in biodiversity, etc. (Bhagwat et al., 2008). In our analysis, we mostly considered the benefit of shading and microclimate buffering to limit the risks of climate extremes on coffee yield.

We assessed this scenario for Latin America, which is home to most of the global coffee production, and have foreseen considerable adaptation of agroforestry practices in coffee agrosystems. In our baseline simulation, shade tree density was set to 60 trees per hectare with a coffee shrub density of 3875 plants per hectare. This is the first scenario that represents typical management, based on available literature and expert knowledge (CATIE, 2023; Ovalle-Rivera et al., 2020; van Oijen et al., 2022; Libert A., personal communications). We then set up a second scenario where shade tree density was increased to 90 trees per hectare. Typically, where tree density is larger, coffee shrub density is slightly smaller. Consequently, in our second scenario, coffee density was decreased to 3750 plants per hectare. These values were set with the help of experts. We called this second scenario "enhanced agroforestry".

3.4. Input data

3.4.1. Data for model validation

In order to check the accuracy of DynACof in simulating coffee growth at different locations, we used data collected at three sites: Montecristo de Guerrero (Chiapas, Mexico), Turrialba (Costa Rica), and Wonago (Ethiopia). We also used data referring to the most common plantation management and average yield for Rwanda. Moreover, to check the model performance at the regional scale, we used data available for southern Brazilian states.

Data from the Mexican site was provided by an expert who worked in the area (Antoine Libert, personal communication). The site is in the Chiapas Sierra Madre, a mountainous area. To set the management parameters, we referred to a commercial polyculture of coffee located at 1087 m asl, with approximately 3333 coffee plants and 97 shade trees per hectare (shade tree: *Inga* spp., annual pruning 70 %, no thinning). Yield data was taken from the Mexican Agricultural Production Statistical Yearbook (SIAP, 2023). We compared DynACof yield estimates vs. recorded yield for three consecutive years (2011−2013).

The site in Costa Rica is a well-established experimental site, run by the Tropical Agricultural Research and Higher Education Center (Ovalle-Rivera et al., 2020; van Oijen et al., 2022; CATIE, 2023). Data were provided by Elias de Melo (personal communication). It is a low altitude (600 m asl), humid weather site. We used data from a specific plot with approximately 5000 coffee plants and 269 shade trees per hectare (shade tree: *Erythrina p.*, annual pruning 90 %, annual thinning 50 %). We compared DynACof yield estimates vs. recorded yields, both averaged out over 16 years (2002–2017).

The Ethiopian site is found in the Wonago district. Its elevation ranges between 1200 and 2100 m (Gidey et al., 2020). Data for parameterization are available in the cited paper. There are approximately 2500 coffee plants and 60 shade trees per hectare (shade tree: *Albizia gummifera*, annual pruning 10 %, no thinning). We compared DynACof yield estimates vs. recorded yields, both averaged out over 7 years (2001–2007).

The dataset for Rwanda was provided by Mattia Guglielmi (personal communication); it includes the most common management practices utilized in the Rwandan production areas: 2500 coffee plants and 60 shade trees per hectare.

Finally, the regional validation was done by using our new tool G-DynACof (see section 2.1), simulating coffee growth in four southeastern Brazilian states (Minas Gerais, Espirito Santo, Sao Paolo, Rio de Janeiro), where nearly 80 % of the Brazilian coffee production occurs. Brazil is the main producer of coffee worldwide (FAOSTAT, 2024). Data were taken from the IBGE (Instituto Brasilero de Geografia e Estatistica) through its portal SIDRA (Sistema IBGE de Recuperação Automática; IBGE, 2023). We used arabica yields recorded in the period 2012–2020, aggregated by mesoregions as defined by IBGE. There are 37 mesoregions in the area we considered. A mesoregion can include several municipalities. In this case, we had no solid information on how the management varies across the region; therefore, in the simulation we used a unique standard management for the whole region, based on available literature (Espindula et al., 2021), i.e. 3333 coffee plants and 97 shade trees per hectare (shade trees: *Erythrina p.*, annual pruning 70 %, no thinning). As a consequence, the resulting yield estimates are still affected by this generalization over a large area. The model results for Brazil were also compared to the yield spatial extrapolation data provided by SPAM (Table 1). The values in SPAM refer to a three-year average around 2005. Therefore, to make the comparison meaningful, we calculated an average of simulated yields around 2005, but with a slightly wider window (2003–2007) to better compensate for yearly oscillations of model predictions on reanalyses of climate observations.

Required data for the site, soil, and meteorological variables were obtained from global geodatasets (see section 3.4.2), except for the Turrialba site, where we used data from a local meteorological station.

3.4.2. Data for simulations at continental scale

We used the global datasets listed in Table 1 to carry out the simulations at a regional scale needed for the main experiments described in section 3.3.1.

All global layers were reprojected, if necessary, to a geographic coordinate system (regular latitude-longitude grid) as that of most climate model projections in use (e.g. CMIP6, ERA5). Layers were cropped to the extent of the regions of interest and resampled to a resolution that depended on the needs. For preliminary simulations and model validation, we used a resolution of 0.1° with ERA reanalyses data as the climate driver for the historical periods, while for regional simulations, the resolution was set to 0.5° with climate projections as the climate driver.

The soil module in DynACof divides the soil profile into three layers: 0–1.25 m, 1.25–1.75 m, and 1.75–3.75 m. Therefore, data derived from the SoilGrids geodataset were elaborated to match the layers implemented in DynACof:

- Properties of SoilGrids' layers 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm and 60–100 cm were averaged out, weighing for layer thickness. The weighted average was assigned to the first DynACof layer (0–125 cm).
- Properties of SoilGrids' layer 100–200 cm were assigned to the second DynACof layer (125–175 cm).
- Since no information was available below 200 cm, the properties of the third DynACof layer could not be set, so default values were used.

Information about the management of coffee and shade trees is much more difficult to establish spatially at the regional level, unlike at plot scale. A generalization at the regional level must be established that would be representative of standard settings for regional simulations, one for the whole of Latin America and another for Africa. Certainly, this approach implies a great simplification since, within the studied regions, there is a wide range of possible situations, from coffee monoculture in full sun to very high tree cover. However, we wanted to have a baseline indicating the potential coffee yield under one standard management with average densities, that can be considered as relevant agroforestry setting in each region. This approach has the advantage of allowing for an estimation of potential yields that is consistent across the region, and enables comparisons between different areas within the region, as well as prediction of the effects of climate changes for the whole region. Specifically, the density of coffee shrubs and shade trees, as well as the pruning rates, were set by averaging out values found in the literature and obtained by experts for each of the regions (CATIE, 2023; Gidey et al., 2020; Ovalle-Rivera et al., 2020; van Oijen et al., 2022; Libert A. and Guglielmi M., personal communications). In our baseline simulation for Latin America, shade tree density was set to 60 trees per hectare, using *Erythrina poeppigiana* as shade tree species, with a coffee density of 3875 plants per hectare. For Africa, shade tree density was set to 60 trees per hectare, using *Albizia gummifera* as tree species, with a coffee density of 2500 plants per hectare. Within the model, some tree parameters were changed according to the species used, namely specific leaf area and maximum leaf area index. Parameters for coffee were left unchanged.

3.5. Simulation runs

We used the version of DynACof implemented in Julia language (Vezy, 2019), because data processing runs much faster than in the R version. We used R (version 4.3.0; R Core Team, 2023) to write the rest of the code (data handling, post processing, etc.). Yield estimates are always null for the first two years because in DynACof, coffee plants start producing berries from the third year onward. Therefore, averages were calculated after the third year.

Within each region, simulations were constrained in those areas for which the SPAM geodataset indicates at least some arabica coffee being harvested. Simulations for climate projections at 0.5 degrees leave significant space for a marginal shift in coffee suitability due to climate change. This is an essential step to run simulations only where appropriate. This step saves computational time, and ensures to come up with realistic estimates: running the model in unsuitable areas, where coffee is probably not grown, would give extremely low yield estimates and would affect the regional average, resulting in systematic underestimation.

The SPAM geodataset not only indicates, for each grid cell, if a crop is grown there but also gives an estimation of the actual harvested area within that cell. We exploited this information to refine the estimation of regional yield averages: the harvested area in each cell is used as a weight to calculate a weighted mean. In this way, cells with larger harvested areas contribute more to the average, resulting in more plausible regional estimates. This mechanism was also implemented to validate the model in southeastern Brazil when estimating yields for each mesoregion.

Information about the management of coffee and shade trees (density, pruning rate, etc.), soil properties, site characteristics, and daily climate variables, as described in section 3.4.2, were used to modify the corresponding input variables in the DynACof model before each run. All other variables were left unchanged, and default model parameters for arabica coffee and shade trees were used.

The main output variable in our analyses was coffee yield expressed as kg of green beans per hectare. Yields obtained for all grid cells and all years were aggregated in the final raster of results as average for present and future periods. Arrays were manipulated to obtain several statistics, including regional yields, as described above.

In fact, our tool realizes a spatially explicit implementation of the DynACof model. Therefore, the main output is a series of maps representing model outputs for selected regions. We always summarize results by averaging them over a certain time period, e.g., 5 years, or even over the whole period where data are available (e.g., 2012–2020). This reduces the importance of inter-annual variations, which are difficult to catch because of many possible reasons that are not known (e.g. change in management, pests).

For estimating past yields and projecting future yields at the continental scale, we used daily climatic data and projections for the periods 1985–2014 and 2036–2065 respectively, from three different climate models: MPI (Max Plank Institute), IPSL (Institute Pierre Simon Laplace), and GFDL (Geophysical Fluid Dynamics Laboratory). We analysed two different Shared Socioeconomic Pathways (SSPs): SSP1–2.6 (Sustainability) with low GHG emissions and SSP5–8.5 (Fossil-fuelled Development) with very high GHG emissions (Table 1).

4. Results

4.1. Sensitivity analysis

The sensitivity analysis revealed the most influential input variables in relation to the target output variable, i.e., coffee yield. The model was very sensitive to climate variables; in particular we found a strong negative correlation with mean temperature, and a positive correlation with precipitation (Fig. 3 a and b).

Another important set of input variables are inherent to soil water retention capacity, in particular field capacity (Fig. 3 c) and wilting point, and in particular for the first soil layer (0–1.25 m). Few global soil databases are available, such as the one we used and described in section 3.4.2; however, their reliability is less strong compared to climate data, because soils are extremely heterogeneous in space and across vertical layers, and so are the methods by which soil data are collected and interpreted in each region of the world.

Finally, many variables related to the management of coffee plants and shade trees proved to be quite influential on coffee yields. Not surprisingly, one of the most influential management variables is coffee planting density: leaving all other variables unchanged, a coffee density decrease of 50 % from standard densities caused yield to decrease by approximately 40 % on average (over a 20-year period). In contrast, an increasing density of 50 % resulted in a small yield increase, just around 7 %. This suggests that the default value for plant density (5580 plants per hectare) may be optimal in the reference site (i.e., the Aquiares site in Costa Rica), and an increase in density would have only a small benefit, while a decrease would have a strong negative effect.

Coffee yield was also sensitive to shade tree density, although the variations are much smaller compared to those caused by coffee density. Such a result shows a relevant instance of how a model can be used to assess the effect of agroforestry approaches and to evaluate the impacts of possible adaptation measures relying on the benefits of shading options. In the specific case of the Aquiares site, an increase in shade tree density by 50 % determined a yield increase of about 2.4 %, while a decrease in shade tree density by 50 % determined a yield decrease of about 3 %.

4.2. Model validation

The predicted yield was close to the observations for all sites simulated (Fig. 4, Rwanda, Ethiopia, Chiapas, and Costa Rica), with an RMSE of 156.8 kg green beans ha^{-1} and an NRMSE of 0.09. Surprisingly, the site from Costa Rica had the highest error.

As expected, the prediction error was larger when the model was applied at the mesoregion scale (Fig. 5, southeastern Brazil) than at the plot scale, with an RMSE of 413.0 kg green beans ha^{-1} and an NRMSE of 0.304. The model tended to underestimate yields in many mesoregions.

When comparing simulated yield to SPAM data in Southeast Brazil, we obtained an RMSE of 641.5 kg green beans ha^{-1} and an NRMSE of 0.560. The RMSE map, visible in the Supplementary Material (Fig. S1), shows that the error magnitude varies spatially. Willmott Index d was 0.53, which implies that the model performs better than taking the mean of the observed values. DynACof overestimated at the lower end of the range and underestimated at the high end of the range (Fig. 6). However, it is also possible that administrative statistics are biased.

4.3. Prediction of yield variation under different climate projections

We assessed the impact of climate changes on coffee yields by comparing results of G-DynACof simulations for historical (1985–2014) vs. future conditions (2036–2065), using three different climate model projections and two different shared socioeconomic pathways (SSPs, see section 3.4.2). Our simulations predicted a general decrease of yield on average for both Latin America and Africa, for all three climate models and both SSPs (Fig. 7). The predicted yield decrease is more pronounced

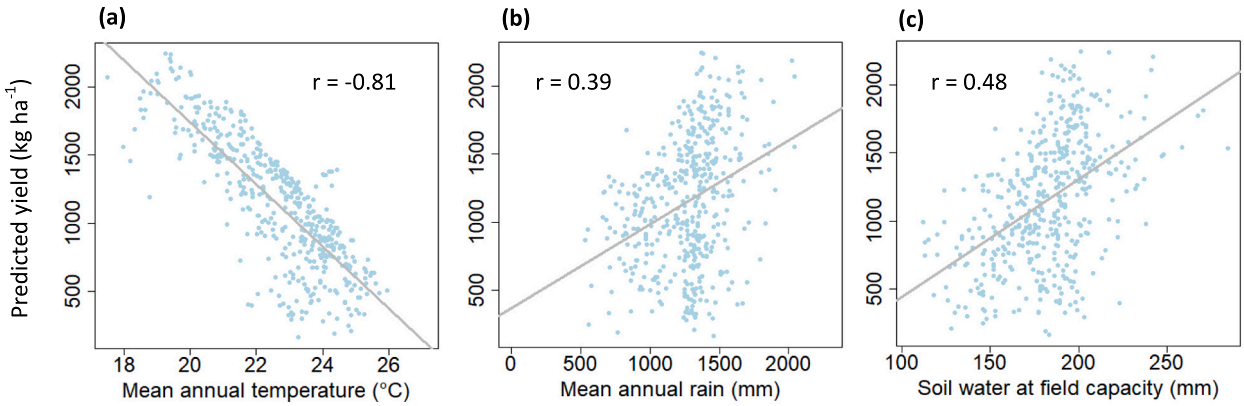

Fig. 3. Correlation between predicted yield and the most influential climate variables. All three correlations are statistically significant (p < 0.05).

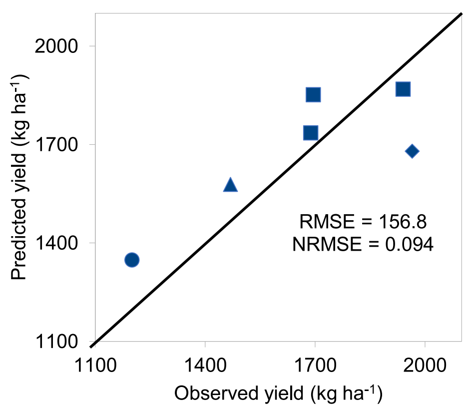

Fig. 4. Predicted (y) vs. observed (x) yield (kg green beans ha^{-1}) at plot scale. Circle: Rwanda; triangle: Ethiopia; squares: Chiapas; diamonds: Costa Rica.

for Latin America than for Africa. As expected, the decrease is more pronounced under SSP5–8.5, i.e. the scenario implying higher GHG emissions, for which the ensemble modelling predicted an average yield decrease of 35 % in Latin America and 21 % in Africa. However, the decrease is evident even in the most optimistic SSP1–2.6 scenario, with a predicted average decrease of 23 % in Latin America and 16 % in Africa. Even considering the most optimistic combinations of climate model and SSP (i.e. IPSL and SSP1–2.6 for Latin America, MPI and SSP1–2.6 for Africa), the expected decrease is still very significant: 23 % in Latin America and 9 % in Africa. Conversely, the most negative combinations (GFDL and SSP5–8.5 for Latin America, IPSL and SSP5–8.5 for Africa) result in a predicted decline of 37 % for Latin America and 26 % for Africa. According to the model, yield decreases will be more pronounced in Latin America than in Africa for every tested scenario, except IPSL SSP1–2.6.

4.3.1. Effect of CO_2 fertilization

The model predicted a positive trade-off due to atmospheric CO_2 concentration on plant physiology and water use efficiency. When running the model under the same future projections but with constant CO_2 concentration (i.e., CO_2 level as for the year 2005), yield is predicted to decrease even more by approximately an additional 3 % on average. This means that there is a visible effect of CO_2 fertilization and that the model can reproduce it. It also means that this fertilization effect is not enough to reverse the trend of yield decline due to more adverse climate conditions.

4.3.2. Spatial heterogeneity of yield variation; shift of suitable areas

The predicted variation of yield for 2050 was very heterogeneous in space, as shown by the spatially explicit representation of yield variation from the climate ensemble for the two regions investigated and the two socio-economic pathways (SSPs) considered in Fig. 8 (see also Figs. S2, S3 and S4 in Supplementary Material). Spatialized simulations predicted

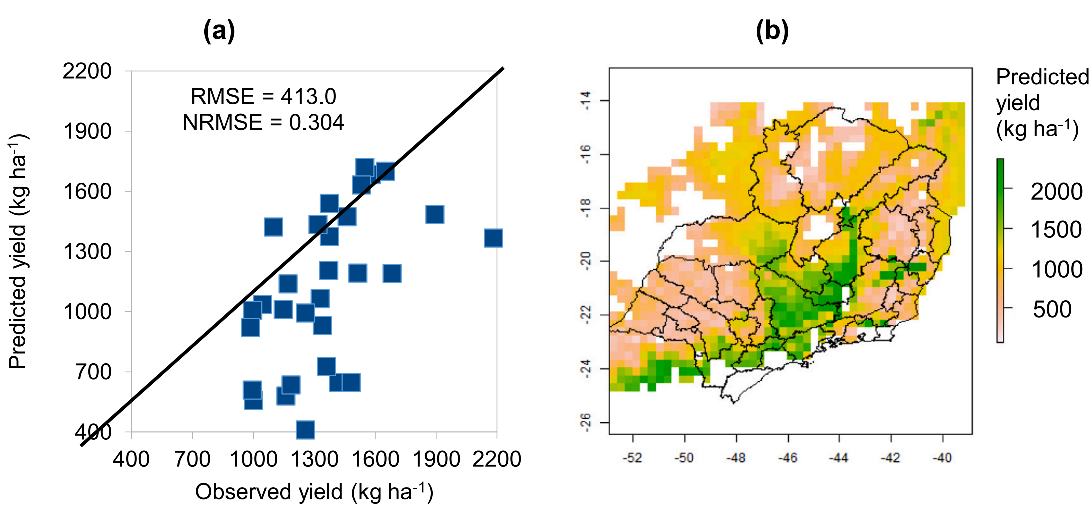

Fig. 5. (a) Predicted vs. observed yield (kg green beans ha^{-1}) in the region of South-eastern Brazil depicted in (b). Each point represents annual averages over the period 2012–2020 for each subregion within the region. (b) Map of the simulated points in (a). The polygons are subregions, i.e. geographical “mesoregions” as defined by IBGE in 1990. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

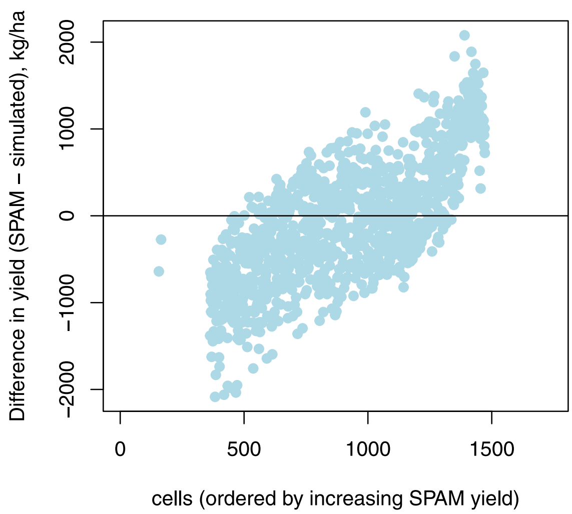

Fig. 6. Residuals of model predictions vs. SPAM yields.

a strong negative impact on most areas. These include central and southeastern Brazilian states, as well as Central Africa, in particular Cameroon and the Democratic Republic of the Congo (DRC). Still, some lower latitudes and higher elevation areas presented higher predicted yields compared to the baseline. In Latin America, it is the case of Paraguay and the Brazilian state of Paraná. In Africa, a positive trend is predicted for Yemen, the western part of DRC, and some locations in Eastern African states, notably Ethiopia, Kenya, Tanzania and Mozambique.

This heterogeneity was partially explained by environmental factors, such as climate and topographic conditions (Fig. 9). For example, yield was positively impacted by lower minimum and maximum annual temperatures, which was related to higher elevation. The average minimum and maximum temperatures of the areas that presented a decrease in predicted yield were 20.0 and 30.8 °C, respectively, significantly higher compared to those for the areas where the model predicted a yield increment (17.0 and 29.1 °C, respectively). The mean elevation of negatively affected areas was 483 m asl, compared to 841 m asl for areas positively affected.

4.4. Effects of the adaptation measure

In our simulations, enhanced agroforestry (i.e. 50 % increase in shade trees, from 60 to 90 trees/ha) mitigated the negative impact of climate changes on 20 % of the area, reducing yield loss by 2 % points on average (median 1.2, interquartile range 0.4–3.3), while on 74 % of the area it further reduced yield (Fig. 10). Although in general these variations were not statistically significant, it's interesting to note that in the first case, G-DynACof predicted a yield improvement even if coffee plant density had been reduced to allow for more shading trees. By analysing environmental characteristics in search of factors influencing the effects of enhanced agroforestry, we found that this measure seems to be more effective at higher altitudes and lower temperatures (Fig. 11).

5. Discussion

Yields simulated by DynACof were highly sensitive to climate variables; in particular, we found a strong negative correlation with mean temperature, and a positive correlation with precipitation (Fig. 3a and b). This result agrees with the literature: generally speaking, an increase in temperature affects yield negatively, while an increase in precipitation can improve it (DaMatta et al., 2018). The sensitivity of the model to climate variables makes it suitable to perform simulations under climate projections.

Soil water retention parameters also showed a significant influence. In DynACof, water availability directly influences the initiation period of flower buds. When water is limited, the dormancy period of buds may be extended, as a specific amount of water is required to potentially break dormancy. Since buds can only emerge if previous buds have not yet broken dormancy (i.e., as long as no flowers have appeared on the plant), water limitation would result in fewer buds, ultimately reducing yield. During a later phenological stage, leaf water potential affects the likelihood of bud dormancy breaking: the lower the leaf water potential, the more likely dormancy will break. This means that when soil moisture is low, flowering tends to become more synchronized over time. Yield could be negatively impacted in extreme cases of flowering synchronizations, as the plant may struggle to supply enough resources to the fruits, since they all demand assimilates simultaneously. The processes underlying these phenomena have been described by several authors (e.g. DaMatta and Cochicho Ramalho, 2006). However, the current version of DynACof does not directly link soil water content to stomatal closure, node number, or light use efficiency. Incorporating these processes could improve the model's accuracy but is challenging due to the scarcity of data. Our result aligns with the findings of Rahn et al. (2018), who also used a process-based model (i.e. CAF2014) to assess the impact of climate change on Arabica coffee, although their study is limited to two specific areas in Uganda and Tanzania. Their sensitivity analysis showed that soil hydraulic parameters strongly influenced simulated yields. The CAF2014 model considers only one homogeneous soil layer, while DynACof implements three distinct layers. We believe the latter may offer a better description of the competition between coffee and shade trees for soil water resources, given the different depths of their root systems.

The model validation for coffee yield showed strong agreement between simulations and observations at the local scale (9 % nRMSE), and acceptable agreement at the regional scale (30 % nRMSE). However,

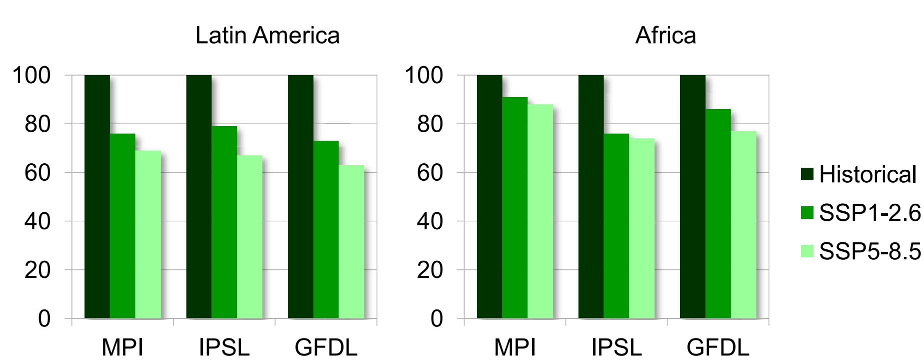

Fig. 7. Normalized average annual potential yield, climate projections (2036–2065) vs. historical climate (1985–2014), where yield under historical climate is set to 100. Climate models: MPI = Max Plank Institute; IPSL = Institute Pierre Simon Laplace; GFDL = NOAA Geophysical Fluid Dynamics Laboratory. Shared Socio-economic Pathways: SSP1–2.6 = Sustainability with low GHG emissions (expected radiative forcing of 2.6 W/m^2); SSP5–8.5 = Fossil-fuelled Development with very high GHG emissions (expected radiative forcing of 8.5 W/m^2).

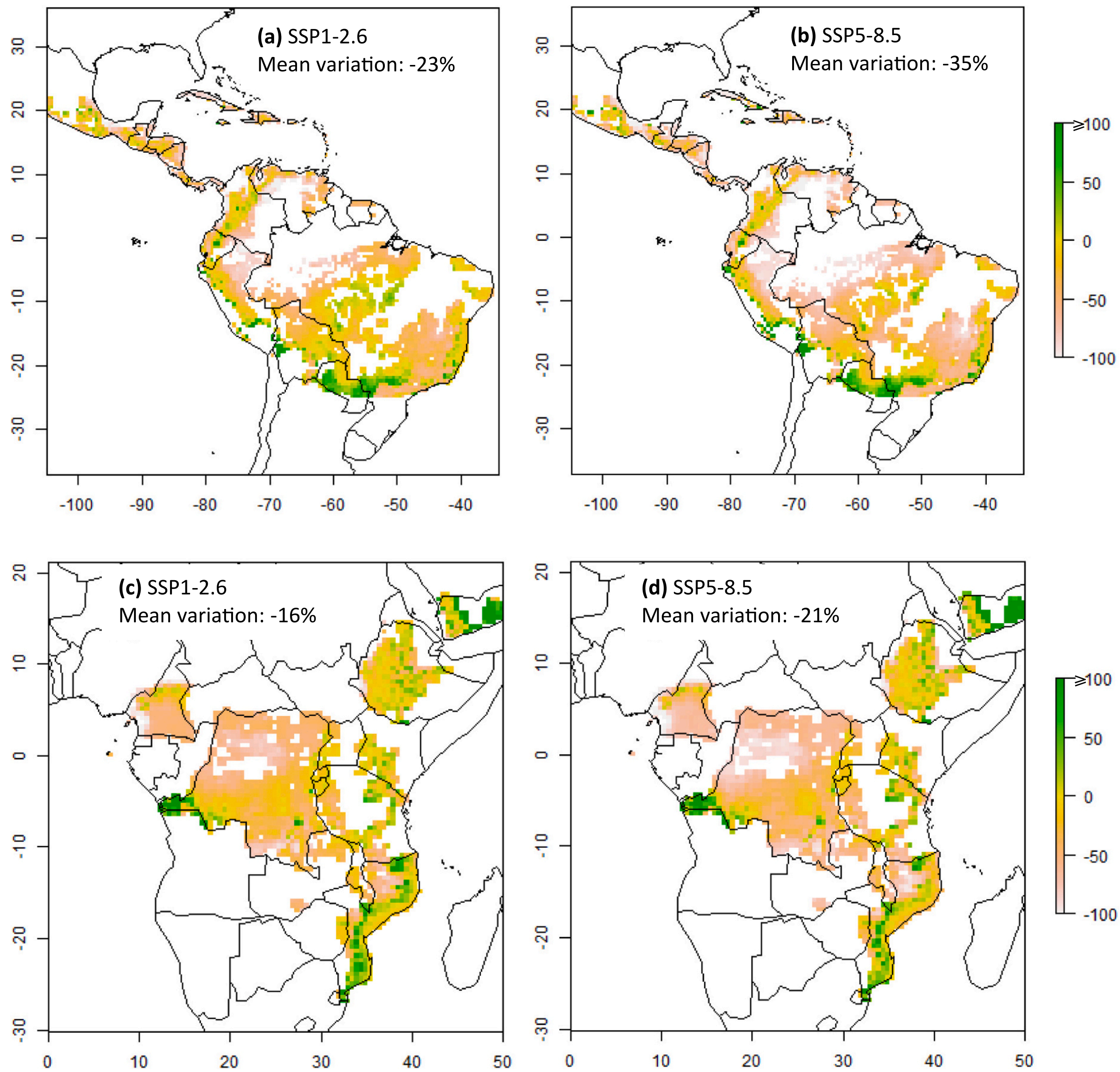

Fig. 8. Predicted variation of potential yield in Latin America and Africa, climate projection (2036–2065) vs. historical climate (1985–2014). Multi-model average for SSP1–2.6 (a, c) and SSP5–8.5 (b, d).

regional validation was constrained by the scarcity and reliability of data, particularly regarding management practices. These results are consistent with previous studies on annual sole crops. For example, Kollas et al. (2015) reported an nRMSE of 31–35 % for an ensemble of 15 crop models applied to ten crops. Similarly, Duarte and Sentelhas (2020) found nRMSE values ranging from 8 to 18 % in a model intercomparison on maize, while Martre et al. (2015) observed nRMSE values between 8 % and 73 % (averaging 29 %) for 27 wheat models, with 80 % of the models falling in the 14–47 % range. The performance of DynACof is especially notable given the challenges of simulating coffee agroforestry systems. Coffee is a perennial crop, meaning that simulation errors may accumulate over the years, and the complex interactions between plants and their environment in agroforestry systems further complicate the modelling process.

The residuals of model predictions vs. SPAM values (Fig. 6) suggest that DynACof may overestimate yields at the lower end of the range, while underestimating them at the high end of the range. However, this bias may also be associated to errors in the SPAM data instead. DynACof yield predictions were consistent with the literature for the site used for its parameterization (Vezy et al., 2020). At other sites, efforts should be made to adjust as much parameters as possible to local conditions. However, such data is generally not available at large scales. Moreover, yield estimates are far less precise when management information is missing, as is the case for regional-scale experiments. In fact, comparing model results to observations is not straightforward at the regional scale. Real coffee yields are subjected to loss by pests or other adverse circumstances (e.g. extreme weather events), and also to variations due to changes in management, both in space and time, whereas our modelling framework estimates potential yields only, i.e. yields obtainable with a standard management, equal for the whole region, given the specific soil, weather and topography found in each region. Observed values at the regional scale are also affected by monitoring biases or errors inherent in the estimation of harvested areas or total production by regional authorities.

According to our new tool G-DynACof, climate change will have a strong negative impact on most areas (Fig. 8). These include south-eastern Brazilian states, which are the most productive areas globally (FAOSTAT, 2024; IBGE, 2023); and Central Africa, in particular Cameroon, where coffee production is very important for the economy (Kuété, 2008) and the Democratic Republic of the Congo, where, however, robusta coffee is dominant (FAOSTAT, 2024). Despite the general negative trend, simulations indicate a positive impact in some areas. In

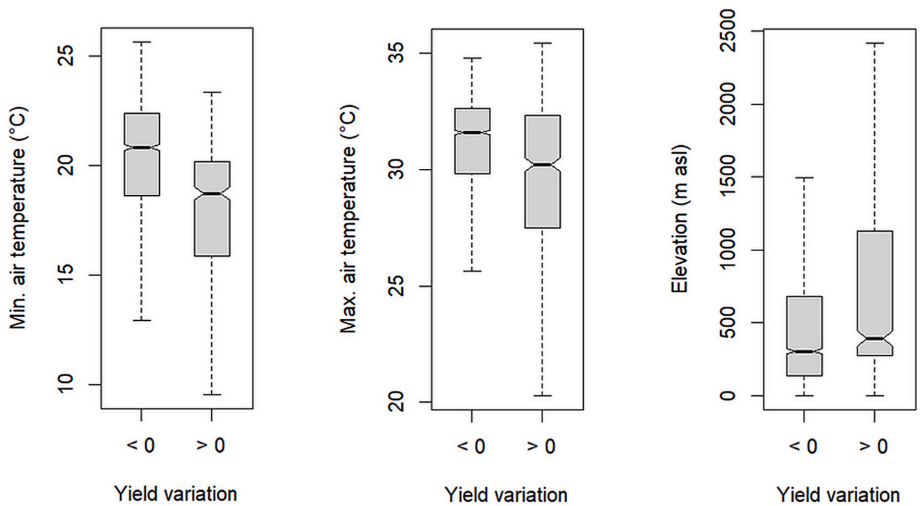

Fig. 9. Boxplots showing the distribution of minimum and maximum annual temperatures and elevation, comparing areas where yield is predicted to decrease (yield variation <0) versus areas where yield is predicted to increase (yield variation >0), in Latin America. Multi-model averages of historic climate (1984–2015). All differences are statistically significant ($p < 0.01$).

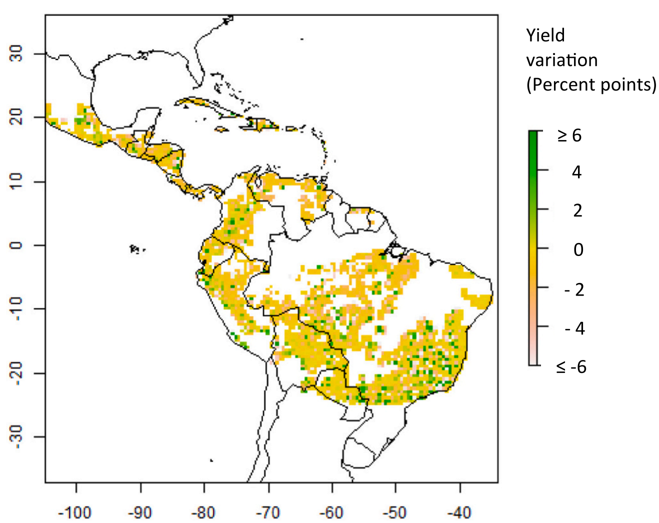

Fig. 10. Difference in coffee yield (percent points) between scenario "enhanced agroforestry" vs. no management change, under SSP1–2.6, according to our simulations. The difference is not statistically significant.

Latin America, this is the case of Paraguay and the Brazilian state of Paraná. This may be attributed to the lower latitude of these areas, implying a more favourable temperature regime. Regarding Africa, we think that the positive trend predicted for Yemen and for some regions in Ethiopia, Kenya, and Tanzania is probably due to the high elevation of coffee plantations, especially in Yemen. Instead, the positive trend in Mozambique may be due to its lower latitude.

Our analyses suggest that yield decrease will be more pronounced in Latin America than in Africa, for every tested scenario (except for the combination of GCM IPSL and SSP1–2.6). By analysing the climate model projections, we realised that in the African production areas, annual minimum temperatures are lower, on average, compared to Latin America. Even if the overall temperature increase is similar in both continents, minimum temperatures reach higher values in Latin America, and this may be the reason why G-DynACof predicts a stronger yield decrease there. For example, the MPI climate model predicts an overall increase of around 0.7 °C for both continents (comparing the historical period 1985–2014 vs. the period 2036–2065 under SSP1–2.6). However, the annual minimum temperature is predicted to rise from 20.8 to 21.6 °C in Africa, while in Latin America the increase would be from 22.0 to 22.7 °C.

Our findings are in line with the results of other studies that investigated the impact of climate change on the suitability of coffee production at the continental scale. All of them used approaches based on species distribution models, usually based on current production locations, and not on biophysical models as in our study. Bunn et al. (2015) used different machine learning algorithms (MaxEnt, Support Vector Machines, and Random Forest) and found that arabica coffee will lose large shares of suitable areas by 2050, mostly at low altitudes below 1000 m asl. The largest loss is predicted in Brazil and South-East Asia, and the lowest loss is in East Africa. Similarly, Ovalle-Rivera et al. (2015) used MaxEnt and predicted a reduction in suitability by 2050, especially at low elevations, with the largest losses in Mesoamerica and Brazil and lower losses in East Africa. Magrach and Ghazoul (2015) also used MaxEnt and predicted a 56 % loss of suitable areas for arabica coffee by 2050 globally, with the largest losses in Brazil, although they also predict a large loss in East Africa. Grüter et al. (2022) adopted a different method, using a decision support system based on crop requirements instead of current production areas; nevertheless, their results are comparable to those of the other studies, and predict a global decrease of suitability by 2050, with the largest losses at lower altitudes and in certain areas including Brazil, while predicting lower losses or even increase of suitability in East Africa. Our findings are well in line with the results of all the above-mentioned studies since we also predict larger productivity losses in Latin America, particularly at lower altitudes, and lower losses in Africa. Similarly to other studies, the main driving factor is the projected increase in mean annual temperatures. As already mentioned above, G-DynACof predicts that yield will decrease more in areas characterized by high temperatures, while it may increase in areas with lower temperatures. This finding is in line with evidence from the literature, suggesting that climate changes will have a negative effect on coffee yields at low elevations, but may have a positive effect at high elevations and lower latitudes (Bunn et al., 2015; Läderach et al., 2017). The optimal temperature regimes for coffee growth are predicted to shift from lower to higher elevations, pushing suitable areas for coffee production upwards. This could affect land use, ecosystem functions, and biodiversity conservation, as mountain areas—where coffee plantations may expand—are typically home to vital forest ecosystems that need preservation. Growing pressures on forest-rich areas at higher elevations to meet increasing coffee demand are raising significant sustainability concerns, both from consumers in the market and, more generally, emerging trade policies. The European Union market, one of

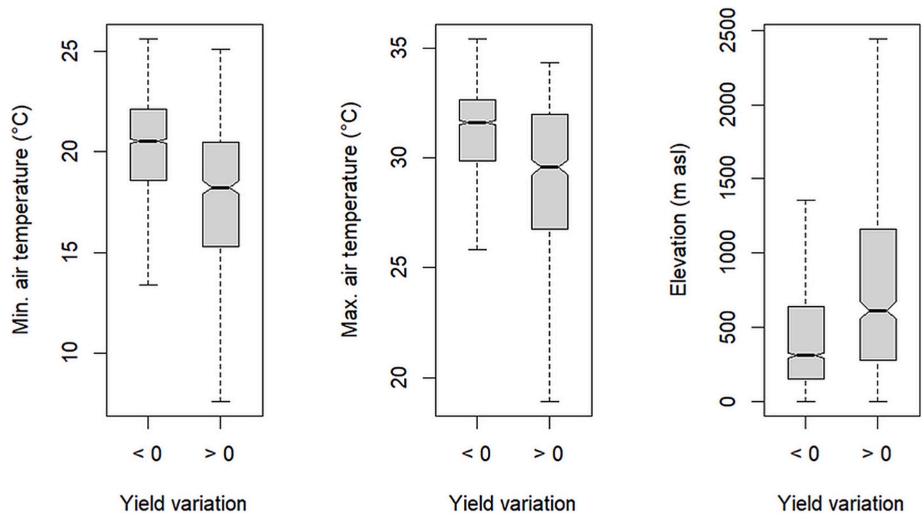

Fig. 11. Boxplots showing the distribution of minimum and maximum annual temperatures and elevation, comparing areas where enhanced agroforestry is predicted to reduce yield loss due to climate changes (yield variation >0), versus areas where it further decreased yield (yield variation <0), in Latin America.

the largest coffee markets in the world, has recently approved the EU Deforestation Regulation, which prevents coffee and other agricultural products sourced from deforested land from being imported and sold in the EU. Thus, optimizing the transition of coffee-growing regions is essential, and the approach in this study can help identify ideal expansion areas while minimizing deforestation risks.

The accordance of our results with those of other studies at the continental scale is promising, even more so considering the radically different approach we used. Our method has the advantage of directly predicting changes in potential yield, although with an associated uncertainty. According to our tool, in the absence of adaptation measures, arabica coffee yield will drastically decrease by 2050 in several regions, with the highest decrease in Latin America (from 23 to 37 % decrease, depending on the climate projection) and lower decrease in Africa (from 9 to 26 %). We did not conduct specific analyses of individual extreme events, as it would be particularly challenging and beyond the scope of our study. Most published crop models are not entirely reliable when it comes to predicting the impacts of extreme events, especially regarding how tipping points may disrupt plant functioning (Rötter et al., 2018; Schewe et al., 2019). However, we believe G-DynACof is well-suited to capture the average variations in temperature and precipitation projected by climate models over the medium to long term, within the ranges on which the model was parameterized.

Also, and perhaps more importantly, G-DynACof allows the evaluation of adaptation measures, by varying parameters related to crop management. According to our simulations in Latin America, enhanced agroforestry seems to have the potential to mitigate the negative impact of climate change on some areas, even if coffee plant density had been reduced to allow for more shading trees. However, it further decreased yields in the majority of Latin America. Therefore, it is very important to understand the conditions for which this measure may have a positive effect on yield. When we analysed environmental factors influencing the effects of enhanced agroforestry, we found that this measure seems to work better at higher altitudes and lower temperatures. This result, which seems counterintuitive, could be due to the fact that at higher elevations, yield may be subject to greater interannual variability, which could be mitigated by enhanced agroforestry. We tested only one specific scenario, therefore our preliminary results are limited in scope. Further research is needed in this regard, testing different agroforestry systems with varying plant densities and different tree species, using higher spatial resolution data. Another issue to consider is that the MAESPA metamodels used in DynACof, which are essential to simulate microclimate in agroforestry systems, were derived for a specific site in Costa Rica, therefore their use under other conditions may require reparameterization.

Despite limitations in gathering sufficient data to validate the model, estimate predictive uncertainty, and set management data at regional and continental scales, we demonstrated the potential to apply scenarios with varying management settings to assess the effectiveness of adaptation measures. The datasets used in this study have their own limitations inherent in the way they were assembled and harmonized; furthermore, the resolution at which they are available is not well-suited to the field scale at which the model was developed and parameterized. This raises considerations about the challenges of scaling in this type of analysis. For example, the vast spatial variability of soils cannot be effectively captured by a global dataset. However, upon a stronger validation and parameterization of the model, it could be possible to obtain medium-term predictive yield estimates under climate change at a sub-regional scale. An even more ambitious goal is to predict short-term yield using seasonal predictions. This would have great relevance for the coffee industry because it would allow for an estimation of coffee production in the next months, with all the consequences related to the global coffee market. However, these developments would require detailed information about management of the coffee plantations.

At the moment, DynACof is parameterized for simulating the species *Coffea arabica* only. Since *C. canephora* (robusta) is expected to become increasingly widespread globally (partly due to its higher resilience to climate change and pests like coffee rust), it would be extremely relevant to also parameterize DynACof for robusta. This requires reliable data about carbon allocation in the different plant parts, as well as other important parameters related to water and light use efficiency.

In this study, we did not consider nutrient limitations or impacts from pests and diseases, as our goal was to isolate the effect of climate. DynACof has the capability to simulate American leaf spot. However, other important diseases are not yet included in the model.

6. Conclusions

Our modelling tool G-DynACof uses the model DynACof at a regional scale to estimate how climate changes may impact coffee yield in the future and can assess the efficacy of possible adaptation measures. The tool was demonstrated to be sensitive to climatic variables as well as to management options.

Results of our experiments indicate that coffee yield will probably decrease in the next decades, even under the most optimistic climate projections. While there is significant uncertainty associated with the modelled yields, our results show a clear trend. According to our simulations, yields decrease will be more pronounced in Latin America (between 23 % and 35 %) than in Africa (between 16 % and 21 %). Yield is predicted to decrease more in areas where air temperatures are higher, i.e., lowlands. In spite of the general decline, yield is predicted to increase in areas at higher altitudes (approximately above 800 m asl). If predictions are confirmed, this pattern could lead in the future to a shift of the most suitable areas for coffee production toward higher elevations. This may have implications for land use change, ecosystem functions, and biodiversity conservation.

Our scenario analyses indicate that an increase of shade tree density by 50 % (compared to a baseline representing a plausible regional average) would partially counteract the negative impact of climate change on coffee yields at some sites; however, in our simulations, the effect of this measure is very heterogeneous in space. Studies by other authors indicate a stronger agroforestry approach as one of the possible adaptation measures, not only to counteract yield decline, but also to improve the provision of other ecosystem services such as biodiversity conservation, collection of firewood and fruits, and so on. Therefore, further investigation should be directed toward understanding the conditions under which this approach can be beneficial.

CRediT authorship contribution statement

Raniero Della Peruta: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Valentina Mereu:** Writing – review & editing, Methodology, Conceptualization. **Donatella Spano:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Serena Marras:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Rémi Vezy:** Writing – review & editing, Software. **Antonio Trabucco:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2025.104353.

Data availability

Data will be made available on request.

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