UNIVERSITÀ DEGLI STUDI DI SASSARI

CORSO DI DOTTORATO DI RICERCA IN SCIENZE AGRARIE

DIPARTIMENTO DI AGRARIA

CURRICULUM AGROMETEOROLOGIA ED ECOFISIOLOGIA DEI SISTEMI AGRARI E FORESTALI

XXXVI CICLO

TITLE

DynACof process-based model parameterization and validation for robusta coffee

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Anno Accademico 2024/2025

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Abstract

Coffee is primarily cultivated in tropical regions across South America, Africa, and Asia. Countries such as Brazil, Colombia, Ethiopia, and Vietnam remain highly productive coffee-growing regions. The two main coffee species, Arabica and Robusta, account for nearly all global coffee production. However, with climate change being ubiquitous, it is altering climate suitability, especially in the long term, and consequently reducing coffee productivity. To better understand these changes, several modelling tools have been developed to assess the effect of climate change on coffee agroecosystems.

A systematic review was conducted to collect information about and implementation of modelling tools in coffee agrecosystems worldwide. This review covered articles published until 2022, and total 60 relevant studies were selected after removing the duplicate articles and afterward conducting three screenings (Title, Abstract and full text assessment). The bibliography analysis indicated that most of the articles were published in the United States, followed by Africa and Asia. Furthermore, most of the models investigated the climate impacts on crop suitability (55% of results), followed by crop productivity (25% of studies), and pests and diseases (20% of results). Additionally, models integrated with Intergovernmental Panel on Climate Change (IPCC) scenarios for future assessment were until 2050 in majority of the studies. The IPCC has developed and refined climate scenarios over time, beginning with the Special Report on Emissions Scenarios (SRES), followed by the Representative Concentration Pathways (RCPs), and more recently, the Shared Socioeconomic Pathways (SSPs), which integrate socioeconomic factors with climate projections to support more comprehensive climate impact assessments. Regarding model specialization, MaxEnt is particularly effective at evaluating climate suitability, while the Insect Life Cycle Modelling Software (ILCYM) is highly efficient for simulating pest distribution. Despite these specific uses, the models reviewed were broadly categorized into three main types based on the underlying processes which included regression models, crop models, and species distribution models.

The DynACof is an agroforestry model, which we modified for Robusta species for climate adaptation purposes. This model comprehensively details the agroforestry systems and can be applied to simulate coffee monoculture systems. During our study, the differences between both species were adjusted in the model to simulate Robusta cropping systems, as originally this model was developed for Arabica Species. This was achieved by selecting critical parameters in the model based on literature and sensitivity analysis. Subsequently, model training and validation were performed on data coming from ten districts in Vietnam. Climate variables for the model were derived from reanalysis data and water content of soil was extracted from SoilGrid raster due to the absence of meteorological stations near the experimental districts. The model performance fluctuated across districts while perfectly consistent in climate conditions favourable for Robusta growth and development. These districts included Dak Song, Dak Glang, Krong Buk, and Chu Prong districts, where the model perfectly captured the trend in observed yield and other variables were according to literature such as bean maturity, biomass distribution in coffee plant. Additionally, model performance was exceptional for bean yield ranges between 2200 kg ha^{-1} to 2700 kg ha^{-1}. These results support the application of DynACof model for Robusta coffee.

The literature review provided extensive information on Arabica coffee compared to Robusta. Despite the importance of Robusta, which contributes about 40% to global coffee production, only limited number of studies (5% of articles) focused on this species, and no study specifically addressed climate adaptation for Robusta cultivation under tree shading. To address this gap, the DynACof model was adapted for Robusta coffee. This is a plot-scale model used to simulate production, canopy cooling, and carbon sequestration. It includes a 3D process-based model (MAESPA) and metamodels that account for complex spatial effects. Although the model has successfully simulated Robusta coffee agrosystems, further improvements are recommended, particularly in respect to the effects of pests, diseases, and nutrient managments. Additionally, the model will be integrated with climate scenarios to support future climate impact assessments on coffee agroecosystems.

Key words: Crop Model, Coffee Agrosystem, DynACof model, Robusta coffee, Climate change climate adaptation

General Introduction

Climate Change Effect on Agricultural Systems

Climate change poses significant threats to global agricultural systems by altering critical environmental conditions such as temperature, precipitation patterns, and the frequency of extreme weather events. Rising global temperatures affect crop phenology, disrupt growing seasons, and reduce yields, particularly in regions already vulnerable to heat stress and water scarcity (IPCC, 2022). For instance, elevated temperatures can accelerate crop maturation, resulting in reduced grain filling periods and lower harvest quality (Lobell et al., 2011). Shifts in precipitation patterns contribute to increased droughts and floods, undermining soil health and water availability for irrigation (Wheeler & von Braun, 2013).

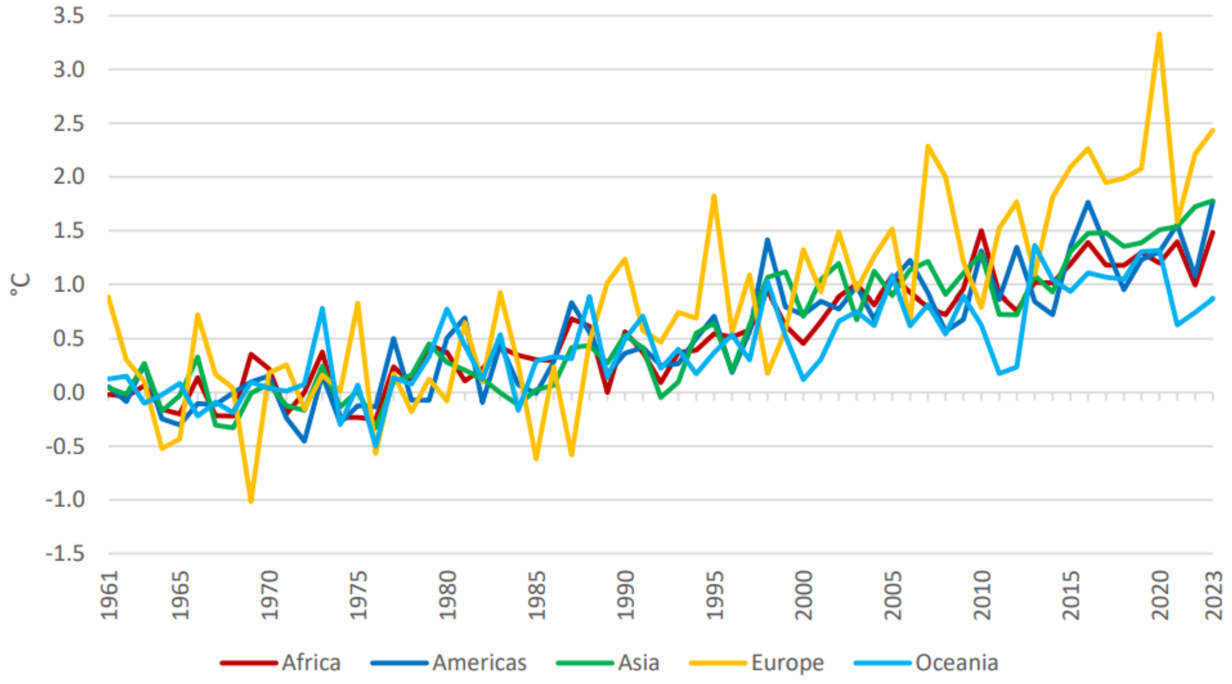

Figure 1. Change in annual mean temperature over region from 2961 to 2023 (FAO, 2024)

These disruptions not only impact crop productivity but also affect livestock systems, fisheries, and the livelihoods of smallholder farmers, who often lack the adaptive capacity to cope with climatic stressors (Thornton et al., 2014). Furthermore, climate change facilitates the spread of pests and diseases into previously unaffected areas, compounding the challenges faced by farmers (Rosenzweig et al., 2014). In response, adaptation strategies such as crop diversification, climate-resilient crop varieties, improved irrigation techniques, and agroecological approaches are being promoted to enhance resilience in agricultural systems (FAO, 2021). However, without coordinated global efforts to mitigate greenhouse gas emissions and support adaptive capacity, climate change is expected to continue undermining food security and agricultural sustainability in many regions.

Climate Change Impact on Coffee Agrosystem

Coffee belongs to the family *Rubiaceae* and comprises more than 80 species. Its native regions are the equatorial forests of East and West Africa, Madagascar, and the islands of the Indian Ocean (Humphries et al., 2024). Climate change is imposing challenge for coffee crop by aletring climate suitability at lower elevation, increased pests and diseases incident (Alfonsi et al., 2019; Imbach et al., 2017). Many top coffee-producing countries reported adverse climate effects during 2023/2024, which led to a 38.8% increase in coffee prices compared to the previous year (Figure 2). These countries included Brazil where supply limited due to hot and dry weather, Vietnam observed prolong dry weather condition and coffee cherries were demanged in Indonesia by intense rainfall (FAO, 2024).

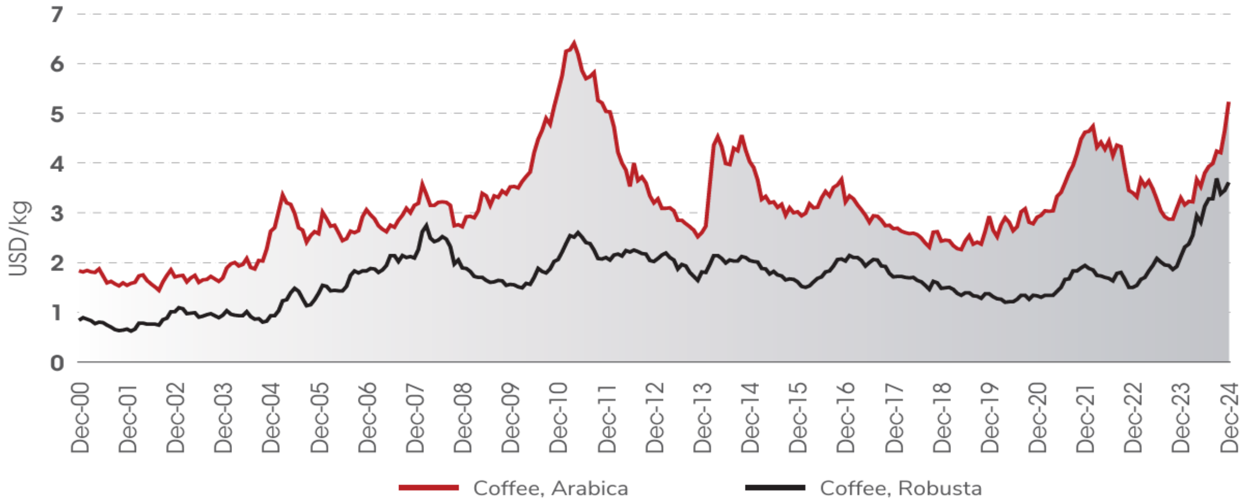

Figure 2. Coffee prices from 2000 to 2024 (FAO, 2024).

This is particularly true for Arabica coffee, which is more sensitive to climate change (Dias et al., 2024; Richardson et al., 2023). In many countries, the suitable climate for Arabica coffee is expected to decrease by 2050, especially at lower elevations. Specifically, climate variables such as rising temperatures and reduced rainfall are likely to occur in Brazil, Indonesia, Vietnam, Nicaragua, Mesoamerica, and Mexico (Purba et al., 2019; Hailu et., 2015; Baca et al., 2014; De Carvalho Alves et al., 2013). In contrast, Robusta Coffee exhibits high resilience and has been recommended for areas previously suitable for Coffea arabica coffee (Bracken et al., 2023; Campuzano-Duque and Blair., 2022). The resilience of robusta coffee is attributed to its ability to modify its morphology and physiological behaviors under stress conditions, such as extending root growth and closing stomata. Additionally, its production of proline in tissues serves as an adaptive mechanism in plants (Covre et al., 2022).

International Coffee Market: Productivity and Trade

Coffee crop is suitable to tropical and subtropical climate condition. This is cultivated in over 80 countries, with production being predominantly high in developing countries. Brazil, Vietnam, Indonesia, and Colombia contribute 68% to the international market (Figure 1) (Krishnan et al., 2021). Moreover, Arabica and Robusta are main species produced and traded worldwide. They account for 99% of global coffee production, with individual shares of 60% and 40%, respectively (Kouadio et al., 2021). While Arabica coffee dominates global trade in terms of quality and market value, Robusta is gaining importance due to its resilience and higher yields (der Vossen et al., 2015). The coffee sector supports livelihood of approximately 100 million people worldwide, both directly and indirectly (Jha et al., 2011)

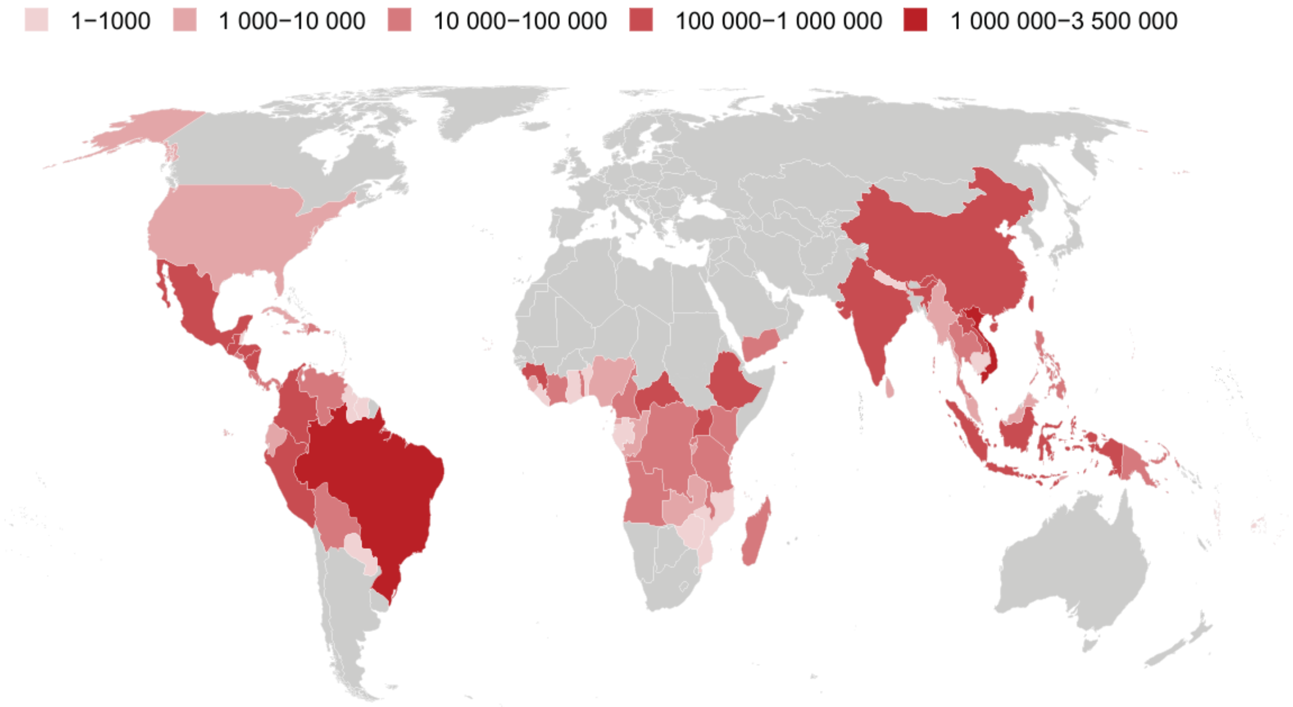

Figure 3. Coffee production worldwide (tones) (FAO, 2024).

Coffee export play an important role for many low-income countries, while generating considerable amount of revenue and securing access to international market for import of good and services. For instance, Africa, Ethopia, Burundi and Uganda earned 33.8%, 22.6% and 15.4% respectively of total merchandise exports in 2023. The cost of coffee production worldwide was estimated over 23 billion USD in 2023 and international trand exceeded 26 billion USD. In total coffee industry generating annual revenue over 200 billion USD worldwide (FAO, 2024). On demond side, this is highly consumned in European Union and United Stated, where imported has been recorded as 43% and 23% respectively (Chain-Guadarrama et al., 2019). Similarly, global coffee consumption is exceeding 400 billion cups per year (Mishra et al., 2012).

Key difference between Robusta and Arabica coffee

Coffee production primarily comes from two main species: Arabica (Coffea arabica) and Robusta (Coffea canephora). These species are cultivated in different geographical and climatic regions due to their distinct growth requirements. Arabica thrives in high-altitude areas with moderate temperatures between 15°C and 24°C, while Robusta grows better in lowland regions with warmer climates and higher humidity, often above 24°C (FAO, 2022; ICO, 2023). Robusta plants typically have higher productivity and take longer to mature, but they are more resistant to pests and diseases such as coffee leaf rust (Hemileia vastatrix) (FAO, 2021). Vietnam, particularly its Central Highlands, provides ideal conditions for Robusta cultivation and has become the world largest producer. Brazil also plays major role in Robusta production.

On the other hand, Colombia is internationally recognized for producing premium-quality Arabica coffee due to its favorable mountain climate and traditional farming methods. Brazil leads the world in total Arabica production (ICO, 2023). Arabica coffee is favored in international markets for its delicate flavors, higher acidity, and pleasant aroma. In contrast, Robusta tends to have a stronger, more bitter taste with lower aromatic complexity, and is often used in espresso blends or instant coffee due to its strong body (FAO, 2020). A comparative summary of both species is presented in Table 1.

Table 1. A detalied comparison of Robusta and Arabica coffee (Campuzano-Duque et al., 2021).

Specie	Arabica coffee	Robusta coffee
Origin	Ethiopia,Sudan,Kenya	GuineaandCongo
Altitude for cultivation in meters above sea level (masl)	1000–2000	0–700
Plant type	Shrub	Treeand/orshrub
Growth habit	Erect	Umbrellashape
Canopy structure	Pyramidal	Irregular
Root type	Deep-rooted	Shallow-rooted
Inflorescences (number)	Lower(2–3peaks/crotch)	Higher(3–5peaks/crotch)
Flowering (regularity)	Regular(afterrains)	Irregular
Grainearliness (monthsfromanthesisto fullyripe)	6–8(earlier)	9–11(later)
Grain-color (beforeroasting)	Greenishtone	Paleandyellowishtone
Biannual production	Present	Absent
Yield (kg/ha) of green coffee	Usually lower performing (1500–3000)	Higher performing (2300–4000) with intensive production 6000
Optimal temperature (C)	18–21	22–30
Optimum precipitation (mm)	1500–2000	2000–3000
Relative humidity required (%)	70%	85%
Rust resistance	Susceptible	Wide resistance spectrum
Nematode resistance	Susceptible	Source of genetic resistance
Planting density	High	Low
Production cost	Higher	Lower (17%) (no irrigation costs)
Price	High	low

Robusta Coffee Cultivation in Vietnam

The Central Highlands of Vietnam are considered one of the most suitable regions globally for cultivating Robusta coffee, owing to its favorable climate and soil conditions. Vietnam currently leads the world in Robusta coffee productivity, maintaining a significant share of the global market (Tran et al., 2021). Robusta coffee thrives in temperatures ranging from 22°C to 30°C, with optimal annual rainfall averaging around 2,792 mm and a maximum relative humidity of up to 85%. Under these ideal conditions, this high-yielding species can produce up to 6,000 kg/ha (Campuzano-Duque et al., 2021; Kath et al., 2021). Key agricultural management practices contribute significantly to maximizing bean yield and sustaining productivity. These practices include systematic pruning, the use of clonal propagation to ensure uniform plant quality, efficient irrigation systems, precise fertilizer application, and intercropping with shade-providing trees (Chumthong et al., 2023; Espindula et al., 2022).

In Vietnam, Robusta coffee has been cultivated under monoculture system by Robusta farmer community for longtime. However, this system has considerable ecological risks such as soil degradation, habitat loss, and a decline in local biodiversity due to the reduction of native vegetation (Depecker et al., 2023). In response to these environmental challenges, there has been a growing movement toward more sustainable coffee cultivation practice. Agroforestry systems which integrate coffee with shade trees and other crops are gaining traction as a resilient alternative. These systems not only help preserve biodiversity and enhance ecosystem services but also contribute to long-term soil health and climate adaptation. As such, the future of Robusta coffee production in Vietnam increasingly depends on the successful implementation of these sustainable agroecological approaches (Clément et al., 2025).

Models on Robusta Coffee and Climate Adaptation

Several statistical models have been developed to evaluate the characteristics of robusta coffee. Examples include the WAVE model (D'haeze et al., 2003), the hierarchical Bayesian model (Kath et al., 2020), the Structural Equation Model (SEM) (Kath et al., 2023), CROPWAT (Byrareddy et al., 2020), and the integrated modeling approach (González-Orozco et al., 2024). These models cover specific aspects of the Robusta coffee agroecosystem with water management has been explored for climate adaptation purpose (Byrareddy et al., 2020; D'haeze et al., 2003). However, most models lack linkages to relevant physical processes associated with climate change and adaptation measures, such as Robusta coffee cultivation in under tree shading.

To address this, the Dynamic Agroforestry Coffee crop model (DynACof) has been developed to simulate agroforestry systems, emphasizing net primary productivity (NPP), growth, yield, mortality, and energy and water balance. Moreover, a metamodel is incorporated into the DynACof model to compute complex spatial effects derived from the 3D process-based model MAESPA (Vezy et al., 2020). Considering the potential of this model, an attempt was made to modify it for the Robusta species. A systematic review was conducted to gather relevant information about Robusta coffee. The model modification was based on information available in the literature and involved evaluating agronomic parameters, biomass distribution, nutrient content in the plant, the reproductive phase, and green bean yield across diverse districts in Vietnam.

Thesis Structure

The thesis is composed of three chapters. The research direction was guided by a systematic review which is the first chapter. This review compiled all relevant information on coffee agroecosystems, both in open-sun and agroforestry systems, while applying a modeling tool to estimate the impacts of climate change. Where, emphasis was on climate suitability, with little attention given to climate adaptation, and no studies conducted on Robusta coffee under shading systems. In second chapter, the DynACof model was employed in the most suitable regions for Robusta coffee in Vietnam. This model was previously parameterized for Arabica coffee; therefore, the primary aim was to adjust for differences between the two species. The model performed well across all districts in simulating the Robusta coffee system. In last chapter, summerizing pervious two chapter along with suggestion for model improvement and future research direction. The model could be integrated to account the effects of nutrient management, pests, and diseases. Additionally, future investigations should examine Robusta coffee under both monoculture and agroforestry systems, with projections for future climate conditions.

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CHAPTER 1

Title

A Systematic Review of Analytical and Modelling Tools to Assess Climate Change Impacts and Adaptation on Coffee Agrosystems

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Published in: Susutainability 2023, 10, 8. https://doi.org/10.3390/su151914582

1. **Abstract**

Several modelling tools reported the climate change impact on the coffee agrosystems. This article has adopted a systematic approach to searching out information from the literature about different modelling approaches to assess climate change impacts or/and adaptation on coffee crops worldwide. The review included all scientific publications from the date of the first relevant article until the end of 2022 and screened 60 relevant articles. Most results report research conducted in America, followed by Africa. The models assessed in the literature generally incorporate Intergov- ernmental Panel on Climate Change (IPCC) emission scenarios (80% of manuscripts), particularly Representative Concentration Pathways (RCP) and Special Report on Emission Scenarios (SRES), with the most common projection periods until 2050 (50% of documents). The selected manuscripts contain qualitative and quantitative modelling tools to simulate climate impact on crop suitability (55% of results), crop productivity (25% of studies), and pests and diseases (20% of the results). According to the analysed literature, MaxEnt is the leading machine learning model to assess the climate suitability of coffee agrosystems. The most authentic and reliable model in pest distribution is the Insect Life Cycle Modelling Software (ILCYM) (version 4.0). Scientific evidence shows a lack of adaptation modelling, especially in shading and irrigation practices, which crop models can assess. Therefore, it is recommended to fill this scientific gap by generating modelling tools to understand better coffee crop phenology and its adaptation under different climate scenarios to support adaptation strategies in coffee-producing countries, especially for the Robusta coffee species, where a lack of studies is reported (6% of the results), even though this species represents 40% of the total coffee production.

Keywords: coffee agrosystems; climate change (CC); impact; adaptation; modelling; IPCC scenarios

2. Introduction

The last Intergovernmental Panel on Climate Change (IPCC) Report [1] gathered extensive evidence that climate change had caused substantial damage and increasingly irreversible losses over terrestrial and marine ecosystems and natural resources. Agriculture is among the sectors most affected by climate change, mainly due to extreme events' increased frequency and intensity, with worsening expectations [2].

Climate change is estimated to increase agricultural production and food access pressures, especially in vulnerable regions, thus undermining food security and human nutrition [1]. It has altered hydrological cycles; extreme events such as droughts, floods, storms, heat waves, and other abnormalities on Earth are becoming more common [3,4]. The uncertainty in precipitation patterns, more intense rainfall, and the increase in soil erosion are regarded as direct climate change impacts on the agrosystems [5,6], which generate abiotic stress on biodiversity. Indeed, flooding and surface runoff are vehicles of soil nutrients, pesticides, and other harmful chemicals into freshwater, depleting soil fertility and polluting groundwater resources [7]. Water scarcity and temperature rise affect plants' biochemical and physiological processes [8]. Increasing temperatures have also caused a substantial decline in crop production and are considered a high risk for crops in the future [9,10], especially at mid and low latitudes. The impact of climate change on the productivity of several staple crops is foreseen to be critical in low-latitude tropical regions [11].

Coffee is one of the most important crops in low-latitude regions where climate changes are expected to impact agricultural systems heavily [2]. Thus, arable land in tropical and subtropical regions may lose a considerable amount of such areas by 2050; for example, South America may lose 1–21%, Africa 1–18%, Europe 11–17%, and India 2–4% [12]. Another study illustrated a critical level of water deficit (0.82 kPa) during the flowering stage of Arabica coffee, after which the yield significantly declined, and predicted that about 90% of countries will breach this benchmark if warming rises to 2.9 °C by 2095 [13].

Coffee is cultivated worldwide by about 20–25 million smallholder farmers on 11 million ha of arable land spread across 60 tropical regions [14]. The international trade in coffee commodities is ranked second after petroleum products. Developing coun- tries contributing considerably to exports to more industrialised countries. The United States imports approximately 23% of total traded coffee beans, while the European Union imports about 43% [15]. The estimated coffee consumption is more than 400 billion cups per year, and almost 100 million people are engaged in this industry and derive their income directly or indirectly from coffee commodities [15,16].

The main commercial coffee species are Arabica (*Coffea arabica* L.) and Robusta (*Coffea canephora* L.), accounting for 99% of the total coffee production, where the individual share of both species is 60% and 40%, respectively [17]. Meanwhile, the worldwide prediction for the productivity of Arabica coffee is 35.5% higher than that of Robusta coffee. Brazil, Vietnam, Indonesia, and Colombia are the leading countries globally, contributing to 68% of the international market [15]. The production of the major coffee species and cumulative production by both species within the last five years, produced by the leading countries worldwide, is shown in Figure 1.

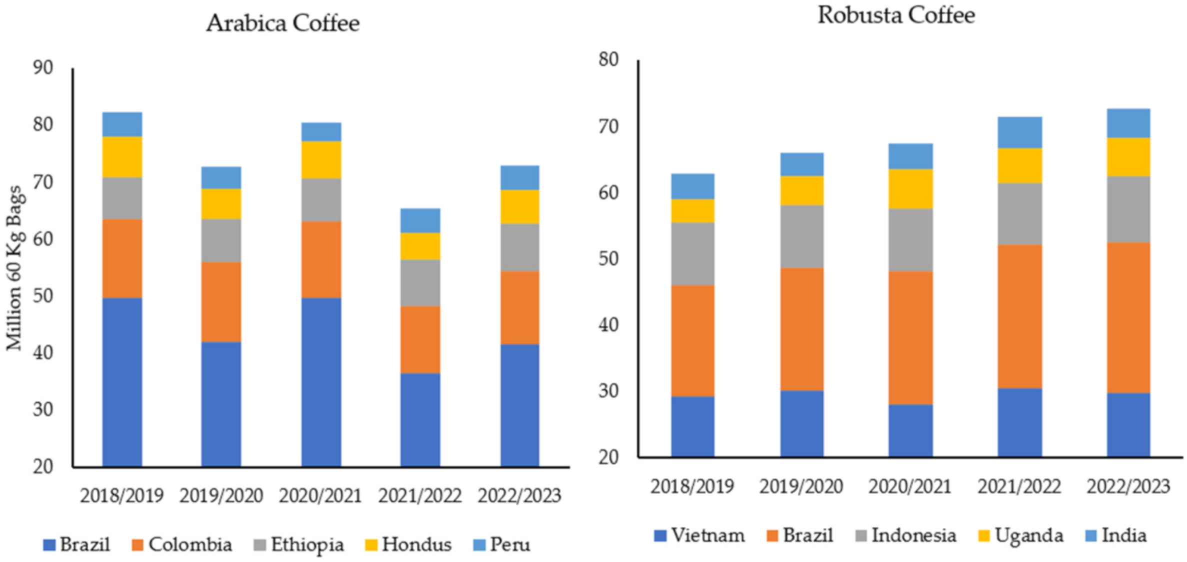

Figure 4. Coffee production in the top five countries worldwide for Arabica and Robusta coffee (data extracted from [18] for 2018–2022).

Climate changes affect coffee crop production due to more frequent insect and pest diseases induced by climate variability [19]. Moreover, high temperatures and reduced precipitation considerably affect the flowering and fruiting of coffee plants and the quality of the beans [20,21]. Coffee crops begin to bloom after the first spring rainfall, but under drought conditions, fewer flowers will sprout, consequently reducing fruit development. On the other hand, under heavy rain conditions, yield loss occurs as flowers and fruits fall off the tree [22,23]. The vegetative and reproductive phases are specifically dependent upon temperature. Temperature rise accelerates the berry ripening, reducing the bean filling duration. Low temperatures lead to defoliation and decreased photosynthesis, causing fluctuation in leaf mass [24]. In addition, low seasonal rainfall is causing branch death, reducing fruit setting resources and damaging coffee beans [25].

Arabica adapts better at high altitudes with an optimal temperature range of 18–22 °C; in contrast, Robusta thrives at lower altitudes with optimal temperatures between 22 and 28 °C. However, neither species can produce abundant yields under adverse conditions nor maintain beverage quality [26]. Several studies have modelled the impact of climate change on coffee production, depicting an upward shift of the crop along with yield losses at lower latitudes [27,28]. Climate uncertainty will affect the coffee production of 9.5 billion kg year^{-1} obtained in 2018, with a 50% reduction by 2050 in suitable environments, thus putting a heavy toll on the coffee trade as a threefold rise in demand is also expected [29]. Specifically, global warming will significantly affect coffee crop production worldwide, with a reduc- tion in 2050 of up to 60% in southern Brazil [30], 90% in Nicaragua [19], and 30–60% in Kenya [31]. Both Robusta and Arabica will be negatively affected by increasing temperature: a 1 °C increase in minimum/maximum temperature (16.2/24 °C) could result in ≈14% or 350–460 kg ha^{-1} Robusta yield reduction [32], even though the Arabica favourable environ- ment could be relocated to 300 m up the altitude gradient in Nicaragua [19]. In addition, high temperatures would make coffee farming susceptible to fungal attacks, such as coffee rust, at lower altitudes and borer damage at high elevations [33,34].

The available literature on coffee presents extensive insights and recommendations for using models and other analytical tools to study climate change impacts and adaptations in coffee production in different regions, such as [35] in Central America, [32] in Vietnam, [36] in Brazil, [37] in Colombia, [38] in Uganda, [39] in Ethiopia, and many more. While the impacts of climate change on coffee have been systematically studied [40], modelling tools still have not received enough attention in terms of systematic review and classification.

The current review is designed for a comprehensive view of the models and tools available to investigate the implications of climate change conditions on coffee growth and yield. The study will also help identify the potential gaps and future trends for research studies to improve modelling tools to guide farming towards sustainable and resilient management of coffee cultivation under climate change conditions. With this aim, a systematic review approach, already consolidated in the climate and agricultural sciences [41–43], is applied to explore the different modelling tools used to investigate climate change impacts and adaptation on the two major coffee species, Robusta and Arabica. We gave special attention to highlighting the eventual capacity of the available tools to assess the effectiveness of adaptation options.

3. Material and methods

The Collaboration for Environmental Evidence (CEE) described a systematic review guideline in which PECO or PICO elements demonstrate the research question in various components [44]. Based on a proper methodology, the research question was formulated, and proposed the following:

"What are the analytical tools for coffee crop modelling under climatic uncertainties?" Based on this question, we developed the PICO elements and the search keywords in Table 1. Once created, we tested the keywords on different search engines, such as Web of Science, Scopus, and Science Direct, on 27 July 2021 (Table 2). To reduce incompatibility between various search engines, we avoided the excessive use of operators (e.g., wildcard, Boolean, braces, etc.). We extracted the complete database on 13 February 2023.

Table 1. The breakdown of the research question into PICO components and related keywords.

PICO	Description	Keywords
Population	Coffee production, focusing on agrosystems and bean production but excluding the processing phases following post-harvest. The study includes impacts, adaptation, and resilience to all climate variables (temperature, rainfall, CO_2).	Coffee, crop, tree, production, agrosystems, farm.
Intervention	The intervention is the tools used to assess impacts, adaptation, and resilience to climate change—variability in temperature and precipitation. The review will consider no time scale. It will include all scenarios investigated in the literature.	Climate change, impact, adaptation, resilience, GHG emission, climate Variable.
Comparator	Qualitative vs. quantitative models; mathematical vs. biophysical models; spatial modelling.	
Outcome	Modelling techniques. Analytical tools. Programming.	Models, modelling, tools, programming.

Table 2. Development, trial, refinement, and screening of search terms. The keywords in bold represent the selected ones since they show a reasonable hit in all databases

Search Term	Science Direct	WoS (All Fields)	Scopus (Title-Abs-Key)	Comments
“climate change” AND coffee	5573	536	538	The search term might include adaptation and resilience of coffee to climate change. It will also include other aspects related to impacts and mitigation or policy documents
“climate change” AND coffee AND (impact OR resilience OR adaptation)	4948	327	299	A good search term. A reasonable number of hits, which include all the words needed to answer the research question.
“climate change” AND coffee AND model AND (impact OR resilience OR adaptation)	3946	113	89	Somehow restrictive search term.
“climate change” AND coffee AND (model OR programme OR tool)	5212	217	187	A good search term. A reasonable number of hits which include all the words needed to answer the research question.
“climate change” AND coffee AND (model OR programme OR tool) AND (impact OR resilience OR adaptation)	4707	149	118	A good search term. A reasonable number of hits which include all the words needed to answer the research question.
climate AND coffee AND (**model OR programme OR tool**)	**15,161**	**387**	**381**	**A good search term. A reasonable number of hits which include all the words needed to answer the research question.**
climate AND coffee AND (model OR programme OR tool) AND (impact OR resilience OR adaptation)	11,453	187	147	A good search term. A reasonable number of hits which include all the words needed to answer the research question.

Besides database sources, the systematic review used search engines and organisation webdistricts in which a maximum of 50 ‘hits’ were recorded from each website (Table 3).

Table 3. List of academic database sources and webdistricts used

Database Sources	Search Webdistricts	Organisation Webdistricts
Web of Science (WoS)	google.com (accessed on 13 February 2023).	World Bank
Scopus	googlescholar.com (accessed on 13 February 2023).	FAO
Science Direct		Consultative Group on International Agricultural Research (CGIAR) International Fund for Agricultural Development (IFAD) Natural Resources Institute Climate Institute Coffee & Climate International Trade Centre Fairtrade Coffee Research Institute International Coffee Organisation

For the literature screening, we adopted the following inclusion criteria: (i) subject relevant (anywhere in the world, small landholder farmer or commercial system); (ii) type of intervention (climate scenario available in the literature, tools to assess impact resilience to climate change); (iii) comparator (Spatial modelling); (iv) method (Qualitative vs. quantitative modelling); (v) outcome (studies that consider production modelling).

The effect modifier restricted access to limited primary data, and less variability in modelling and potential impacts (GHG emission scenarios, crop varieties, different production systems and techniques, different agro-ecological conditions, etc.) was unavoidable. Therefore, the review team agreed to adopt narrative analysis and, where possible, quantitative evidence instead of meta-analysis. Interpreting broad subjects with a narrative approach is more suitable, producing a disparate range of outcomes. The narrative analysis approach can acquire the attention of stakeholders and decision-makers by providing them with research gaps in targeted research areas [40–43]. The review team carefully reduced any source of biases in evaluating climate change mitigation and adaptation impacts on the coffee cropping systems.

The literature review did not include a timeframe and was extended until 31 December 2022, based on different search keywords tested on 27 July 2021. Available literature published in English was considered, without specific field restrictions. Keyword search outcomes were recorded and exported to “Mendeley” (a bibliographic software package). The inclusion criteria were applied by selecting relevant title papers, then abstract evaluation, and, finally, reviewing full texts (Figure 2). Obtained data were tabulated using a common spreadsheet format (i.e., MS Excel). During data extraction, transparency was ensured to avoid heterogeneity in data documentation, and all the review steps were recorded using the PRISMA checklist.

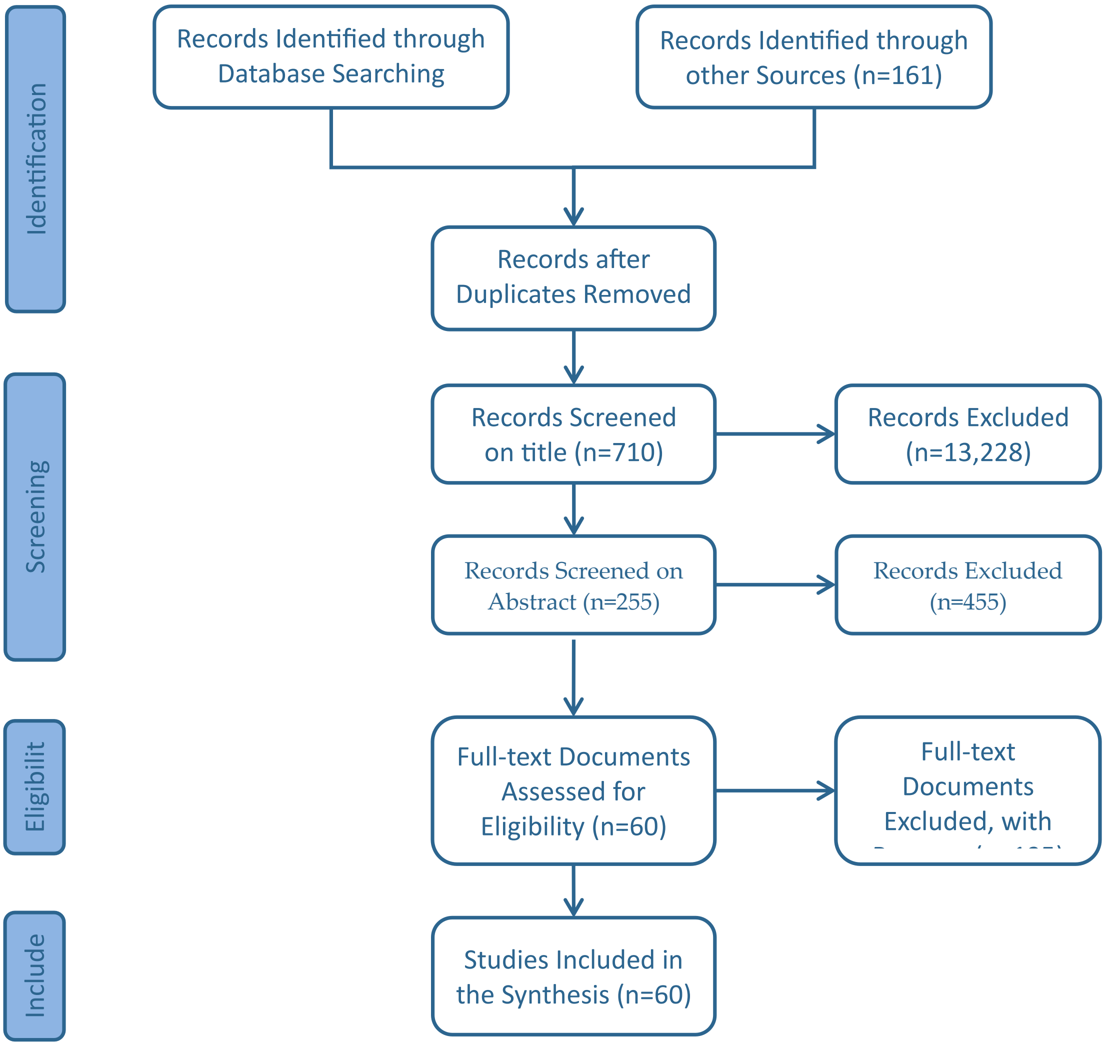

Figure 2. Flow diagram of the systematic review process (after [45]).

3. Results

The results are divided into three different sections. They will first present a general statistical analysis of the screened database, then assess the latter according to climate change processes reviewed to address the models and tools found in the literature in the final section.

3.1. Bibliometric Analysis

A total of 60 eligible studies were retrieved from the literature on modelling climate-driven aspects related to coffee production (Figure 2). The documents were comprehensively searched and categorised according to different categories: region, year of publication, model type, data used to validate the models, coffee species, climate scenarios, climate impact, and climate adaptation (Supplementary Materials). All documents showing simulation models and producing predictions for specific periods for data synthesis were considered. The number of documents were identified and classified according to publication years. Indeed, even though not constantly linear, the trend over time in publication numbers shows an increase over the last decade (Figure 3), with peaks in the number of publications in 2017 and 2022 (*n* = 8, and *n* = 9), while also 2011, 2015, 2018, and 2020 show a consistent number of publications (i.e., 5 and 6).

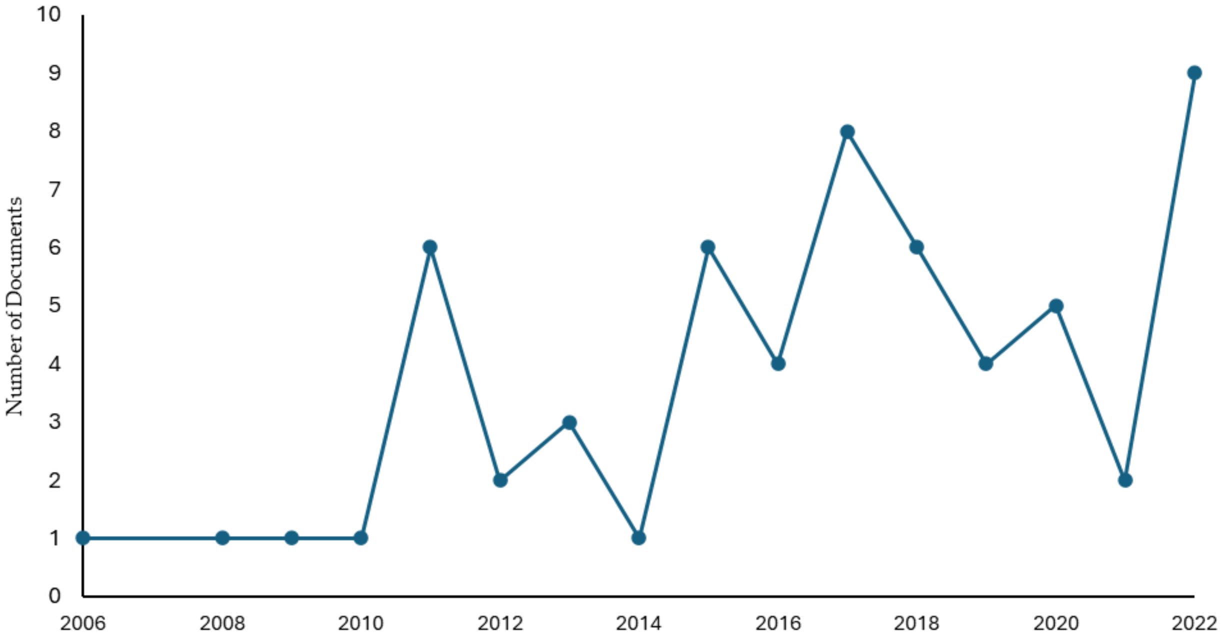

Figure 3. Documents published each year depicting modelling tools to simulate climate change impacts and adaptation on coffee production until 2022.

From another side, Figure 4 depicts the literature published on coffee production in different countries, most of which relate to Brazil (*n* = 14). The research on the coffee crop in Ethiopia is reported in seven documents, whereas we obtained a similar number of documents (*n* = 2) for Indonesia, Tanzania, Mexico, Colombia, Zimbabwe, and Costa Rica. Some articles combined studies including many countries (*n* = 14), and a few (*n* = 4) analysed climate-related aspects of coffee crops worldwide.

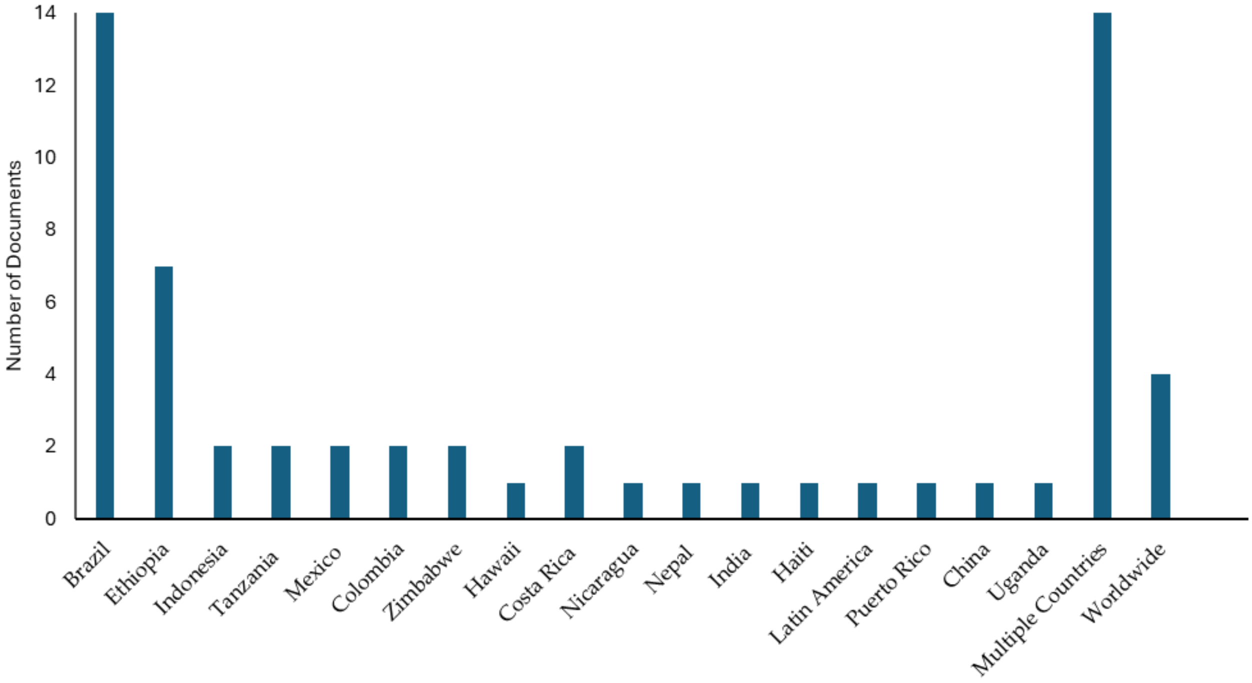

Figure 4. The number of documents published in different countries modelling impacts and adaptation to climate change in coffee production till 2022

The available literature mainly focused on *Coffea arabica* L., as reported in **Table 4**. Most documents included results for the American (South America = 18, North America = 15) and the African (*n* = 20) continents and four papers carried out global research, focusing on *Coffea arabica* L. species. A few documents did not define the assessed species (*n* = 6). Among document types, the available literature is covered mainly by research articles (*n* = 55).

Table 4. The number of documents published in different continents, document types, and coffee species

Continents	**Document Type**			**Species**				**Total**
	Research	**Chapter**	**Report**	***Arabica Coffee* L.**	***Coffea robusta* L.**	**Both Species**	**Not Mentioned**	
North America	12	1	2	12		1	2	**15**
South America	18			15	1	1	1	**18**
Africa	18	1	1	15	2	1	2	**20**
Asia	3			1		1	1	**3**
Worldwide	4			3		1		**4**
Total	**55**	**2**	**3**	**46**	**3**	**5**	**6**	**60**

3.2. Processes Reviewed

The results identified two climate change processes using modelling tools: impacts and adaptation. The values in Figure 6 refer to the percentage of documents related to climate variability's effect on coffee production.

The impacts of climate change on coffee production are thoroughly assessed in the literature (82%;, in particular, the climate suitability (55%), increased incidence of pests and disease (20%), and decline in production (25%). A consistent number of reviewed studies proposed different adaptation strategies (18%).

3.3. Analysis of Models and Tools

A model is a simplified representation of reality though a functional scheme that allows one to investigate the properties of a system and, in some cases, predict its future outcome. Different models were developed for coffee crops to estimate current and future production and distribution, considering climate variability as a driving factor. Based on the review, the models were classified into deterministic, stochastic, and mixed stochastic/deterministic (Table 5). Deterministic models do not account for randomness in data, nor have a probability function, so a set of inputs and established relationships determines the output.

On the contrary, a stochastic model includes a random component that uses a distribution as one of the inputs and results in a distribution as output. It presents data and predicts outcomes that account for certain levels of unpredictability or randomness. In addition, some models are stochastic and become deterministic after training. The training installs rules into a network that prescribes its behaviours, so an untrained model shows inconsistent behaviours. These models were included in the mixed model type.

The Eta model was excluded from this classification; it was used once in the literature to assess future suitability ranges, expressed in percentage, of coffee in Southeast Brazil based on annual mean water and temperature restrictions of the Arabica coffee [46]. Among the other 59 models identified in the literature, as reported in Table 5, 41 are stochastic models. Species distribution models are the most common (*n* = 34), followed by crop models (*n* = 10). Additionally, species distribution models include deterministic and stochastic models. Hence, the total number of deterministic models is 17, most of them being regression models (*n* = 12).

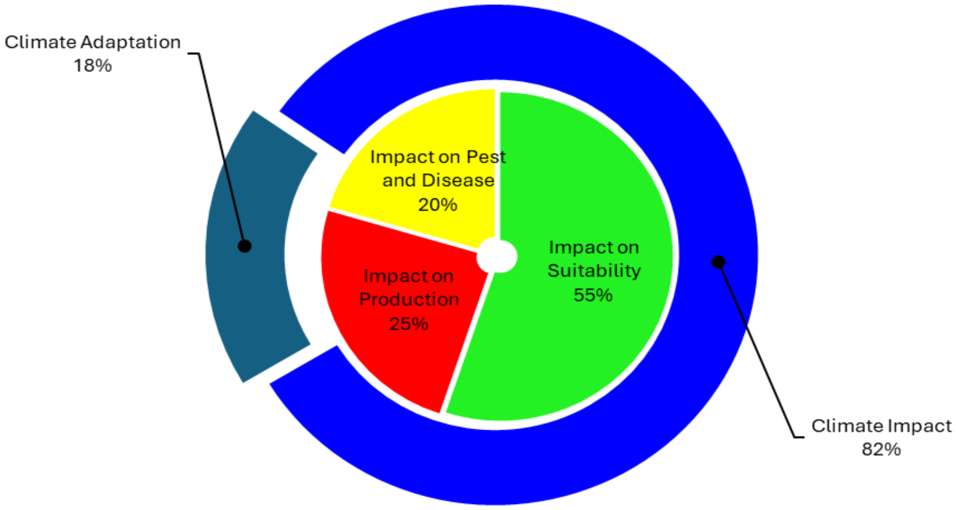

Figure 5. Percentage of documents reviewed according to climate process (climate impact, adaptation). The climate impact is further divided into three categories: impact on suitability, impact on production, and impact on pests and diseases.

Table 5. Classification of the reviewed models.

		Model types			**Total**
		Deterministic Models	**Stochastic Models**	**Deterministic and Stochastic**	
Model Category	Regression models	12	3		**15**
	Crop models	2	8		**10**
	Species distribution models	3	30	1	**34**
Total Models		**17**	**41**	**1**	**59**

3.3.1. Models' Categories

In addition to the first model's classification, another conceptual modelling classification was applied to the modelling tools based on the type of mathematical function/process used to estimate climate change impacts and adaptation. This classification identified regression, crop, and species distribution models as the three main categories (**Table 5**). A description of each model category is reported in the following sections.

Regression Models

Regression models are simple models used to establish relationships between climate (and other environmental) variables and crop outcomes by fitting regression equations. These models are effective in detecting more general trends and projecting future scenarios. The literature comprises various regression models, including non-linear regression models, multivariate analysis, AutoRegressive Integrated Moving Average (ARIMA) models, climate-based statistical models, econometric models, Generalised Linear Model (GLM), and the Generalised Additive Model (GAM).

Regression models are extensively used to study the impact of climate change on coffee crop yields. Climate-based statistical models, such as those used by [22], predict yields of Coffea arabica L. and Coffea robusta L. in India for specific years (2010–2012) based on temperature, rainfall, and humidity variables. ARIMA models are employed by [47,48] to assess the influence of climate change on coffee yield in Tanzania and Brazil. The linear regression models predict coffee yield in Ethiopia until 2060 and investigate climate suitability for Arabica coffee until 2080 [49,50].

Non-linear regression equations are applied to study the effects of factors, such as temperature, leaf wetness, and distribution in the sun and shade-grown systems, on coffee rust and coffee crop vulnerability in Brazil and provide projections under climate change until 2080 [51–54]. Bio-economic models are used to predict the impact of the Coffee Berry Borer (CBB) on coffee crops in East Africa and examine the influence of climate on CBB in both full-sun and shade-grown systems [55]. Various studies used econometric models to investigate the correlation between coffee yield and climate variables and identify climate-vulnerable areas in different countries, such as Mexico, Brazil, and Colombia. The principal component analysis is also used to predict the vulnerability in Brazil's coffee region to climate change until 2080 [20,28,56].

Crop Process-Based Models

Crop models are process-based models that simulate the growth and development of crops in specific environmental conditions and simulate biogeochemical processes to predict crop growth and yields and optimise crop management strategies under present and projected climatic conditions. However, these models require extensive effort in equations and parameter calibration. In the existing literature, several crop models have been identified, including mechanistic models, the yield-safe model, the DynACof model, dynamic models, Irrigation Management System (IManSys) model, and agrometeorological models.

Several studies applying crop models (e.g., DynACof) focus explicitly on agroforestry systems and compare them with open sun-grown systems under changing climate variables in Costa Rica, Guatemala, Nicaragua, Colombia, and Brazil [24,57–59]. The yield-safe model determines coffee yield under changing climate scenarios in Ethiopia [21]. Agrometeorological models incorporate irrigation methods to counter the effects of high temperatures and frost from 2040 to 2070 in Brazil. Other studies focus on shade levels to mitigate drought intensity in East Africa, and the IManSys model is used to calculate irrigation requirements for coffee crops under IPCC scenarios in Hawaii [60–64].

Species Distribution Models

Species distribution models identify the distribution among environmental and spatial gradients of a particular species and confirm the suitability of its niche, considering climate impact and other environmental variables. Some reviewed models driven by machine-learning algorithms [39] can investigate climate suitability and include Maximum Entropy (MaxEnt), Random Forests (RF), Boosted Regression Trees (BRT), Generalised Boosted regression Model (GBM), Support Vector Machine (SVM), and Multivariate Adaptive Regression Spline (MARS) models. Moreover, other suitability models are (i) the agro-ecological land elevation model for Coffea arabica L. (ALIECA), (ii) the EcoCrop Model, and (iii) the crop niche selection for tropical agriculture (CaNaStA).

Furthermore, the ensemble modelling approach, which combines different models to perform specific scientific activities, has become more common lately to ensure the projections' reliability and reduce modelling uncertainty. Other various modelling tools exist for pest species distribution and disease occurrence. They are (i) the bio-economic models, (ii) the empirical disease models, (iii) the Dinamica EGO model, (iv) the Climex model, (v) the thermal constant model, and (vi) the Insect Life Cycle Modelling Software (ILCYM). The species distribution models are more common in the literature.

The MaxEnt model is widely used to assess the climate suitability of Arabica coffee and predict its future implications worldwide. The model uses various environmental factors as explanatory variables, including temperature, precipitation, aridity, evapotranspiration, soil slope, and land cover [65], to simulate (i) climate suitability in Nepal, Indonesia and Haiti, (ii) the impact on indigenous Arabica coffee in Sudan and Ethiopia, (iii) the adaptation strategy for coffee communities in Mexico, and (iv) to assess climate vulnerability in Puerto Rico by 2099 and Mesoamerica by 2050 [66–70].

Furthermore, the MaxEnt model applied in Indonesia and Zimbabwe produced climate suitability until 2050 and extended projections for China (2060) and Ethiopia (2070) [71–74]. It also assesses the coffee-pollinating species occurrence in Latin America in response to climate variability (temperature, precipitation, and dry season) and sets the suitable ecological zones in Costa Rica against temperature, elevation, and diurnal range [75,76]. Finally, the MaxEnt model assesses agroforestry systems for adaptation in Brazil and Mesoamerica by 2050, respectively, in response to temperature, precipitation, and bioclimatic variables [30,77].

The influence of climate variability (temperature, rainfall, and evapotranspiration) on Arabica agroclimatic zoning and coffee production was also investigated in Brazil using Eta, a regional climate modelling tool [46].

Random Forest (RF) models are run worldwide to classify the agro-ecological zones for Arabica coffee based on climate variables (temperature, precipitation, and dry months) [78]. An empirical disease model determined the incubation period of coffee rust (Hemileia vastatrix) in response to maximum and minimum temperatures and interpolated them to make predictions in Brazil [79]. Ecological modelling tools are also used to evaluate Brazil's phoma leaf spot distribution related to temperature and relative humidity [80]. The Dinamica EGO model produces the distribution of understorey coffee occurrences in Ethiopia [81]. Generalised Regression Models (GRM) are applied globally to assess the impact of Vapour Pressure Development (VPD) on Arabica coffee yield. In Ethiopia, GRM evaluated the influences of extreme agroclimatic indicators on Arabica coffee's overground biomass (AGB) until 2060 [13,82].

In Zimbabwe, the Coffee White Borer (CWB) occurrence probability until 2050 is assessed against temperature and precipitation factors by an ensemble of modelling approaches (BRT and GLM models) [34]. Another ensemble approach uses several machine-learning algorithms (SVM, MaxEnt, and RF) to investigate the worldwide distribution of coffee crops (Arabica and Robusta coffee) [27]. Another ensemble of modelling techniques (GLM, MaxEnt, RF, MARS, GAM, and GBM) examines the resilience potential for Arabica coffee in Ethiopia and the risk extinction of wild Arabica species in Ethiopian and Sudan while taking into account several climate variables [83,84].

The MaxEnt and CaNaStA models also use climate variables, such as temperature and precipitation, as an ensemble of models to generate climate suitability and the quality of Arabica coffee in Nicaragua and evaluate adaptation and mitigation options in Central America [19,85]. Moreover, an integrated approach of machine-learning algorithms (BFT, RF, and SVM) investigate the influence of climate variability (temperature and precipitation) and topological (elevation, soil slope angle) and soil characteristics (pH, soil Cation Exchange Capacity (CEC), apparent Bulk Density (BD), Soil Organic Carbon (SOC)) on the speciality of the coffee sector in Ethiopia under current and future scenarios [39]. Species distribution models (GAM, MaxEnt, and BRT) also predict Robusta's ecological and genomic vulnerability in its native region by 2050 [86].

The ALIECA model predicts the land suitability of Arabica coffee production using agro-ecological variables in Central America. An EcoCrop model assesses the climate suitability of a coffee-based cropping system in Uganda for the long term (2038) [87,88]. The Climex model accounts for the spatial distribution of CBB, considering the effect of environmental variables (temperature, moisture parameters, and other environmental constraints) [89]. Based on Brazil’s air and soil temperature, the thermal constant model simulates the geographic distribution of coffee nematodes and leaf miners until 2080 [90]. Finally, the Insect Life Cycle Modelling software (ILCYM) predicts the coffee stink bug (Antestiopsis thunbergii) in Tanzania based on the Establishment of Risk Index (ERI), the Generation Index (GI), and the Activity Risk (AI) that corresponds to changes in critical factors/thresholds linked to coffee stink bug distribution based on air temperature [91].

3.3.2. **Climate Change Scenarios**

A total of 48 papers analyses the impact of future climate change conditions. The analyses follow the Intergovernmental Panel on Climate Change (IPCC) climate scenarios based on the emission and concentration of greenhouse gases in the atmosphere. Over the years, the IPCC has developed several scenarios, including the Special Report on Emission Scenarios (SRES) for the third and fourth Assessment Reports (AR3 in 2001 and AR4 in 2007) [92], characterised by four qualitative storyline scenarios (A1, A2, B1, and B2) representing different demographic, social, and technological advancements. Further, the IPCC has recently developed advanced sets of scenarios: the Representative Concentration Pathway (RCP) and the Shared Socioeconomic Pathway (SSP), presented in AR4 [93] and AR6 [94], respectively. Both have a valid framework for projections until the end of the current century (2100). However, the RCP provides the concentration of greenhouse gases and radiative forcing levels associated with different emission pathways. In contrast, the SSP setup has a different approach considering greenhouse gas emissions, including population growth, economic development, energy use, land use, and other factors. The RCP is further subdivided into RCP 2.6 (optimistic), RCP 4.5 and 6.0 (intermediate), and RCP 8.5 (business as usual), and the set of the SSP scenarios are SSP126 (sustainable development), SSP245 (middle of the road development), SSP370 (regional rivalry), SSP460 (inequity), and SSP585 (full fossil-fuelled development) pathways.

The available literature has been more consolidated over the last decade. Therefore, the RCP are more prevalent than the SRES scenarios, commonly used by the literature in the earlier years (2008–2019), and were gradually, but not entirely, replaced by the RCP scenarios between 2015 and 2022. In the review results, the RCP scenarios prevail (23 papers), followed by the SRES (21 manuscripts) and the SSP (4 studies) (Figure 5A). The use and frequency of different scenarios across the results indicate that the highest number of papers (n = 7) adopted RCP 4.5 and RCP 8.5, followed by RCP 4.5, SRES A2A, SRES A2, and SRES A2 (n = 5 for each scenario). The other scenarios found in the literature (RCP (2.6, 4.5, 6.0 and 8.5), SRES (A2 and B2), and SSP (126, 245, 370 and 585)) are adopted in two research papers each (Figure 5B). The remaining scenarios were used only once in the literature, including RCP (2.6 and 8.5), (2.6 and 6.0), (2.6, 4.5 and 6.0), (2.6, 6.0 and 8.5), SRES (B1 and A2), (B1, and A1F1), (A2A, and A1F1), (A1B, A2A and B2A), (A2, B2, A2A and B2A), (A1, A1B and B2), and SSP (126, 245 and 585) (Figure 5C,D).

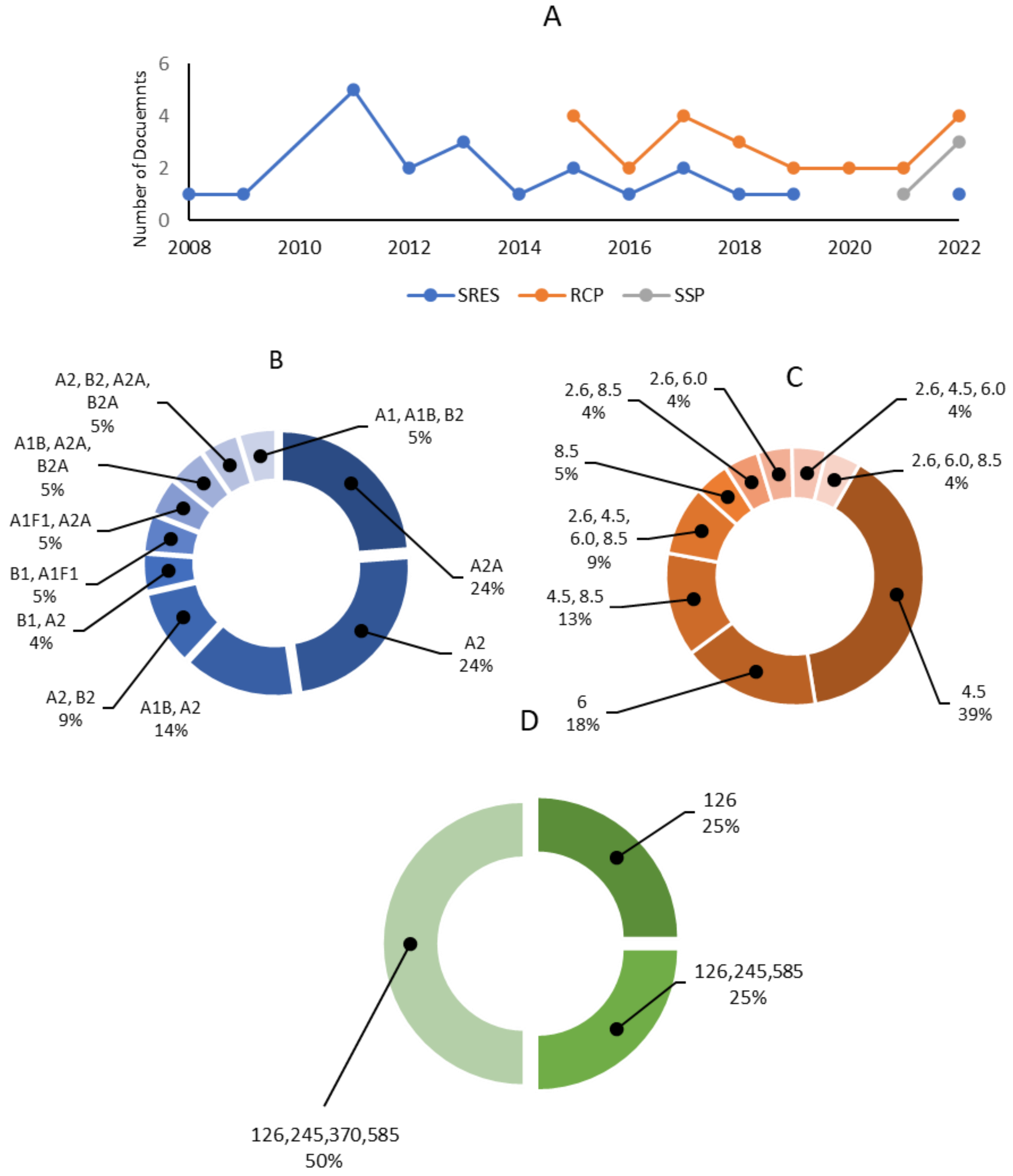

Figure 6. The coffee agrosystems are analysed using IPCC scenarios illustrating the trend of various scenarios (A), along with the frequency of sub-scenarios found in the literature, which are presented as SRES (B), RCPs (C), and SSPs (D), respectively.

4. Discussions

The literature was extensively searched to put together information on published modelling tools used to predict the impacts and adaptation of coffee agrosystems to climate change. Arabica is at a greater risk between the two major coffee species than Robusta; thus, research focused primarily on this species. Most models in the screened literature have incorporated the IPCC scenarios and evaluated climate change’s impact on coffee agrosystems. Less attention is given to the adoption of adaptation practices. Most models have incorporated the IPCC scenarios, using projections until 2050, particularly the medium-emission sub-scenario RCP 4.5, either solely or combined with other sub-scenarios. The SERS’ high-emission scenarios (A2) were also commonly used in the reviewed literature. The Supplementary Materials contain detailed information about each document screened for review.

Among the various regression models, econometric models based on multiple regression equations, which integrate the economic and climate variables, are commonly used to capture the effect of extreme events on coffee yield. The quadratic functional farm generates multi-collinearity, which does not affect the model’s prediction but makes the estimator less accurate [28]. The AutoRegressive Integrated Moving Average (ARIMA) is particularly efficient in forecasting time series analysis, but its application with non-linear regression can compromise the model’s accuracy [88]. The climate-based regression models monitor the coffee crop under critical stages, considering the effect of climate variables to analyse the coffee growth and developments at different growth cycles [22].

The MaxENT model is widely applied to determine the climate suitability of coffee crops. The model output is 1, considered the maximum probability, and 0, where species have a less suitable climate. The model calculates these values by dividing each weighted variable’s sum by a scaling constant. This model is robust because it incorporates statistical and machine-learning techniques. However, the parameter selection is crucial, otherwise, the results may be biased. There is an inbuilt option to check the quality of the model using the Area Under Curve (AUC) index, as it provides a single overall measure of model accuracy [19,30].

A Random Forest (RF) model is also a popular machine learning classifier with high efficiency over large datasets without overfitting [22]. The Crop Niche Selection in Tropical Agriculture (CaNaSTA) is built on Bayesian statistics, aiming to determine a species’ presence or absence and appraise the crop’s performance. However, this model only works with its specific dataset format, and expertise in Bayesian statistics is also required, making it complicated and time-consuming.

Another model, EcoCrop (EC), determines the crop niche using environmental ranges, expressed in percentage, producing overall crop suitability [61]. The model gives individual suitability values for temperature and precipitation. Expert knowledge is essential for the model’s accuracy in setting the crop parameters. The EcoCrop (EC) model can assess climate suitability even with limited ecological and environmental information [80].

The ensemble modelling approach is more efficient in suitability-related tasks because different machine learning and regression models perform together, highlighting modelling uncertainty and conservative choices for specific tasks. For example, integrating RF, CaNaStA, and MaxEnt has more precise results than the output produced by individual models [29]. The Dinamica’s EGO model applies Weight of Evidence (WoE) to find the coffee occurrence understorey [74]. The agro-ecological land elevation model for Coffea arabica L. (ALIECA) is based on a Bayesian algorithm and provides information about land suitability in percentages, but does not provide data about the presence or absence of coffee crops. This model can also provide accurate results when the data are missing or uncertain [81].

The literature has applied and described several models for Identifying pests in coffee agroecosystems under climate change scenarios, including the ILCYM, climax, and thermal constant models. All these models have their strengths, but the ILCYM model stands out due to its ability to provide detailed information at a very high geographical scale, resulting in more precise results than other pest distribution models. However, the thermal constant model and ILCYM are based on temperature variables. They lack flexibility in accepting other climate variables important for pest–crop interactions, such as rainfall and relative humidity. Furthermore, neither model offers any crop or pest adaptation options. In addition, these models require daily or hourly data on a short time scale because pest–crop interactions may occur within 24 hours [83,84]. The empirical disease and non-linear regression models use air temperature to determine the occurrence and intensity of diseases [72,89]. On the other hand, bioeconomic models are more flexible in considering shading, coffee berry borer (CBB) infestation, and temperature to generate information along with economic variables to estimate the shading value according to the disease infestation intensity [48].

Crop models are commonly used to assess climate impacts against adaptation strategies while modifying crop management systems. The available crop models recommend the shading level for optimal coffee yield in various regions [19,51,52]. However, few studies explored other adaptation options. As agrometeorological models, the Irrigation Management System (IManSys) model and the Yield SAFE model have been developed to enhance irrigation techniques and the efficiency of CO2 fertilisation in a coffee production system [53,55,57]. All models obtained in each article are available in a supplementary file submitted with this manuscript.

5. Conclusions

Various modelling approaches have been applied to determine the climate change impact and adaptation of coffee agrosystems. The research adopted the systematic review approach to assess and classify the available literature according to (i) categories (regression models, crop models, species distribution models), (ii) types (deterministic, stochastic, mixed), and (iii) processes (climate impacts, climate adaptation). The results also included an assessment of the scenarios used to run different modelling tools.

In conclusion, machine learning models have complex algorithms and are stochastic, which produce predictions in situations where data include uncertainty or randomness, thereby generating more accurate results. The ILCYM model is particularly efficient in pest distribution due to its flexibility in accepting multiple variables, thus providing reliable data. The application of crop models was limited to a few studies on crop agrosystems.

Therefore, based on our results, we recommend intensifying adaptation research to explore the best options for different case studies. We advocate applying crop models to fill the gap for coffee phenology and propose adaptation strategies, for example, introducing new varieties, water conservation methods, shading management at various altitudes, and soil organic matter management. The Robusta coffee species also needs to be further investigated in the literature because it is underestimated, despite having a higher adaptation potential.

We finally address these results to decision-makers to support scientific and applied policy design and implementation in climate change resilience and adaptation.

Supplementary Materials: The following supporting information is available in Excel sheet format, which can be downloaded at: www.mdpi.com/xxx/s1.

Author Contributions: Data curation, M.F. and D.E.C.; Formal analysis, M.F. and D.E.C.; Investigation, M.F. and D.E.C.; Methodology, M.F. and D.E.C.; Writing—original draft, M.F. and D.E.C.; Writing—review & editing, M.F. and D.E.C., V.M., A.T., S.M., D.S.; Supervision, V.M., A.T., S.M.,

D.S.; Funding acquisition, D.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was developed within the framework of the strategic project "CAT4—Agriculture Management Analysis for Adaptation" promoted by the Euro-Mediterranean Centre on Climate Change (CMCC) Foundation.

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Chapter 2

DynACof process-based model parameterization and validation for Robusta coffee

This article is prepared for submission

1. Abstract

Coffee Arabica and Robusta are the main species for coffee production. Both these species are grown in different suitable climate. For instance, suitable environmental conditions for Robusta species are found in lowland areas of Vietnam with relatively high temperatures and precipitation. Although, this species is resilient to climate change, but the impact of climate change has been documented in the literature. Moreover, until now, models have applied water management as adaptation approach. However, no model has considered Robusta coffee cultivation under agroforestry systems. Therefore, the present study was conducted to modify the DynACof model to simulate the Robusta coffee in agroforestry systems. It is important to mention that dataset used to modify this model was obtained from Robusta coffee open sun system due to lack of information on agroforestry systems. The study was conducted in ten districts of Vietnam where climate is highly suitable for Robusta coffee cultivation. The DynACof model was previously developed for Arabica coffee thus our aim was to modify the model to improve its capabilities for Robusta coffee. The climate data for historical period was retrieved from European Centre for Medium-Range Weather Forecasts, Reanalysis v5 (ERA5). The statistical indicators were applied to evaluate the model performance based on observed and predicted bean yield. In most districts, the model achieved a high coefficient of determination (R^2), approximately 0.5, along with low error in some districts, ranging from 8.7% to 21.5%, in districts such as Dak Song, Krong Nang, Lam Ha, Duc Trong, and Krong Buk. The D-Index indicated the reliable predictions, with most values falling in the range of 0.7 to 0.8, particularly in districts like Dak Song, Dak Glang, Krong Nang, and Chu Prong. Some districts, such as Lagari, Duc Trong, and Lam Ha, examined the high nRMSE values ranging from 29.6% to 35.5%. Thus, residual plot shows the downward trend in error distribution. On average, the model predicted a bean yield of 2,700 kg/ha in districts where the bean maturity duration was around 260 days with an optimal climatic condition.

These results demonstrate the potential of the model for evaluating the coffee yield and guiding sustainable management strategies to address the challenges posed by climate change.

Keywors: DynACof Model, Robusta coffee, Crop Model, Climate adaptation, Coffee Agroforestry Systems

2. Introduction

The coffee crop is suitable for tropical to subtropical climate and is cultivated on around 10.2 million hectares across 80 countries (Shao et al., 2009). Coffee belongs to the *Rubiaceae* family and has more than 80 species, native to the equatorial forests of East and West Africa, Madagascar, and islands of the Indian Ocean (Humphries et al., 2024). According to the report (2023/24) on coffee production, Arabica coffee and Robusta coffee consistently contribute to global market with 57% and 42% respectively (Asfaw, 2023). Like other crops, coffee crop has been affected by climate variability, resulting in a reduction in suitable growing conditions, an increase in the incidence of pests and diseases, and consequently, a decline in yield. This is particularly true for Arabica coffee due to its low tolerance to high temperatures and particular pest diseases, like coffee leaf rust (Dias et al., 2024; Richardson et al., 2023; Atallah etval., 2018; Kutywayo et al., 2013).

On the other hand, Robusta coffee, which has a higher resilience, has been recommended for cultivation in many areas previously suitable for Arabica coffee. Similarly, it is important to note that Robusta coffee is less documented, considering climate change scenarios (Faraz et al., 2023). Water deficiency and high temperatures are increasing stress on coffee grown in agro-forest systems. However, Robusta coffee tolerates such conditions by altering its morphological characteristics and physiological behaviours, including extended root growth and decreased stomatal conductance, which consequently reduces photosynthetic activity (Covre et al., 2022; Roonprapant et al., 2021; Praxedes et al., 2006; Pinheiro et al., 2005). Leaf proline levels progressively increase with prolonged exposure to these conditions. The accumulation of proline in plant tissues is an indicator of plant tolerance, acting as an adaptive mechanism in plants (Tesfaye et al., 2014). Similarly, when both species grown during the winter season, Robusta coffee exhibited proline and ascorbate contents that were three times higher than those found in arabica coffee (Da Matta et al., 1997).

Robusta coffee (*Coffea canephora*) thrives in tropical climate, with temperatures ranges between 22-30 ^{o}C. The mean optimum rainfall varies around 2792 mm year^{-1} and maximum relative humidity is 85 %. The bean production can reach high as much as 6000 kg/ha (Campuzano-Duque et al., 2021; Kath et al., 2021). Agriculture management practices used to enhance the Robusta coffee yield are clonal propagation (Espindula et al., 2022), irrigation practices (Tran et al., 2021), fertilizer management (Byrareddy et al., 2019), and intercropping with shaded trees (Chumthong et al., 2023). However, monoculture systems raise ecological concerns such as habitat loss and biodiversity decline (Depecker et al., 2023; Tumwebaze et al., 2016). Recently the emphasis on coffee cultivation has shifted toward sustaining production through agroforestry system (Clément et al., 2025). The central high land of Vietnam is suitable climate for Robusta coffee, and most importantly lead the world in Robusta coffee productivity (Tran et al., 2021). However, spreading of Robusta coffee cultivation is occurring to several other regions, for which growing conditions may facilitate the farming over Arabica coffee.

Table 1. The Coffee robusta farming system has been characterize by 13 models, each model is specialized in specific aspects.

Country	**Model**	**Purpose**	**Reference**
Vietnam	Hierarchical Bayesian Model	Water Managment	Byrareddy et al., 2020
Vietnam, Indonesian	Hierarchical Bayesian Model	Temperature Sensitivity at Flowering Stage	Kath et al., 2020
Vietnam	Generalized linear mixed models (GLMMs)	Temperature and Rainfall effect on Bean Characteristics	Kath et al., 2021
Brazil	Linear regression model	Ecological Vulnerability of Coffee Agroecosystem	de Carvalho Alves et al., 2013
India	Multiple Regression Models	Predicting Coffee Yield in Humid Tropical Condition	Jayakumar et al., 2016
Vietnam	Multiple Linear Regression Models	Vegetative Biophysical Variables to Forecast Coffee Yield	Thao et al., 2022
Multiple Countries	Ensembled model	Climate Suitability Based on Latitude, Longitude and Land-Use Classes	Bunn et al., 2015
Multiple Countries	Species Distribution Model	Ecological and Genomic Vulnerability	Tournebize et al., 2022
Vietnam	Water and Agrochemicals in the Vadose Environment (WAVE) Model	Water Managment	D'haeze et al., 2003
Colombia	Integrated Modelling Approach	Biophysical and Socio-Economic Potential to Grow Coffee Robusta	González-Orozco et al., 2024
Vietnam	Process-Based Model	Predicting Robusta coffee Growth and Development	Kouadio et al., 2021
Vietnam	Structural Equation Model (SEM)	Phenological Shifts in Response to Climate and Management Factors	Kath et al., 2023
Uganda	EcoCrop model	Climate Suitability	Mulinde et al., 2022

The Robusta farming system has been extensively assessed by total 13 models with most frequently the studing climate suitability. Meanwhile adaptation to stress conditions has primerly been addressed through water management (Table 1). Yet no model has focused on processes linking coffee growth to climate change and adaptation measures (e.g. agroforestry vs full-sun systems). Physical-based crop models are sophisticated computational tool employed to predict crop growth, development and yield based on soil condition, environmental variables, genetic, and management practices. They rely on mathematical equations to simulate physical and biological processes (Zhao et al., 2019). In crop models, the input data related to the management practices depend upon specific agricultural system, including shading, irrigation type, pruning, tillage, nutrient management and other practices (Byrareddy et al., 2020; D'haeze et al., 2003). Additionally, these models can simulate the valuable insights for the changing conditions of future by assessing the different stages of crops like crop phenological responses to climate change, frequent attack of pests and diseases (Alfonsi et al., 2019; Imbach et al., 2017; Ghini et al., 2011), decreasing in crop suitability and productivity, (Muslihah et al., 2020; Purba et al., 2019; Moat et al., 2019) and challenges related to water scarcity (González-Orozco et al., 2024; Koh et al., 2020; Verhage et al., 2017). Similarly, many crop models are developed to investigate the adaptation options for crops under stress conditions which included the crop cultivation under shade, water conservation approaches, improving water use efficiency through different irrigation method, and integrated pest management.

To this end, Dynamic Agroforestry Coffee crop model (DynACof) has been developed to simulate coffee agroforest system and parameterized for Arabica coffee, with particular emphasis on net primary productivity (NPP), growth, yield, mortality, energy and water balance (Vezy et al., 2018). Additionally, it considers the ecosystem services such as canopy cooling effect and carbon sequestration, and interactions with tree covers (agroforestry systems). Moreover, a metamodel is incorporated into DynACof to compute complex spatial effects, which is derived from the 3D process-based model MAESPA. Moreover, this coffee model comprises key feature to obtain realistic carbon distribution among flowers and fruits (Vezy et al., 2020).

Considering the potential of DynACof model, the objective of this study is to fill the knowledge gap about Robusta coffee grown in agroforestry system. For this purpose, the model modification was carried out to simulate bio-physical processes of Robusta coffee species. To refine and validate the DynACof model, key parameters were identified and adjusted to accurately simulate the Robusta coffee cropping systems. This was achieved by evaluating the agronomic parameters, biomass distribution and nutrient content in the coffee plant, as well as the reproductive stages and green bean yields across diverse districts in Vietnam.

3. Material and Methods

3.1. Study Area Overview

This study was conducted in a Robusta coffee growing region, in the Central Highlands of Vietnam. Vietnam is the world's largest producer, contributing 18% to global production (Kath et al., 2023). The climate condition of this region is characterised by humid tropical climate with maximum average temperature of around 24 ◦C. Rainfall ranges from 1800 to 2900 mm/year, while monthly solar radiation varies between 430 and 700 MJ m^{-2} across this growing region (Kath et al., 2023; Kouadio et al., 2021).

3.2. Data Collection and Description

3.2.1. Reference Bean Yield Data

The University of Queensland in Australia provided us the observed yield data of Robusta coffee for model training and validation. They collected the data at farm level through surveys conducted from year 2008 to 2017. The survey was conducted in ten districts across the provinces of Dak Lak, Gia Lai, and Lam Dong. An important note about data: since it was collected in open sun coffee systems, the effect of shade was not considered during the model modification process, hence the number of trees was kept as low as possible. Additionally, the coffee tree density was not recorded specifically at each site, thus the same density of 1100 coffee plants per hectare was used at all districts (Byrareddy et al., 2020). These districts were divided into two group with seven districts used for model training and three for validation (Figure 1). The distance among districts is shown in Table 2 and 3.

Figure 1. The districts in Vietnam were divided into two groups, with red colour used for DynACof model training and blue for Validation.

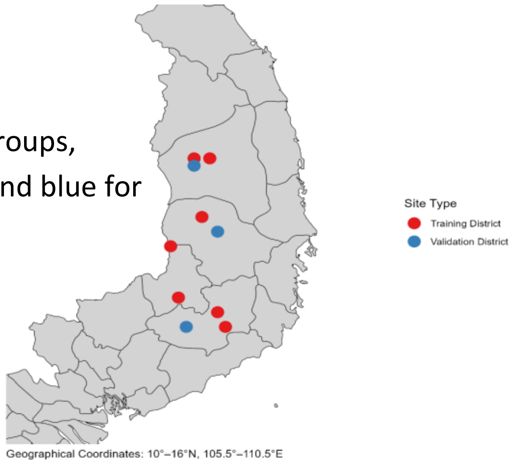

Table 2: Distance (km) between the districts used for model calibration.

Provinces	Dak Lak		Gia Lai		Lam Dong		
Districts	Dak Song	Dak Glang	Krong Nang	Lagari	Dak Doa	Lam Ha	Duc Trong
Dak Song	0	79	62	137	144	120	144
Dak Glang	79	0	127	213	216	59	79
Krong Nang	62	127	0	90	90	146	170
Lagari	137	213	90	0	22	236	260
Dak Doa	144	216	90	22	0	234	257
Lam Ha	120	59	146	236	234	0	25
Duc Trong	144	79	170	260	257	25	0

Table 3: Distance (km) between the districts used for model validation.

Provinces	Gia Lai	Dak Lak	Lam Dong
Districts	Boa loc	Chu Prong	Krong Buk
Boa Loc	0	245	151
Chu Prong	245	0	105
Krong Buk	151	105	0

3.2.2. Climate and Soil Data

The coffee plant requires three years to reach maturity, therefore climate variables were adjusted as to generate bean yield for all respective years of observed yield. Consequently, the ranges spans from 2005 to 2017. The climate variables were retrieved and integrated from two sources: Agrotechnological indicators from 2005 to 2017 derived from reanalysis. Copernicus climate change services (C3S) Climate Data Store (CDS): https://cds.climate.copernicus.eu (Accessed on 1-10-2024) (Buontempo et al., 2022). Temperature and precipitation data were downloaded from Figshare (https://figshare.com/), which is open research repositories. The reanalysis data was used since no weather stations were installed near the experimental districts, moreover the data facilitates the model training and validation processes. The water content of soil is extracted from SoilGrid raster and then calculating the average difference to match DynACof soil layer depth.

3.3. DynACof Model

DynACof is an agroforestry model that simulates the net primary productivity (NPP), growth, yield, mortality, energy and water balance of coffee tree shading and management practices (Figure 2). The management practices include the coffee plant pruning and tree density. Additionally, several plot scale ecosystem services are simulated by model such as production, canopy cooling effect, or potential C sequestration. Similarly, the model is integrated with 3D process-based model (MAESPA) and metamodels to account for complex spatial effects. Furthermore, fruit carbon demand is controlled by coffee flower bud and fruit cohort module over the years, which maintain realistic competition between sinks (Vezy et al., 2020; Murthy, 2004).

DynACof model is developed in both the R and Julia programming languages. Here we used Julia version in R-Studio, since Julia has high computation speed and enhance the efficiency of model execution.

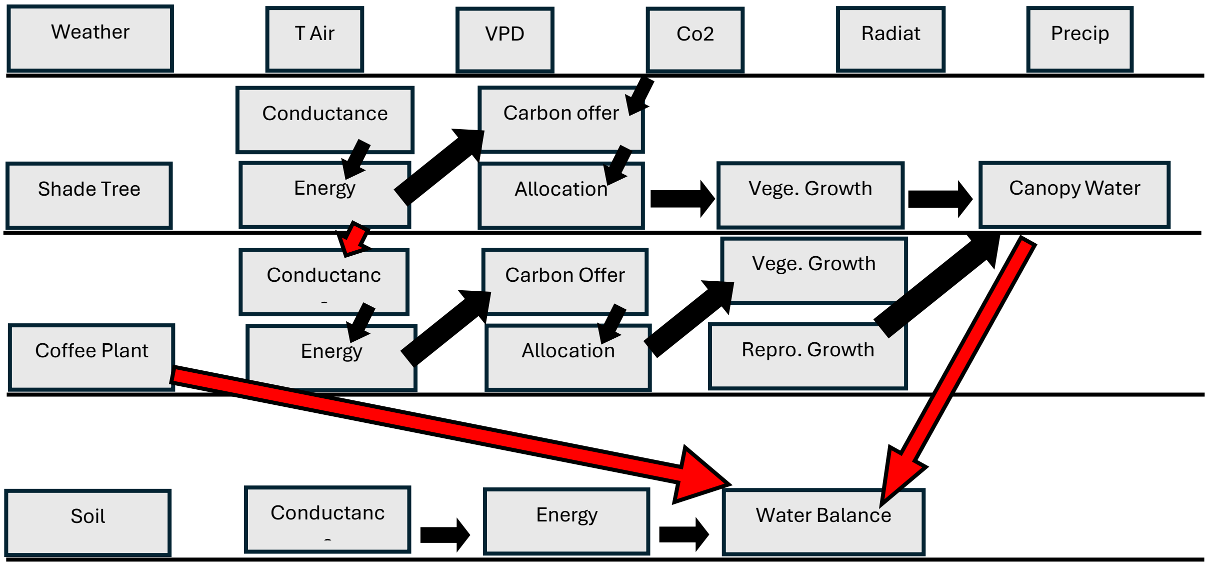

Figure 2. Flow chart of DynACof Model (Della Peruta et al., 2025, modified)

3.4. Model Input and output data

DynACof model parameters were modified for the simulations. The parameters related to Robusta species were adjusted in coffee model as mentioned in Table 4. While climate and soil input data sources are mentioned in Climate and Soil data section. Moreover, the climate variables are maximum temperature, minimum temperature, mean temperature, solar radiation, precipitation, relative humidity, and wind speed. Additionally, derived variables were computed, including vapor pressure deficit, degree days, photosynthetically active radiation, air pressure, and diffuse light fraction.

The soil input data has several parameters for soil but all of them were not available. However, moisture content in first two layers was extracted from SoilGrid database such as minimum water content and soil filed capacity condition. The soilGrid layer from 0 to 100 cm data was used for DynACof first layer (1-125 cm) and similarly from 100 to 200 cm data was assigned to second layer (125-175 cm). Whereas default values were used for third layer due to lack of information. Additionally, total extractable water content was calculated from minimum water content and soil filed capacity. Site model parameters were updated to include geographical location of each district as time zone, latitude, longitude and elevation.

The model describes in detail the agroforest system. It has 245 output variables, which are related to energy balance, water balance, carbon assimilation and allocation, respiration, plant growth, yield and mortality for each organ type.

3.5. Key Differences between Arabic and Robusta Coffee

This model was originally developed for the Arabica coffee species. Therefore, modifications to the coffee model were primarily based on the phenological differences between the two species. The main differences between Robusta and Arabica were identified by conducting a literature review. Based on literature, nitrogen content and plant height were left unchanged since no significant differences were observed between the two species (Carréra et al., 2023; Koutouleas et al., 2023; Melke et al., 2014; Pangestika et al., 2021; Prastowo and Arimarsetiowati, 2019; Dossa et al., 2008), Moreover, growth respiration is not significantly different between species; therefore, default values were used in the model (Ryan, 1991). The prominent features of Robusta coffee compared to Arabica that differentiate both species are longer reproductive phase, high resilience and high bean yield (Campuzano-Duque et al., 2021). These features were incorporated in the model via adjustments to degree days, biomass distribution, and other agronomic parameters. Additionally, soil and districts variables were updated based on the information for each site.

3.6. Model Parameterization

The coffee model was further refined by adjusting the selected parameters as detailed in Table 4. The range for each parameter was based on information available in literature and model formulation. Most of the parameters listed are related to floral bud and bean development at various stages. Therefore, the degree days (DD) allocated to various development phases were increased and number of buds were also increased to generate higher coffee bean yield. The adjustment began allocating more time for formation of first floral bud (F_Tffb), followed by optimizing maximum bud initiation (a_bud) and ensuring an appropriate degree day to bud development in two distinct stages as F_buds1 and F_buds1. The model also alleviated the pressure on bud during dormant period through a_p and B_p parameters, while increasing bud break per day with the help of Max_Bud_Break parameter. The fruit to seed ratio (FtS) and reserved carbon (Kres) adjusted to improve model outcome.

The bud maturity was adjusted by F_over parameter, since it represents the time until fruits become overripened. Adjustment was based on the difference of degree days (DD) between both species during bean development, while extending the duration of bean maturity. Subsequently, U_log parameter was computed from F_over, to ensure logistic growth of bean. For biomass distribution, the model compute values using coffee plant density and the DELM (Max leaf carbon demand), DELM values were increased to maintain a balanced biomass distribution. Lastly, other agronomic characteristics were set in the model such as specific leaf area (SLA) and leaf width (Wleaf).

3.7. Model Training and Validation

The selected parameters were analysed to find a combination that produce realistic results in selected districts for model training. For this purpose, 500 parameter sets produced by a Monte Carlo analysis were evaluated. Afterward, a set of parameters were selected that produced near to realistic results at all training districts. Subsequently, statistical indicators were applied to check more accurately the simulated bean yield. Lastly, the calibrated model was validated at three additional districts. The simulated results of these districts were quite well.

3.8. Sensitivity Analysis

The sensitivity analysis was conducted using a Monte Carlo approach on input variables that are selected for coffee model modification, which were compiled from literature (Table 4). This approach helps us to find important variable for targeted output, especially biomass distribution in coffee plant, bean maturation and green bean yield. In addition to this, the parameters combination was used to identify perfect combination for model training. Moreover, information about climate, soil, and topography was updated according to each district. The Monte Carlo analysis produced 500 parameter sets, resulting in different output from the model.

An issue was encountered in the model when dealing with low coffee density plant, as it significantly reduced biomass in leaf and fruit. To correct the biomass distribution, the leaf carbon demand was increased as cited in literature (Prezotti et al., 2013; Braganca et al., 2010). This adjustment had positive affect on carbon biomass distribution to the fruit cohorts.

The leaf carbon demand is calculated by equation 1:

Leaf demand = DELM x Stocking/10,000 (1)

Where, DELM is maximum leaf carbon demand (gc /plant day) per coffee plant. Stocking is the density of coffee plant (Plant/ha).

3.9. Statistical Indicator for Model Assessment

A comprehensive assessment of model accuracy was performed across ten districts within three provinces. This assessment included statistical indicators for quantitative analysis of model such as coefficient of determination (R^2), Index of Agreement (D-index), and Normalized Root Mean Square Error (nRMSE). For deeper analysis of the model, a residual plot was created. All of these calculation was carried out in R-Studio.

The equations for statistical indicators are as follows.

The coefficient of determination (R^2)

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}}$$

Where:

- $Sum\ of\ Square_{\ residual} = \sum(y_i - \hat{y}_i)^2$
- $Sum\ of\ Square_{\ total} = \sum(y_i - \bar{y})^2$

Index of Agreement (D-index)

$$D - index = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(|y_i - \bar{y}| + |y_i - \bar{y})^2}$$

Normalized Root Mean Square Error (nRMSE)

$$\text{nRMSE} = \frac{\sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}}}{Range\ of\ observed\ values} \times 100$$

$$Range\ of\ observed\ values = max(y_i) - min(y_i)$$

Residuals (e_i) are calculated as

$$e_i = y_i - \hat{y}_i$$

Where:

- $y_i = Oberved\ bean\ yield$
- $\hat{y}_i = Predicted\ bean\ yield$
- $\bar{y} = Mean\ of\ observed\ bean\ yield$
- $n = Number\ of\ Observations$

The coefficient of determination (R^2) calculates the proportion of variance of observed bean yield predicted by model. its value ranges between 1 and 0, where 1 indicate that model perfectly capture the variability in observed bean yield and 0 means none of variability is explain by model. The D-index evaluate the accuracy of model prediction, designed to detect at which degree the prediction match observed bean yield. The D-Index used same scale as R^2, where 1 confirm perfect agreement between predicted and observed bean yield and 0 denote no match between two datasets. The nRMSE represents root mean square error (RMSE) normalised by range, mean or standard deviation of observed data. It expresses error as a percentage. Lastly the residual error examines the distribution of error in dataset. In ideal case, the errors are evenly scattered around the zero line in residual plot. This shows that model is unbiased and has no systematic error.

Table 4. The parameterisation of coffee model.

Parameters	Description	Unite	Initial Value	Range for Testing^a	Value after Caliberation	Reference
SLA	Specific leaf area	m^2/kg dry mass	11	11-13,	12.97	Venancio et al., 2019; Rodríguez-Lópezet al., 2013
Wleaf	leaf width	m	0.09	0.09-0.2	0.174	Pangestika et al., 2021; Prastowo and Arimarsetiowati 2019; Ramadiana et al., 2018
DELM	Max leaf carbon demand	gC/ plant day	15	15-19	18.8	Vezy et al., 2020
kres	Maximum carbon proportion extracted from reserves mass per day	0-1	0.06	0.06-0.11	0.087	Cambou (2012)
F_buds1	Bud development stage 1	Degree day	720	720-840	725	Salazar et al., 2019
F_buds2	Bud development stage 2	Degree day	2562	2562-2690	2627	Salazar et al., 2019
a_bud	Parameter for bud initiation	Bud per day	0.009	0.009-0.012	0.0112	Cambou (2012)
F_Tffb	Time of first floral buds	Degree day	4500	4500-5500	5059	Salazar et al., 2019
a_p	Parameter for bud dormancy break	1	3	3-4.78	3.46	Salazar et al., 2019
b_p	Parameter for bud dormancy break	1	1.9	1.9-2.1	2	Salazar et al., 2019
Max_Bud_Break	Max number of nodes that can break dormancy daily	Buds/node	16	16-19	17	Salazar et al., 2019
F_over	Duration until fruit stage 5 overripe in the soil	Degree day	3404	3404-3600	3459	Salazar et al., 2019
u_log	Parameters for the logistic fruit growth pattern (Fruit Maturation/2)	Degree day	1480	1480-1600	1559	
FtS	Fruit to seed ratio	g/g	0.63	0.63-0.7	0.686	Wintgens (2004)

4. Results

4.1. Quantifying Model Performance

The model predictive capability was evaluated through statistical indicators as shown in Table 5. The evaluation demonstrated that model explains considerable proportion of variability in observed bean yield along with low error in several districts such as Dak Song, Krong Nang, Che Prong, Dak Glang and Krong Buk, where the R^2 value was above 0.4, except Dak Glang (R^2= 0.3) and most importantly nRMSE below 20%. In addition, these districts indicating high degree of model fitness and accuracy as reflected by D-index values, which ranges from 0.6-0.8.

This is followed by moderate model performance in districts Lagari, Lam Ha and Duc Trong. Even though model achieving satisfactory fit overall in these districts as shown by R^2 (Value 0.4 to 0.5) and high D-index (Value 0.5 to 0.6) but errors (RMSE = 29% to 35%) are relatively high. This suggests that while the model captures the general trend well, its performance at finer scales could be improved.

Table 5. The statistical indicator computed for each district during model training and validation. Districts 1-7 were used for model training, while districts 8-10 for validation.

S.No	Province	District	R2	d-index	nRMSE (%)
1	Dak Lak	Dak Song	0.5	0.8	8.7
2		Dak Glang	0.3	0.7	12.2
3	Gia Lai	Krong Nang	0.5	0.8	11.9
4		Lagari	0.4	0.6	35.6
5	Lam Dong	Dak Doa	0.1	0.5	19.2
6		Lam Ha	0.5	0.5	29.6
7		Duc Trong	0.5	0.5	31.6
8	Gia Lai	Bao Loc	0.2	0.5	19.0
9	Dak Lak	Chu Prong	0.4	0.7	17.8
10	Lam Dong	Krong Buk	0.5	0.6	20.9

4.2. Comparison of Predicted and Observed Bean Yield.

4.2.1. Correlation of Predicted and Observed Bean Yield

The correlation between simulated and observed bean yield is presented separately for each district in Figure 3, where the model was trained, and combined in Figure 5. Subsequently, model validation is demonstrated in Figure 4, while all results are presented together in Figure 6. The trend line indicates general moderate correlation across the districts; however, some districts show strong correlation in predicting referenced bean yield which included districts Krong Nang, Chu Prong, and Krong Buk.

The values scattered closest to the trendline in several districts show consistency in model predictions particularly in Dak Song, Lam Ha, and Duc Trong. This is followed by districts Dak Glang, Lagari, Dak Doa, Krong Buk and Ba Loc where model performance is moderate. Nevertheless, model failed to perfectly capture the observed yields in several district, resulting in outliers. These districts are Dak Doa, Krong Nang, Chu Prong, and Krong Buk, where high fluctuation exists in referenced yield.

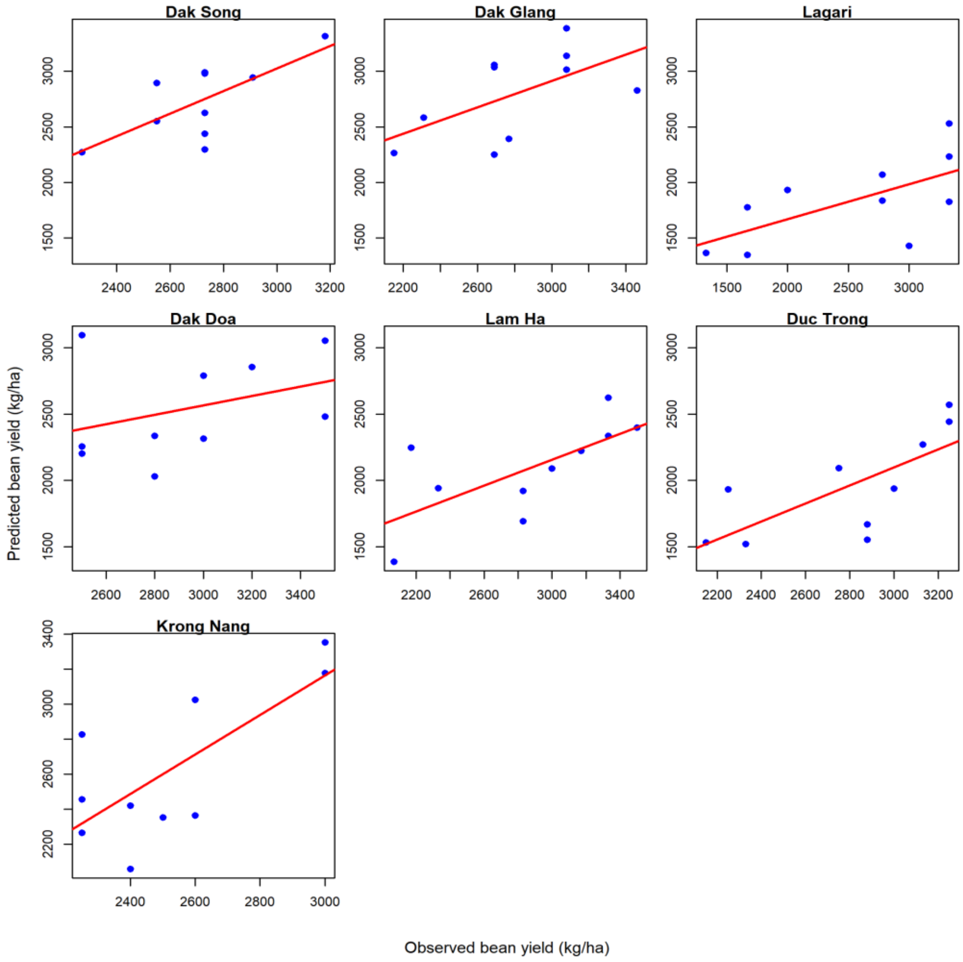

Figure 3. The co-relation between predicted and observed bean yield across districts used for training**.**

There is a general positive relationship between observed and predicted bean yields, as presented in Figures 5 and 6, for both training and validation districts. The model performance, in terms of capturing variability, is higher at the training districts compared to the validation districts, where the data is closer to the trendline.

These results highlight the model overall robustness with high predictive accuracy in most districts, while also identifying specific area where performance variability require further improvement.

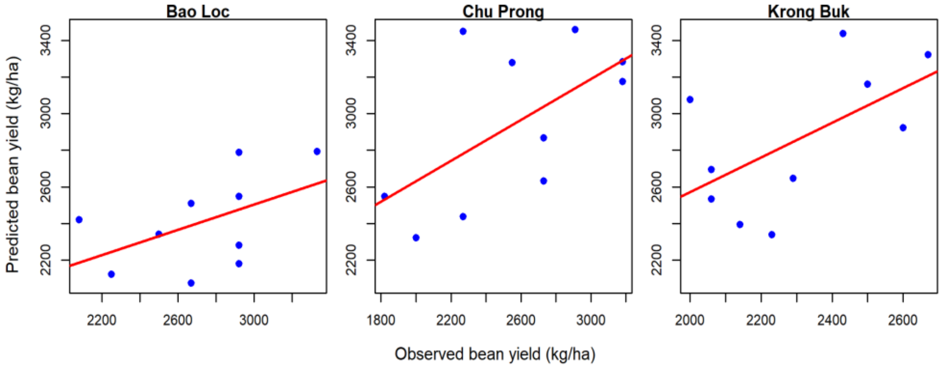

Figure 4. The scatter plot shows the relationship between predicted and observed Robusta coffee bean yield across districts used for validation.

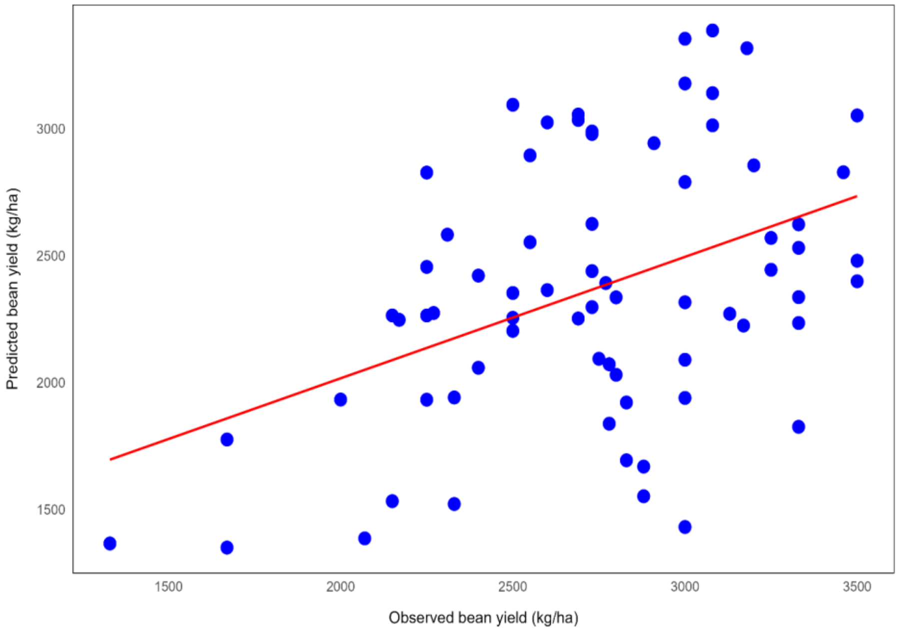

Figure 5. A combined plot for all districts used in model training

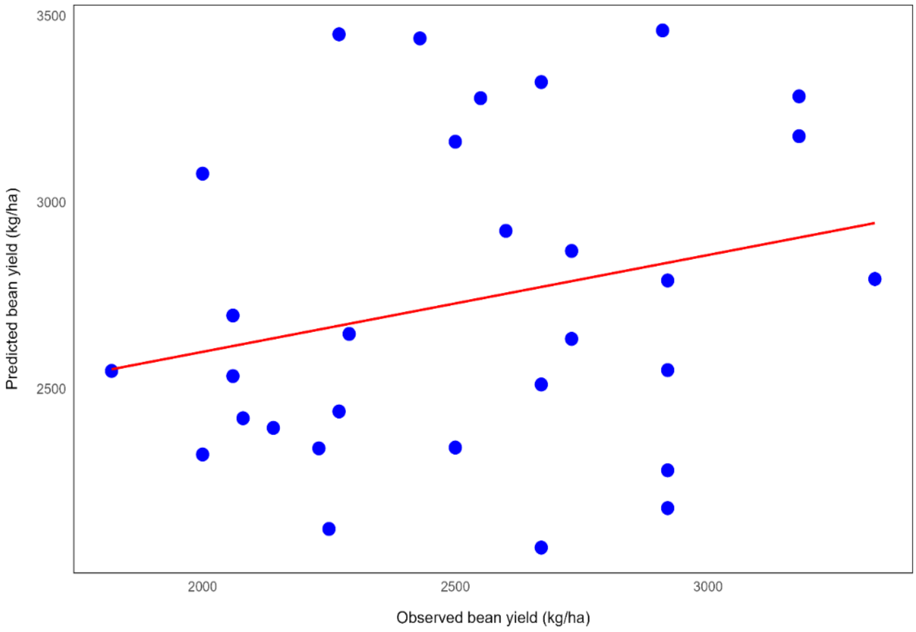

Figure 6. The validation districts are combined into a scatter plots.

4.2.2. Temporal Trends in Robusta Coffee Bean Yields

The coffee bean yield in training and validation districts is illustrated in Figure 7 and 8 with red line for predicted bean yield and blue for observed bean yield. The model was optimised on seven districts, enabling it to follow the key patterns of observed yield. The performance of model was validated at additional three districts.

The trend lines indicate most accurate bean yield predictions in Dak Song, Dak Doa, Dak Glang, and Krong Nang districts, followed by slightly inaccurate predictions in Chu prong and Krong Buk districts, during some years. Notably, the model successfully captured the extreme periods, closely aligning the lowest values in observed bean yield. For instance, in 2010 model prediction were closed to referenced yield in districts such as Dak Song, Krong Nang, and Dak Glang, where simulated values were 2270, 2250, 2150 kg/ha, respectively. In addition, the model performance was consistent in these districts, particularly when predicting high observed bean yield. In 2011, model bean yield was 3000, 3080, and 2727 kg/ha for Dak Doa, Dak Glang, and Chu prong, respectively.

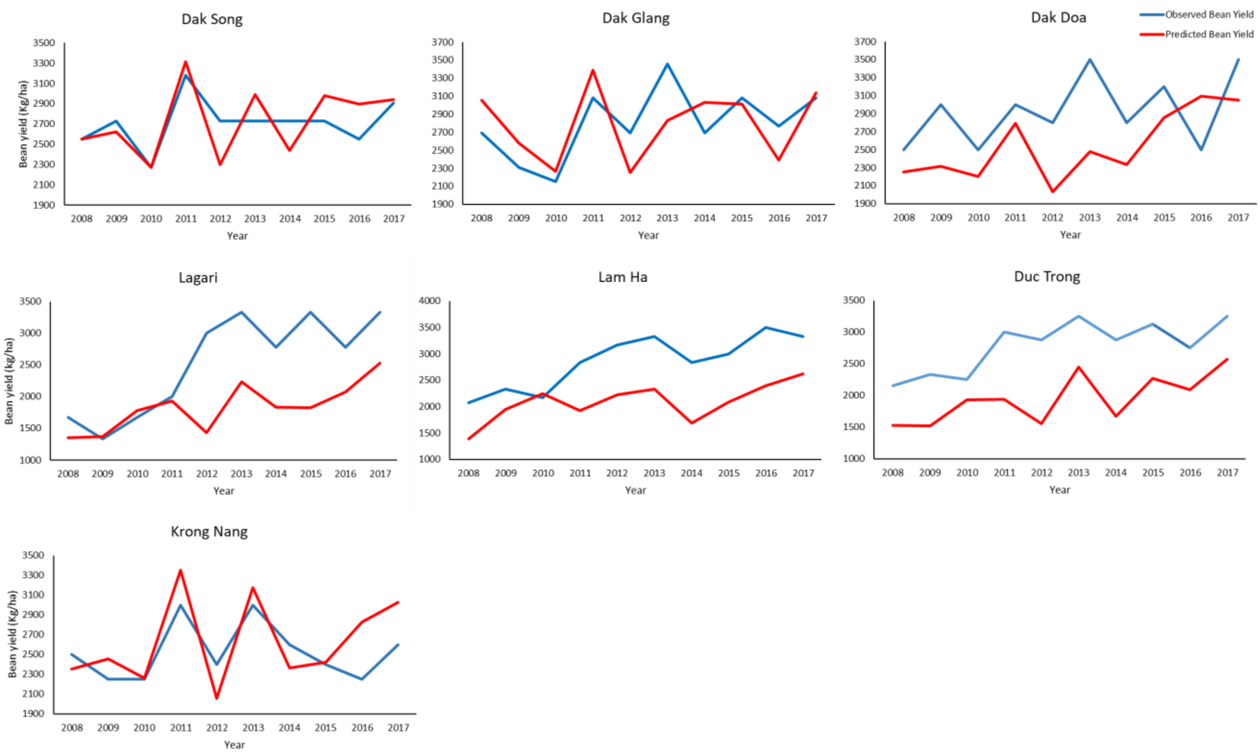

Figure 7. Trend in bean yield of the districts used for model training.

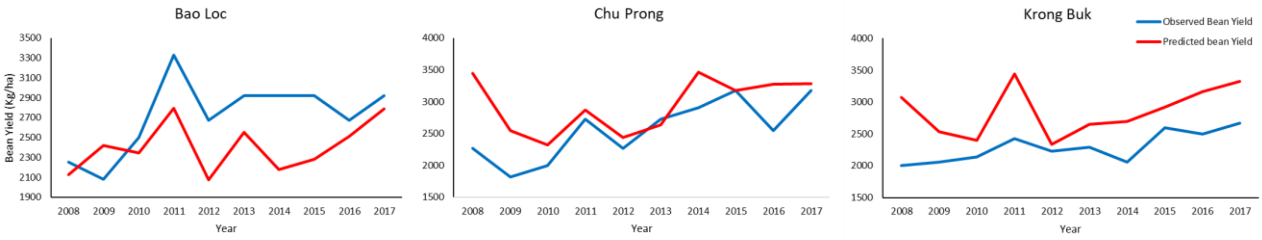

Figure 8. Bean yield comparison for model validation.

In contrast, the model underestimated the observed bean yield in a few districts, which include Lam Ha, Lagari, Duc Trong, and Bao Luc. Despite this, the fluctuations in predicted bean yield were approximately in the same range as shown by observed yield. Besides this, the model predicted observed bean yield quite accurately for many years. For example, in 2016 the district Lagari, Duc Trong, and Bao Luc, showed simulated bean yield of 2780, 2750, 2428 bean kg/ha, respectively, which were very close to observed bean yield.

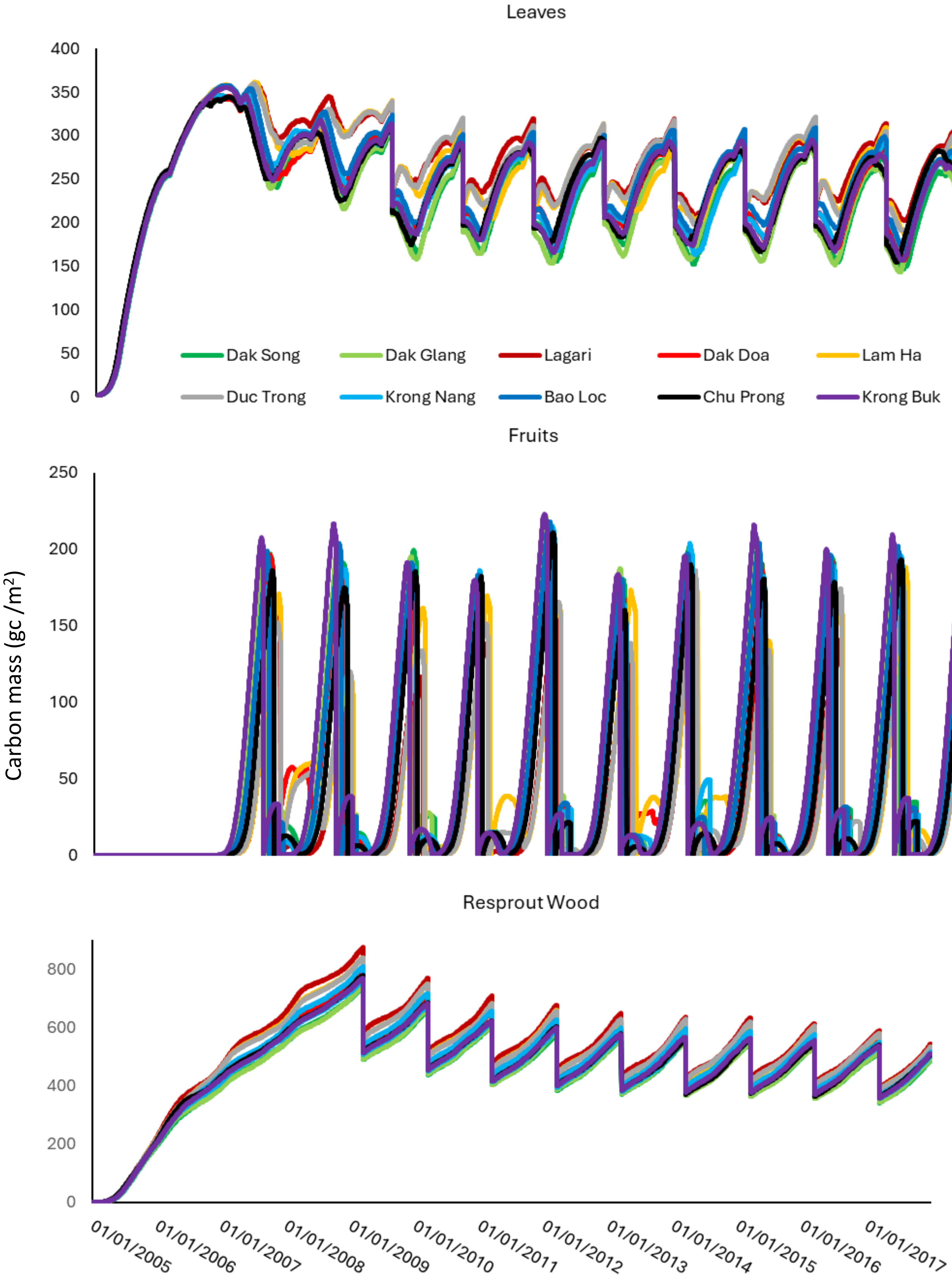

Figure 9a. Simulated carbon biomass in leaves, fruits and resprout word of coffee plant over full plantation cycle across the districts

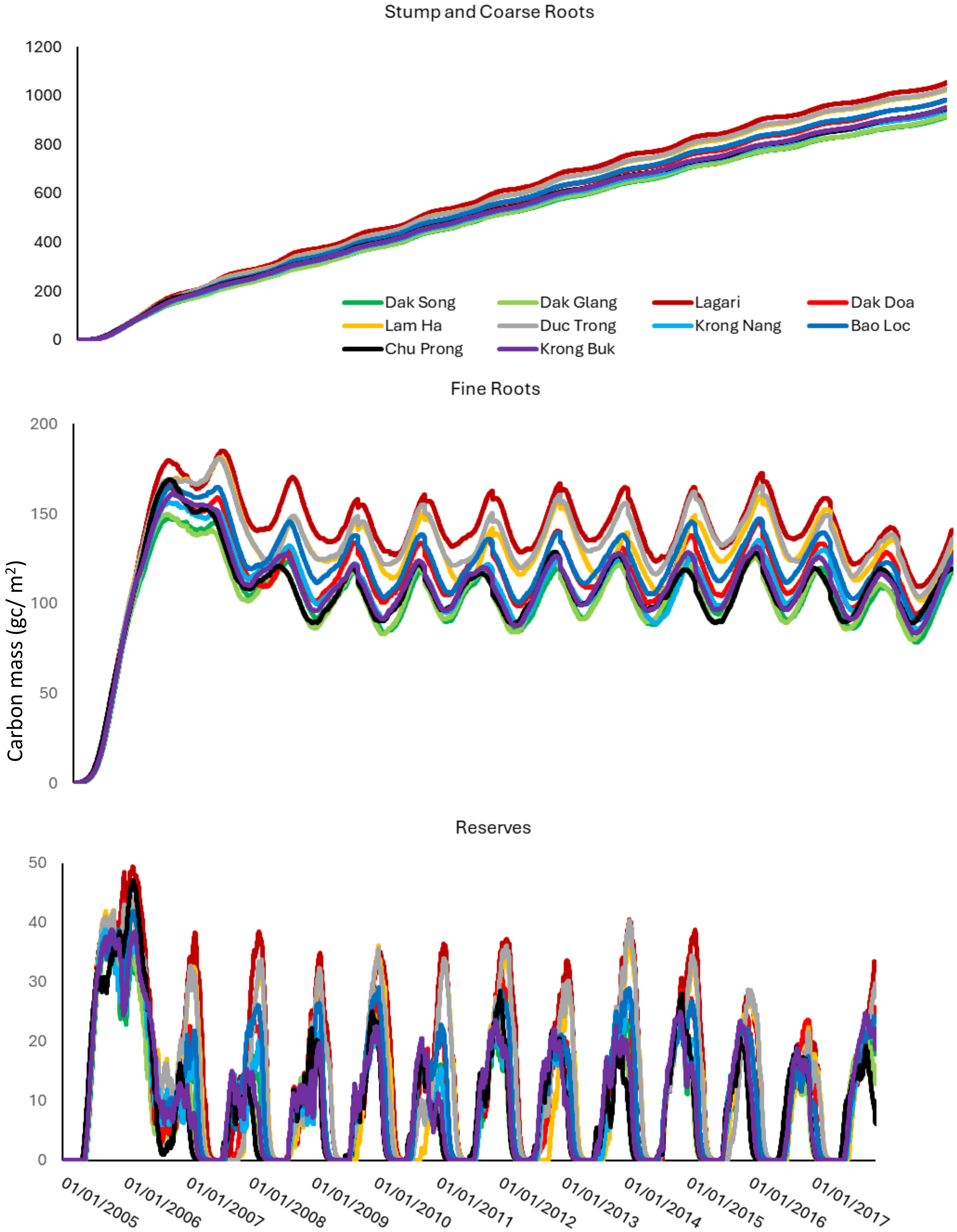

Figure 9b. Simulated carbon biomass in fine root, reserve and stump and coarse root of coffee plant over full plantation cycle across the districts

4.3. Growth and Yield

The model simulated carbon mass flux to various coffee plant organ during full growing cycle from 2005 to 2017 is plotted in Figure 9a and 9b. The carbon mass steadily increases in the leaves at beginning of vegetative phase. Maximum carbon mass was noticed in districts Lam Ha, where simulated value reached 361 gc/m^2 followed by Duc Trong and Lagari both with 357 gc/m^2. Similarly, model simulated LAI (Figure 10) retained similar trend likewise leaves, while reached its highest values (around 9.5 m^2/m^2) in 2007 in majority districts. Afterward, both were highly fluctuated till end of simulation due to plants pruning in March of each year. As result leaves carbon mass varied between 355 gc/m^2 to 281 gc/m^2 and LAI observed from 8.9 to 4 m^2/m^2. Districts such as Duc Trong, Krong Buk, Bao Loc and Lagari dominated in accumulating maximum carbon mass in leaves (above = 280 gc/m^2) and maintaining high LAI (above = 8 m^2/m^2). In comparison, lower carbon mass and smaller LAI was examined in districts such as Dak Glang, Dak Song, Chu Prong.

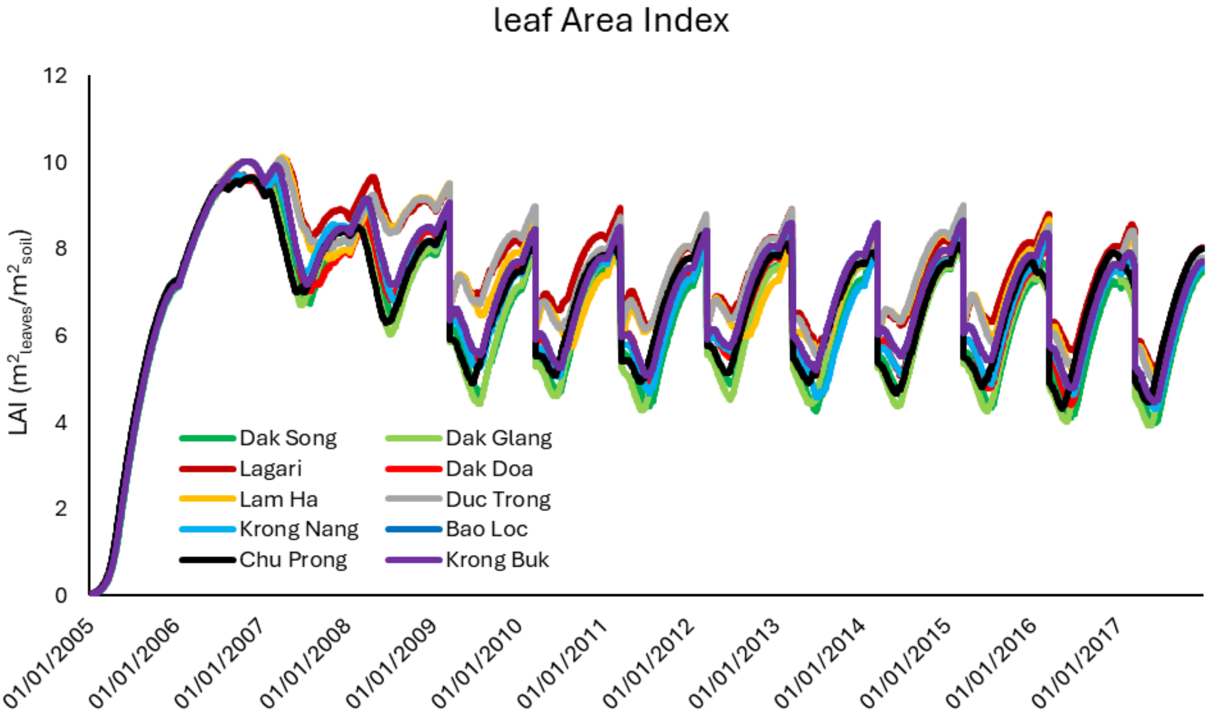

Figure 10. Simulated LAI of coffee plant in crop cycle across districts

Regarding carbon mass flow to fruit, it shows interesting trend, as the carbon mass was significantly varied in early year of plant bean yield. For instance, in 2008, it varied from 163 to 205 gc/m^2, but by 2017, the range was narrower as 187 to 201 gc/m^2. On the other hand, the model consistently simulated high carbon mass in fruit at Krong Buk, Krong Nang, and Dak Glang throughout the growing cycle (205 gC m^{-2} in 2008 and 201 gc/m^2 in 2017). Moreover, predicted bean yield in these districts showed reasonably high yield compared values compared to other district, even though model overestimate referenced bean yield at Krong Buk (Figure 6). Notably, the model performance was gradually improved over time with respect to distribution of carbon mass to the fruit cohort, especially in Duc Trong, Lam Ha, and Dak Doa. Meanwhile, model highly underestimate bean yield in these districts (Figure 5).

Much like the leaves, the branches grew rapidly, particularly during the first four years. The exponential growth was observed in Lagari district in 2009, where carbon mass (874 gc/m^2) in resprout wood compartment was higher than compared other districts. This is followed by Lam Ha and Duc Trong, which exhibits similar levels of carbon mass (840 gc/m^2). However, the branches growth was more steady compared to that of the leaves when plants were pruned, although the downward trend in growth was common across all districts during crop cycle. For instance, districts such Lagari, Duc Troung, Bao Loc and Kron Buk remained dominant after pruning accumulating over 700 gc/m^2 of carbon mass in resprout wood compartment in 2010. However, this value dropped below 550 gc/m^2 by 2017.

Stump and coarse root are perennial compartments, which grew progressively during the crop cycle due to their long lifespan and not subjected to pruning. The highest values were observed in Lagari, Lam Ha, and Duc Trong in 2017 (Over 1020 gc/m^2), whereas less growth was observed in Dak Song and Dak Glang (913 and 917 gc/m^2). The fine root compartment showed a similar trend to leaves. The fluctuation was a combined effect of natural mortality and pruning, although carbon mass levels remained stable from year to year.

Regarding reserved carbon mass in plant was significantly fluctuated during reproductive stage. The model directed maximum carbon flux toward fruit development. Therefore, maximum reserved was accumulated during the early vegetative stage across all districts, as result it was all time high, specially in 2006 (Over 30 gc/m^2). Later, during fruit development phase, the reserves were significantly declined in most districts. Most importantly, a few districts, including Lagari, Duc Trong, and Lam Ha, were consistently accumulated the highest reserves after fruit harvest (30 to 40 gc/m^2). Nonetheless, the range of reserve values became 15 to 30 gc/m^2 across all districts in later simulations.

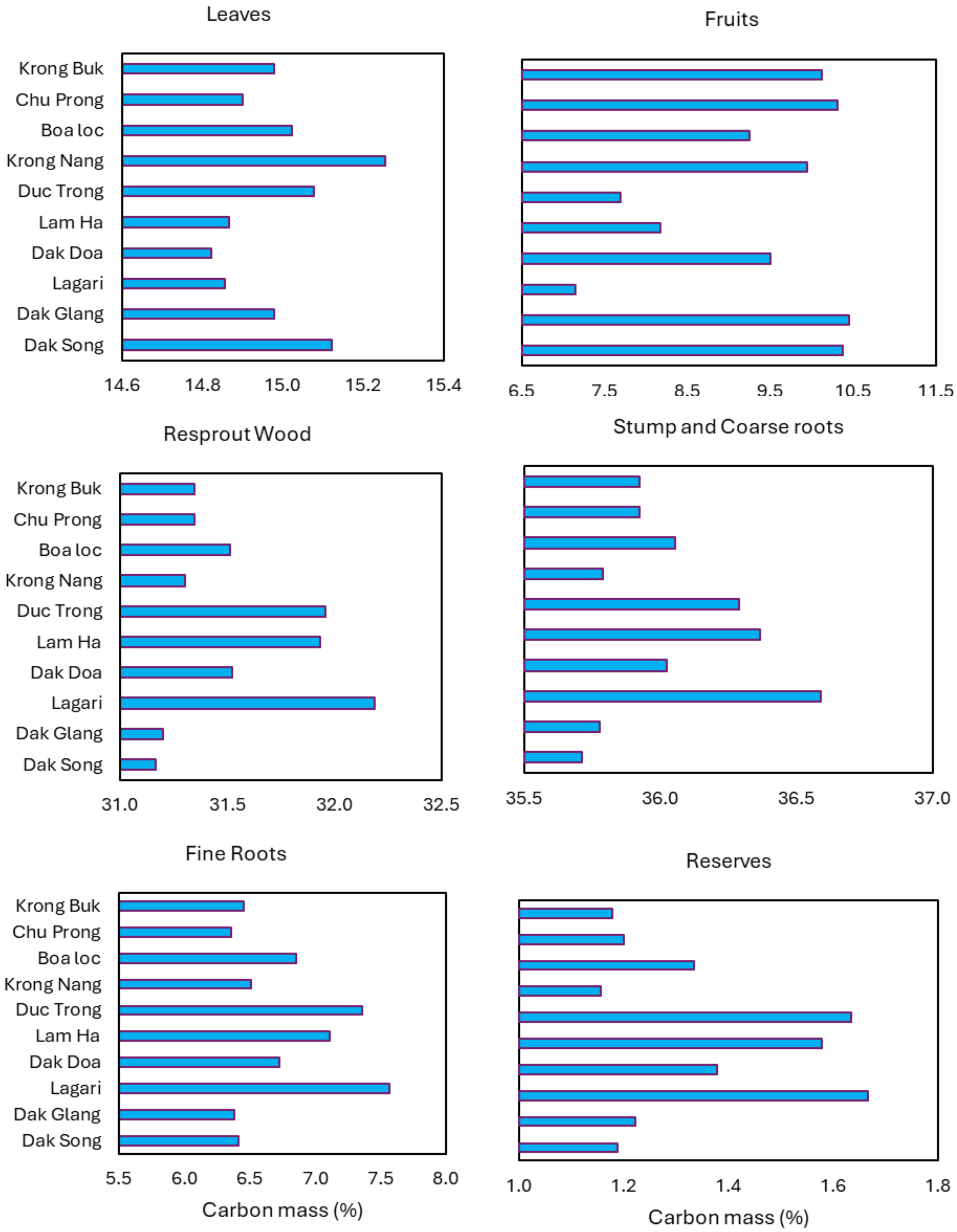

Figure 11. Simulated carbon mass to different segments of robusta coffee plant in ten districts.

4.4. Distribution of Carbon Mass in the Coffee plant

The carbon mass accumulated in each plant organ was calculated, while initial five years were excluded form calculation (Figure 11). The simulated carbon mass was considerably varied across all districts, particularly maximum variability was exhibited by fruit compartment which ranged from 7.1% to 10.4%. Furthermore, several districts exhibited over 10% of carbon mass in fruit compartment, except Lagari, Duc Trong and Lam Ha, where it was below 8%. Notably, carbon mass to other pant parts were high in these districts compared to other. Beside this, model significantly underestimate the observed yield in these districts (Figure 6). With over 10% flow to fruit, the model performance was satisfactory in most of the districts such as Dak Song, Dak Glang, Krong Buk, Krong Nang and Chu Prong as evaluated by statistical indicator (Tabel 4) and comparison between predicted and observed bean yield (Figure 6).

4.5. Bean Maturity

The bean maturity is key characteristic of Robusta coffee species which is highly varied across the districts (Figure 12). Climate variables such as temperature and rainfall influence the bean maturity. For instance, low temperature and less rainfall (as shown in complementary material figure and figure) at Lam ha, Lagri, and Dak Glang slow the process of bean ripening. This is particularly evident during period from 2008 to 2015, when duration of bean maturity varied between 253 to 283 days due to considerable fluctuation. Similarly, model simulated demonstrated interesting trend in bean maturity after 2013, where period shortened over the time and variability among districts decreased (range from 240 to 220 days). This is due to sharp

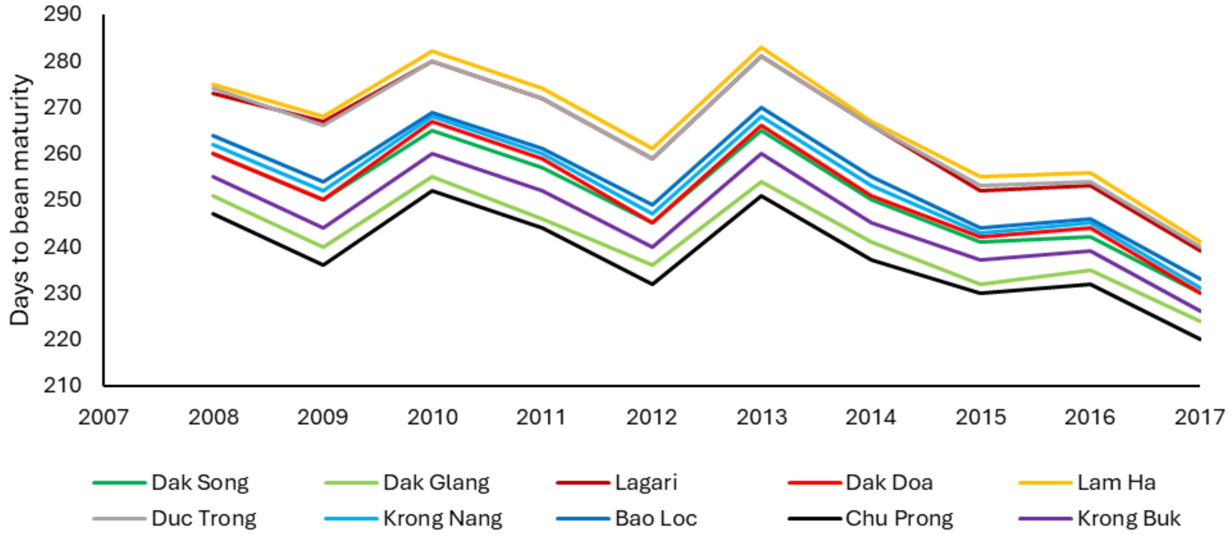

Figure 12. Bean maturity pattern across districts

increase in temperature that period while rainfall remained consistent except for 2014 and 2015, which accelerated the breaking of bean dormancy and flow of biomass to bean compartment. Additionally, in 2016 slight increase in day to maturity was due to increase in rainfall.

4.6. Residual Distribution for Model Assessment

Residual plot provides detailed visual evaluation, complementing the statistical metrics and confirming the overall performance of model (Figure 13). The residual plot demonstrates the distribution of prediction error for all districts across the productivity gradient. The residuals generally scatter around zero suggesting no strong systematic bias. However, there are large residuals which correspond to higher nRMSE values. For instance, high prediction error is observed in districts such as Lagari, Lam Ha and Duc Trong. Additionally, the pattern in data exhibits downward trend as predicted values increases suggesting underestimation for larger values and overestimation for smaller values.

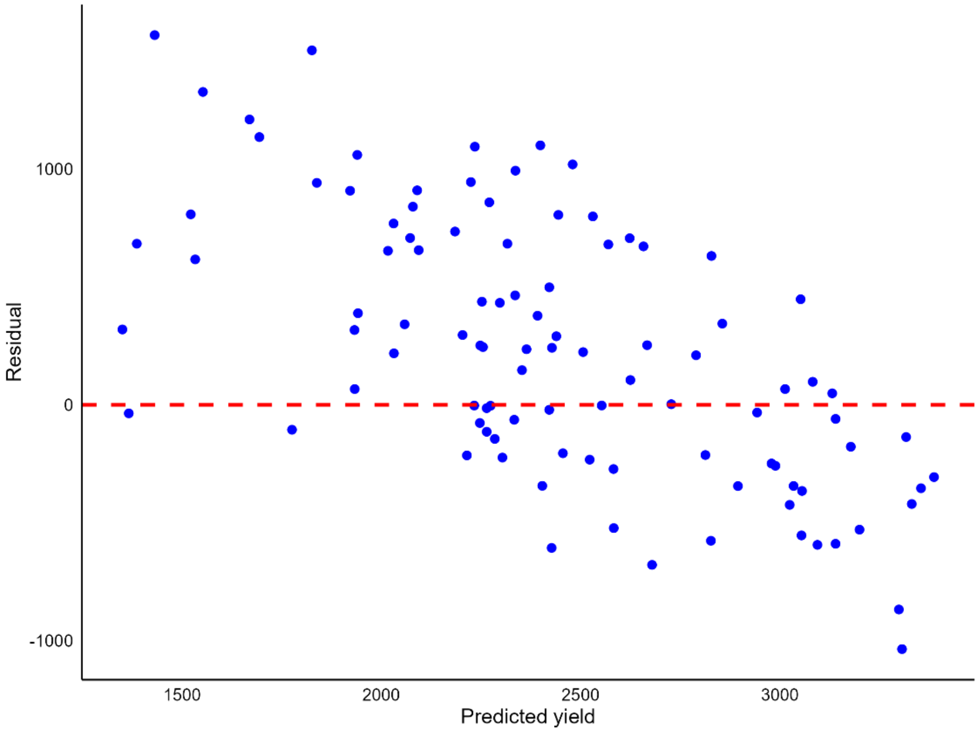

Figure 13. The visual presentation of residual distribution.

5. Discussion

Coffee agroecosystem has been extensively assessed in the context of climate change, with information systematically compiled through literature review. The literature focused almost exclusively on Arabica coffee, whereas only 5% of studies addressed the Robusta coffee. Most of studies investigating climate suitability and coffee productivity with relatively limited attention was given to climate adaptation strategies. Notably, significant decline in suitable climate is expected by 2050 for both species. Therefore, exploring climate adaptation options were suggested in literature. Few articles focused on Arabica farming system, while considering water management, and tree shading. But literature lack information about Robusta coffee considering climate adaptation especially Robusta farming under trees shading (Faraz et al., 2023). For this purpose, DynACof model has been selected to fill this knowledge gap, which is an agroforest model.

Vietnam is selected as study area because of its suitable climate for Robusta coffee cultivation. The country has high annual rainfall (1,800–2,500 mm) and average temperature (rang from 20°C to 27°C) which are optimal for Robusta coffee growth and evelopment (Dinh et al., 2022; Nguyen and Baker, 2003). Most importantly, Vietnam is world largest producer of Robusta coffee, with approximately 40% contributing to global coffee market (ICO, 2021). The combination of favorable agro-climatic conditions, established coffee-growing infrastructure, which makes Vietnam an ideal location for studying the factors influencing Robusta coffee productivity and sustainability (Tran et al., 2015).

DynACof model simulates coffee growth and development on a daily scale, incorporating two vegetative layers (shade trees and coffee plants) and three soil layers, along with management options (monoculture and agroforestry system). It is particularly useful for agroforestry system fluxes, as it integrates with the MAESPA model, which describes forest ecosystems at the voxel scale. Furthermore, it manages individual plants of different tree species, considering their physical and physiological parameters along with the overall structure at the plot scale. The model computes energy, water interception, and carbon fluxes of forest plants and soil based on canopy heterogeneity (Charbonnier et al., 2013; Vezy et al., 2018). Additionally, the MAESPA model is used to simulate metamodels for transpiration, plant sensible heat flux, diffuse and direct shade light extinction coefficients, and the light use efficiency of both shade trees and coffee plants (Vezy et al., 2020).

Robusta coffee agrosystem has been successfully simulated by DynACof model under full sun after adjusting their parameters. Most of the adjustment in model were related to degree days for flowering, dormancy and bean maturity stages. Coffee full sun system was selected due to lack of information about Robusta coffee in agroforestry system. The statistical indicators were applied to evaluate the model performance based on observed bean yield. The model successfully reproduced the observed bean yield with high efficiency, accurately following the trend over time. Previous research has shown that phenological stages are important indicator of coffee productivity, especially the flowering and dormancy stages (Nogueira et al., 2018).

Based on statistical indicators, seven districts had values within acceptable ranges, with nRMSE ranging from 8.7% to 20.9% and R^2 between 0.4 and 0.5. Regarding the d-index, four districts fall within the range of 0.7 to 0.8. Previous research on Robusta coffee in Vietnam utilized both crop and statistical models, which performed comparably to the DynACof model (Dinh et al., 2022; Kouadio et al., 2021). Nonetheless, Robusta coffee yield was predicted based on different combination biophysiological variables (Leaf Area Index, normalized difference vegetation index, fraction of absorbed photosynthetically active radiation (FAPAR) with the help of multiple regression models. Although, these models resulted with low error (REMS below 10%) and explained high proportion variability (R^2 above 0.70) in referenced bean yield, this performance might be attributed to fact that analysis focused on single province (Dak Lak), where the reference yield did not fluctuate significantly (Thao et al., 2022).

Moreover, the model demonstrated an issue with biomass distribution, particularly at low coffee density region. This was addressed by adjusting the leaf carbon demand while maintaining an adequate supply within the coffee plant. The carbon mass measured in each part of plant was varied between districts as leaves (14.8% to 15.3%), fruits (7.1% to 10.4%), resprout wood (31.2 to 32.2%), stump and coarse roots (35.7% to 36.6%), fine root (6.4% to 36.6%) and reserve (1.2 to 1.7) (Figure 11). These findings are supported by studies from Prezotti et al. (2013) and Bragança et al. (2010), who examined the dry matter distribution in different parts of the Conilon coffee plant, reported values were 17–19% in the leaf, 8–12% in the fruit, and 75–73% in the root and stem combined. Furthermore, the carbon mass flux to resprout wood throughout the simulations noticed a downward trend (Figure 9a). A similar trend was observed during initial ten years in previous version of DynACof model developed for Coffee arabica (Vezy et al., 2020).

The model efficiently simulated the coffee agrosystem in majority of districts including Dak Song, Krong Nang, Dak Glang and Krong Buk, Dak Glang. Where simulated carbon mass distribution was properly balanced between vegetative and reproductive stages (Figure 11). Consequently, fruit development took place in 240 to 264 days in 2008, but early maturity observed in 2017 decreasing it by 14 to 31 days (Figure 12). Early maturity might be due increased temperature over time and particularly the sharp decrease in days between 2013 to 2016 was due to less rainfall in that duration (Temperature and rainfall data is available in supplementary material section in figure 14). In addition to this, referenced yield data were highly fluctuated from year to year, meanwhile model preformed reasonably well to predict the reference yield with ranges between 2100 kg/ha to 3500 kg/ha. These climate conditions are in line with the finding of Campuzano-Duque et al. (2021) and Ghosh et al. (2014). Similarly, the bean maturation duration for Robusta coffee in Vietnam has been documented as minimum 270 days (Dinh et al., 2022). Moreover, bean yield observed in Vietnam and Indonesia ranges from 2,500 to 3,000 kg/ha (Byrareddy et al., 2019).

Che Prong was only district with extreme climate conditions; however, model performance was satisfactory in relation to the assessment by statistical indicators. Where, high temperature produced early maturity of bean and rainfall accelerated the biomass production, as results model maintain balanced biomass distribution to develop fruits and vegetative growth such as leaf area index (LAI) (Figure 10). Temperature and rainfall play a critical role in the phenological development of coffee plants. For instance, Teixeira et al. (2013) found that under higher temperatures, C. arabica tends to mature earlier, while rainfall trigger the coffee bean.

Similarly, climate condition in Lam Ha, Duc Trong, and Lagari was not fully suitable for Robusta coffee. For instance, temperature and rainfall were in acceptable range for Robusta coffee growth and development, (Available in supplementary material section Figure 14). Thus, model allocated maximum carbon mass for vegetative growth which resulted in bigger coffee plant canopy was observed compared to other districts as demonstrated by high LAI (Figure 10). Even though, the bean took longer to mature but low carbon mass supply to fruit cohort resulted in underestimating the referenced bean yield (Figure 11 and Figure 7). This is in line with finding obtained in Uganda, where optimal temperature for Robusta coffee is between 23 to 27 °C (Lwiza and Barkley, 2025). The annual rainfall is between 2000 to 3000 mm/year (Campuzano-Duque et al 2012).

Finally, residual plot analysis clearly indicates that the acceptable range for the model to predict bean yield is between 2,200 and 2,700 kg/ha. These results were observed in Dak Song, Dak Glang, Krong Buk, and Chu Prong districts, where the model perfectly captured the trend in observed yield with low error (nRMSE = 8.7% to 20.9%), a high correlation coefficient ($R^2 = 0.5$), and prediction accuracy (d-index = 0.6 to 0.8). Despite this bean, maturity and biomass distribution was according to values reported in literature. Additionally, climate condition in these districts were highly suitable for Robusta coffee growth and development. This verifies the model application for Robusta coffee species.

6. Conclusion

DynACof is an agroforest model with two vegetative layers and three soil layers. This was developed to simulate coffee growth under various management option (monoculture system or agroforestry system). High intra-plot variability exists in DynACof model which give priority over other available coffee models. In current study, it was modified for Robusta coffee with primary focus on adjusting parameters related to the reproductive stage. The model successfully predicted observed bean yield, biomass distribution, and phenological development. The dataset used for model training and validation was based on coffee crops grown in an open-sun system, due to limited available information on agroforestry systems.

The model performance varied with climate conditions across the districts; however, satisfactory results were obtained in most of them. Statistical indicators such as R^2, the D-index, and nRMSE were applied to evaluate model performance based on referenced bean yield. Seven out of ten districts outperformed (nRMSE below 21%), six districts had an R^2 of 0.5, and the minimum D-index across all districts was 0.5. Additionally, biomass distribution in the coffee plant, plant canopy structure, bean maturity, and bean yield were referenced from the literature. Overall model performance by scatter plot for combined training and validation districts demonstrated a positive relationship, though greater scatter was observed in the validation data compared to the training data. Nevertheless, downward trend in residual plot suggested that model has capacity for further improvement to obtained more precise outputs.

DynACof model provide extensive information about coffee agrosystem which included phenological and physiological behaviour. While together with tree model it could be useful tool to explore many aspects related to agroforestry system such as coffee productivity, tree shading and carbon sequestration. Additionally, exploring different levels of shading may improve the resilience of the Robusta coffee under climate change scenarios. Furthermore, the model can be extended by adding new modules to investigate other important aspects such as pests, nutrient cycles, and soil organic matter.

Similarly, model implementation in R and Julia facilitates the collaboration and enhance accessibility. This dual implementation improves the model flexibility and computational efficiency, making it a robust framework for analysing agroforestry practices.

7. Supplementary Material

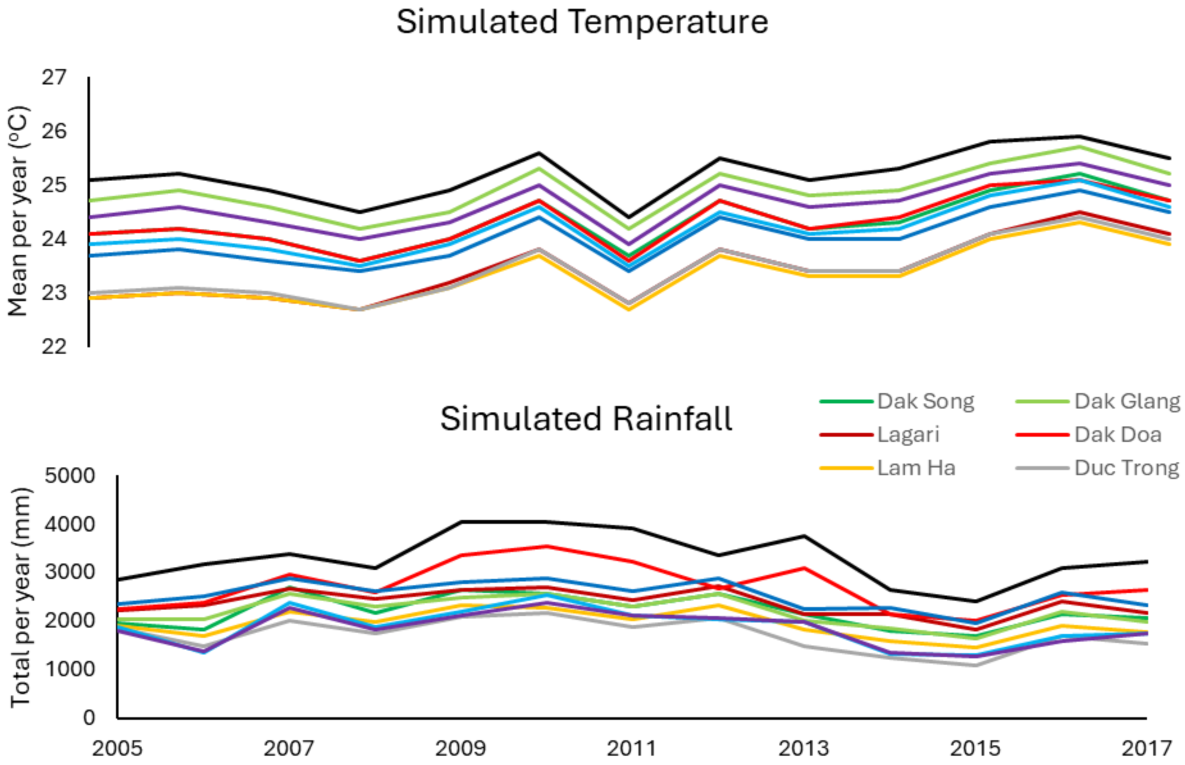

Figure 14. Temperature and rainfall across districts during coffee growth and development.

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Chapter 3

General Conclusion

Arabica Coffee and Robusta Coffee

Coffee primarily comes from two species: Arabica and Robusta, which together account for approximately 90% of global coffee production (Davis and Rakotonasolo, 2021). Arabica coffee has a complex flavour profile with low caffeine content, making it smoother and less bitter (Sunarharum et al., 2014). Its best quality is produced at high altitudes in cooler climates, such as in Brazil, Ethiopia, and Colombia (Damatta et al., 2018). However, Arabica coffee plants are delicate and susceptible to diseases like coffee rust. In contrast, Robusta coffee has an intense flavour and contains twice the caffeine of Arabica. It is more resilient and can be cultivated at lower altitudes. Its suitable growing regions include Vietnam, Indonesia, and parts of Africa (Hameed et al., 2020). Vietnam's Central Highlands offer an ideal climate and soil for Robusta coffee, contributing 40% of the global market supply (D'haeze et al., 2005).

Modelling Tools Applied in Coffee Agrosystem

Several modelling tools have been applied in coffee agroecosystems to evaluate the effects of climate change. The literature shows that climate suitability has been extensively assessed for both species, mostly using the MaxEnt model, which predicts species distribution based on climate variables (Bradie and Leung, 2017). Moreover, studies investigating the effects of climate change on coffee production are more prevalent compared to those focusing on pests and diseases in coffee agroecosystems. Regression models have been trained to predict coffee bean yield under different climate change scenarios, as well as to scale and distribute disease incidence. Most pest distribution models are based on temperature, with the ILCYM model producing reliable results (Faraz et al., 2023).

Despite the impacts of climate change, adaptation strategies have been proposed with the help of crop models. These models aim to mitigate negative effects by focusing on the water requirements of coffee plants, nutrient management, and growing coffee under shade systems. Furthermore, an ensemble modelling approach has been adopted to improve prediction accuracy (Seni and Elder, 2010). In coffee agroecosystems, machine learning models such as MaxEnt, Random Forest, Multivariate Adaptive Regression Spline (MARS), and

Generalized Additive Models (GAM) are frequently combined to enhance accuracy, reduce overfitting, and improve robustness (Zuza, 2023).

Classification of Model

Models were further studied based on the mathematical equations and processes used to assess the effects of climate change or climate adaptation. This classification identified three main categories of models: species distribution models, crop models, and regression models. Species distribution models confirm the suitable niche for a species and predict its distribution while considering climate variables (Faraz et al., 2023). Crop models link climate variables, soil parameters, crop characteristics, and management practices to simulate crop growth and development. Management options in these models are frequently applied to adapt to climate variability (Hansen and Jones, 2000). Additionally, crop models require extensive work for training and validation specific to each crop species (Pasley et al., 2023).

Regression models operate using regression equations to establish relationships between climate variables and crop outcomes. They are useful for detecting general trends in data (Shi et al., 2013). Whereas ensembled modelled approaches has been adopted to put together multiple models, which eventually enhance the performance of individual model. The result obtained by ensembled models are mush more precise and correct compared individual model.

Model Integrated with IPCC Scenarios

The IPCC climate change scenarios are projections of future climate conditions based on different levels of greenhouse gas emissions and socio-economic developments. These scenarios are modelled using climate systems to understand potential temperature rises, sea level changes, and extreme weather events. The RCP pathways have been frequently applied in coffee agroecosystems. RCP focus on greenhouse gas concentration levels, ranging from RCP2.6 (low emissions) to RCP8.5 (high emissions) (Aslam et al., 2024; Riahi et al 2011). In the case of the DynACof model, IPCC scenarios can be used to understand the effects of different levels of tree shading under various climate conditions, considering climate variables such as temperature and rainfall. Moreover, the Shared Socioeconomic Pathways (SSPs) provide more comprehensive insights by incorporating socio-economic variables.

Climate Change Impact on Coffee Crop

Coffee crops are negatively affected by climate variables such as increasing temperatures and decreasing rainfall. These changes create uncertainty in climate conditions at high altitudes, particularly for Arabica coffee, where suitable growing conditions are declining. An increase of just 1°C in minimum temperature can reduce bean yield by approximately 350–460 kg ha^{-1} (Borgo et al., 2024; Cassamo et al., 2023).

Additionally, projections up to 2050 indicate that bean yield could decline by up to 60%, depending on the region as 30–60% in Kenya, 90% in Nicaragua, and 60% in southern Brazil (Lemma and Megersa, 2021; Bunn, 2015; Haggar et al 2011). However, in Nicaragua, the suitable climate for Arabica coffee is expected to shift 300 meters higher in altitude (Läderach et al., 2017). Moreover, rising temperatures will make coffee farming more susceptible to fungal and pest attacks, such as coffee rust and the coffee borer (Ogundeji et al 2019).

Knowledge Gap in the Current Literature

The coffee agroecosystem has been systematically assessed, and the information compiled in the form of a systematic review. This review focused on the effects of climate change on coffee farming systems. The existing literature has predominantly concentrated on Arabica coffee farming, whereas only about 5% of studies have discussed Robusta coffee farming. Additionally, IPCC scenarios have been applied for future climate analysis. However, most studies have emphasized climate suitability and coffee production, with relatively limited attention given to climate adaptation strategies (Faraz et al 2023).

Climate adaptation is important for coffee farming systems, and several models have been developed focusing on water management and tree shading (Garcia et al., 2021). More specifically, different shading trees at various levels have been associated with Arabica farming systems and various types of irrigation (Nguyen and Silva, 2022). Some studies have considered Arabica coffee in relation to water management practices; however, no model is currently available for simulating coffee cultivation under tree shading (Mendoza et al., 2023).

Therefore, it is important to conduct research on Robusta coffee farming systems in the context of climate change. This research could focus on nutrient management, water conservation practices, pest and disease control, and agroforestry systems.

DynACof Model Modification

The DynACof model, originally developed for Arabica coffee, provides detailed insights into coffee growth and development. To adapt the model for Robusta coffee, the focus was placed on key differences between the two species. Adjustments were made to agronomic characteristics, floral buds, bud initiation, dormancy, developmental stages, and bean maturity. Additionally, soil and site parameters were updated for each location.

Model training and validation were conducted across ten districts in Vietnam. The model successfully simulated each site with reliable predictions, particularly for bean yield. Its performance was assessed using statistical indicators, demonstrating satisfactory accuracy. Overall, this model serves as a valuable tool for studying Robusta coffee cultivation in both monoculture and agroforestry systems.

Further DynACof Model Development and Research Opportunities

The DynACof model provides comprehensive details on coffee crop growth and development. It uses metamodels to compute complex spatial effects, which are derived from the 3D process-based model. Additional metamodels can be integrated to enhance the model for a more precise and reliable approach. These could include nutrient management, as well as the effects of pests and diseases. Furthermore, Robusta coffee could be studied under various shading levels in both current and future conditions.

The IPCC scenarios are appropriate for future analysis, allowing comparisons between Robusta coffee grown in monoculture and agroforestry systems. Finally, climate change impact assessments could be cross-checked with socio-economic indicators to better understand climate risks and support adaptation recommendations.

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ACKNOWLEDGEMENT

We would like to sincerely acknowledge the Agro-Meteorology and Ecophysiology of Agriculture and Forestry Systems Group within the Agricultural Department of the University of Sassari for graciously providing the research facilities. We would also like to express our heartfelt gratitude to the University of Southern Queensland, Australia, for their invaluable assistance with the data for our research. Additionally, I am deeply grateful to the Agricultural Research and International Cooperation Organization (CIRAD), France, for offering me the internship opportunity.