Chapter

Modeling the Impacts of Climate Change on Cocoa

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Abstract

Understanding the future of cocoa production under climate change requires robust modeling approaches. This paper reviews the existing literature on cocoa suitability and impact assessment, focusing on both statistical and process-based models. While statistical models have been widely used to predict changes in cocoa-growing regions, process-based models offer a mechanistic understanding of crop-climate interactions. We highlight key findings from suitability studies and discuss the strengths and limitations of the very few process-based models such as JULES, CASEJ, and ALMANAC. To deepen this comparison, we offer an analysis replicating the approach of Asante et al. (2025) using ALMANAC, for the first time assessing whether and how results differ between process-based cocoa models. By synthesizing past research and conducting a targeted model comparison, this work aims to clarify gaps and future directions in cocoa-climate impact modeling. Our ALMANAC simulations produced plausible yield estimates without requiring post hoc scaling, compared to CASEJ, which heavily overestimated yields before applying yield gap adjustments. Both models predicted yield increases under climate change, but, in ALMANAC, only when including the CO_2 fertilization effect and improved management. The magnitude of the CO_2 effect also differed substantially between models. These findings underscore the need for further model development, long-term field validation, and careful interpretation of predictions that depend heavily on assumptions about CO_2 response, management intensity, or tree aging. We hope to see more attention and resources dedicated to developing process-based cocoa models to help narrow projection ranges and better understand future uncertainties.

Keywords: climate change, crop models, statistical, process-based, yields, CO_2

1. Introduction

Cocoa (*Theobroma cacao*) is one of the world's most commercially important crops and the primary raw material for global chocolate production. The crop is cultivated across the humid tropics by an estimated 5–6 million smallholder farmers [1]. Approximately 70% of global production originates from West Africa, with Côte d'Ivoire and Ghana accounting for over 60% in the 2020/2021 season [2]. Other major producing countries are Indonesia in Southeast Asia and Brazil in South America [3, 4]. For these countries, cocoa farming constitutes a key export commodity that generates foreign exchange revenue and supports national development [3].

The millions of smallholders along the value chain also rely on the crop for income and subsistence [1, 4–6].

Cocoa is extremely sensitive to climatic conditions, and shifts in climate pose a significant threat to sustainable production [5]. The crop thrives in regions with temperatures between 21°C and 32°C, high humidity, and annual rainfall amounts between 1200 mm and 2000 mm [3]. It prefers slightly acidic, well-drained loamy soils, rich in organic matter [4]. Yields are significantly impacted by dry spells, waterlogging, and extreme temperatures [6].

Historically, cocoa supply dynamics were dictated by colonial trade policies, shifting global market prices, and disparate structural agricultural policies. Current challenges farmers encounter include aging trees, inadequate infrastructure, fluctuating farm gate prices, limited access to extension services, land degradation, poor market access, and child labor [3, 7, 8]. Climate change further exacerbates the problems of cocoa production in several regions [5, 9–11].

In West Africa, where the bulk of cocoa is produced, a decline in rainfall in production areas during the second half of the twentieth century resulted in significant areas becoming unsuitable for cultivation [12]. The rapid climate deterioration has since seen some improvements during the last decade [12, 13]; however, climate projections indicate increasing temperatures and higher evapotranspiration rates, suggesting greater drought stress and declining climate suitability for cocoa in the region [5].

Beyond climate, cocoa productivity also depends on good agronomic practices such as proper spacing, mulching, pruning, pest and disease control, and controlled fertilization [3]. Pests like capsid insects and diseases such as *Phytophthora* black pod continue to pose serious risks to output and require constant monitoring and management [4, 14]. Most cocoa farms are managed using traditional practices passed down through generations. Ref. [15] noted that "most farmers are smallholders relying on traditional methods and customary knowledge," limiting the adoption of innovations such as integrated pest management, which is important for enhancing resilience [6].

2. Statistical and suitability models

In recent years, researchers have increasingly used statistical and suitability models to assess the effects of climate change on cocoa production and to identify potential future cocoa-growing zones worldwide [3]. These models include the Maximum Entropy Species Distribution Model (Maxent), Limiting Factor Analysis, Random Forest Classification, EcoCrop, and an ensemble species distribution model approach.

Ref. [5] used Maxent to model future climatic suitability for cocoa cultivation in Côte d'Ivoire and Ghana. Using downscaled data from 19 climate models under scenario SRES-A2 (business as usual), they found many lowland regions would become less suitable due to increased temperatures and evapotranspiration, while higher elevation areas could become more suitable. The authors recommended adaptation strategies such as developing drought-resistant cocoa varieties, shifting cocoa production to higher altitudes, and encouraging diversification. Maxent is a general-purpose, machine-learning approach that considers the interactions between climate variables that make one location suitable over another. It assumes that everywhere cocoa is grown today constitutes a suitable climate, and as long as a future climate matches a current zone it can be considered suitable. This, however, assumes that cocoa varieties and cropping systems do not vary widely. Despite its usefulness, the Maxent model has key limitations, which include reliance on presence-only data, its assumption of static species-climate relationships, and its failure to incorporate factors such as land-use change, socio-economic conditions, or farmer adaptation, which can lead to misclassification or overestimation of suitability zones [5].

Ref. [6] expanded this approach across the West African cocoa belt using Maxent and Limiting Factor Analysis and scenario RCP6.0 to identify climatic constraints, such as limited rainfall during the dry season and high maximum temperatures. The study results pointed to rising heat and water stress in the cocoa production area in the northern zones, noting that climatically suitable areas could also lose viability due to land degradation and deforestation. Based on the findings, the authors suggested integrated land-use planning as part of broader adaptation strategies. Like [5], this modeling study also retained the same limitations, especially its reliance on static ecological assumptions and the non-inclusion of socio-economic dynamics [6].

Taking a global perspective under the same climate scenario (RCP6.0), Ref. [3] used Random Forest classification to map current and future cocoa suitability. Trained on a comprehensive global dataset of cocoa-growing locations, their model showed a decline in highly suitable production zones and identified new potential areas. While Random Forest provided strong classification performance, the authors noted that it is data-intensive, has limited interpretability, and is sensitive to rainfall uncertainties across different climate models [3]. Furthermore, it still suffers from the assumption that current production areas are indicative of future suitability.

Ref. [4] utilize the crop suitability model, Ecocrop, to assess cocoa suitability in Nigeria under RCP8.5 near the end of the century (2070–2089). They find global warming leads to decreased highly suitable areas and increased marginal and unsuitable areas. However, Ecocrop is a very simple suitability model that only considers monthly average temperature and total precipitation, and they only use output from one climate model. In [16]—one of the first to compare multiple crop models and include soil in a distribution model, they use an ensemble approach selecting four species distribution models available from BiodiversityR. They use downscaled data from seven climate models under scenarios SSP1-2.6 and SSP5-8.5 and two 20-year time periods (2021–2040 and 2041–2060). By the 2050s under SSP5-8.5, there were many new suitable regions for cocoa in West Africa, particularly in Côte d'Ivoire and Nigeria with some losses in Cameroon and Ghana. However, they note that many of the new regions would contribute to deforestation if utilized. In agreement with [6], they found temperature seasonality to be more important than precipitation.

3. Process-based models

To date, there are very few studies that have employed process-based models to simulate cocoa yields [17]. Different from statistical or suitability models, process-based crop models replicate the processes within the plant producing a mechanistic representation of how inputs affect the crop, rather than relying on simplified, observed patterns of relation. This latter approach suffers from the inability to stay reasonable once conditions such as climate go outside the range of values in the historic data. It can also neglect interactions and feedbacks between relevant parameters, especially if highly non-linear.

Process-based models can also offer another invaluable parameter: management practices. Some, but not all, can specify realistic or hypothetical choices like fertilizer application, pesticides, planting dates, harvesting dates, pruning amounts and dates, irrigation, and more. They also allow for the adjustment of the plant parameters which can represent the effect of utilizing or creating different cultivars more resistant to biotic or abiotic stressors. As a tree crop, it is especially difficult to study the interactions of cocoa and its environment over multiple decades. As such many field and lab experiments are done on young trees [18–22] and not in the typical agroforestry setting. Process based models therefore offer a tool for simulating multidecadal changes and interactions when properly parameterized. These abilities allow us to test plausible reactions to the climate and discover what breeds could survive or what management adaptations would be necessary. When modeling future changes for cocoa, including these functionalities are essential for plausible results, since in reality we would not sit idly by, making no management changes, as yields worsen year after year.

Despite the importance of cocoa to global consumption and cocoa-farmer livelihoods, there have been few efforts to develop properly parameterized process-based models specifically for cocoa, especially compared to other crops [17]. As far as we can tell, only three general purpose models exist which can simulate cocoa, include relevant processes, and have been used to predict future changes: JULES [18], CASEJ [23], and ALMANAC [24]. While others exist and have been summarized in [17], they focus primarily on the effects of pests and disease, simulate highly specific agroforestry pairs not applicable to other regions, do not include enough input variables, or have not been used to predict future yields yet [16, 25–28].

In contrast to past suitability studies, these process-based cocoa models, which include the effect of CO_2 fertilization, predict stable and even increasing yields, highlighting the importance of developing and utilizing these kinds of models. However, a significant challenge of developing process-based models is adequate and accurate ground observations of yields at large scales to validate the models. The on-farm performance data [29] used in the parameterization of these models reported a wide range of annual yields, with average yields higher than the national average. Additionally, most of these studies only report yields for a couple of years. Therefore, a grain of salt is needed when interpreting how realistic the model output is given the observed yield estimates are somewhat incomplete to begin with.

3.1 Jules

The Joint UK Land Environment Simulator (JULES) model [30, 31] is the land model for the UK Met Office Hadley Centre earth system model, UKESM. It was used in [18] to simulate the change in cocoa tree net primary production (NPP) (as a proxy for yields). The model was run offline and forced with daily weather data (precipitation, mean temperature, diurnal temperature range, downwelling shortwave radiation, downwelling longwave radiation, specific humidity, surface pressure and wind speed) from the U.K. on Partnership for Advanced Computing in Europe (PRACE) Weather Resolving Simulations of Climate for Global Environmental Risk (UPSCALE) project runs with a resolution of 25 km [32]. They included five ensemble members for the present and 3 ensemble members for the future.

In order to study the impacts of climate change on cocoa, they developed a new plant functional type based on their own laboratory experiments. To quantify the effect of CO_2 on cocoa, they grew saplings in a greenhouse setting under ambient (400 ppm) and elevated (700 ppm) CO_2 conditions for about 5 months. They then adjusted their model to capture the observed photosynthesis and leaf level stomatal conductance rates and ran offline simulations under RCP8.5 scenario from years

2070–2100 with 935 ppm. The present day was represented by the years 1990–2012 with 343 ppm.

Strengths of the JULES model include its representation of light interception and competition within a multi-layer canopy [31]—important for a tree crop often grown in the shade of other trees—and its ability to run offline or coupled so land and atmosphere interactions can be determined. The model is also calibrated based directly on laboratory experiments, although the parametrization would be more robust if results had been based on multiple experiments from the literature and included mature trees. The parameters they derived from the greenhouse experiment were based on young seedlings, not even a full year old. The effect of CO_2 could be quite different on mature trees. One other major downside of this model is the output type. While the authors argue NPP is closely related to crop yield, this model cannot specifically provide yield and production estimates, which are more important to stakeholders.

Lastly, two shortcomings of their experiment design are their choice of RCP8.5 as the global warming scenario and the use of fixed CO_2 values. Utilizing constant CO_2 values for the present and future scenarios might affect tree growth in a significant way, depending on the model sensitivities, and therefore affect the results. Simulating cocoa under RCP8.5 scenario at the end of the century does not offer much practical insight, as RCP8.5 is a path we are no longer likely to go down [33] and the extreme CO_2, temperature, and precipitation will not be realized.

With the benefits and drawbacks of the model in mind, authors determined NPP would increase nearly universally in West Africa despite the increases in temperature. Their climate model simulated increases in maximum, minimum, and mean temperature of about 5°C over most of the region, with little heterogeneity and small increases in precipitation. They determined the CO_2 fertilization effect was able to offset the rising temperatures and variable rainfall through a series of idealized experiments in which one of four variables were altered: CO_2, temperature, precipitation, or humidity. They found that without the additional CO_2, the plants would have suffered from the high heat. However, their model showed the optimal temperature increased with CO_2, in agreement with many studies on other types of crops [34–38], allowing the plant to tolerate the higher temperatures. They also found that the increased rainfall, particularly during the dry season, could allow more regions in the north to become suitable for cocoa. These results challenge previous estimates from [5, 6], that predicted rising temperatures would dominate any changes in precipitation and lead to reduced suitability in the region. This study demonstrated the importance of including CO_2 effects which may be able to offset the harms caused by warming.

3.2 CASEJ

CASEJ is the latest version of the model SUCROS-cocoa, also known as CASE2, [39] and was used in Ref. [23] to predict future cocoa yields in West Africa. Wageningen University augmented the old version of the Fortran model by adding an R interface (RCASE2 [40]). The model was then updated to include CO_2 modulated photosynthesis [23]. SUCROS-cocoa, hereon referred to as CASE2, was parameterized based on literature in [41] to include about 85 parameters characterizing the crops morphology and physiology [39]. These parameters were based on greenhouse experiments, observations, and field experiments across different climate regimes, variety types and cropping systems. This was used to determine relationships between factors like tree age and size, available light and water, and average temperature to factors like biomass, photosynthetic rates, growth respiration, maintenance respiration, specific leaf area, root weights and lengths, leaf production and loss, and fruit development. In CASE2, fruits are produced every day and automatically harvested when ripe [39].

CASE2 captures many crop processes such as biomass production and allocation, photosynthesis, respiration, evapotranspiration, and light interception [39, 40] on a daily time step. It requires at least 8 years of daily or monthly minimum and maximum temperature, precipitation, solar radiation, and early morning vapor pressure [39] which can be approximated using minimum temperature [40]. If monthly or long-term weather is supplied, daily weather will be generated [39]. It also requires information about the soil thickness, number of layers and texture according to the Driessen soil type [42] to determine water content at saturation, field capacity, wilting point, and air-dry [23, 39]. It assumes the range of growing temperatures to be 10–40°C and minimum annual precipitation to be 1250 mm [23, 40]. There are limited management choices available in CASE2. Users can choose to implement shade or irrigation, but it cannot simulate nutrient limitations. The model also cannot simulate juvenile trees. Users select the tree age (3–40 years), the planting density (700–2500 kg/ha), and the shade level (0–3 shade tree leaf area index (SLAI)) [40]. Shade is applied uniformly as a leaf-only layer, based on the selected SLAI and an assumed light extinction coefficient of 0.6 [40]. This means shade trees do not compete for water or nutrients, only light, and the shade canopy does not photosynthesize or grow [39]. It serves only to block some of the incoming radiation.

When simulating water-limited (rainfed, non-limited nutrients, and no pests or disease) initially 4 yr. old cocoa trees at a planting density of 1000 trees/ha and 10% shade with 35 years of monthly weather data, [39] found yields in Tafo, Ghana could reach 5023 kg/ha, compared to 3500 kg/ha in an experimental field study [43]. Simulated leaf area and standing biomass were in general agreement with observed values, but biomass production, litter production, and bean yield were often higher than observed, especially in Ghana and Brazil. This could be due to the simplified and idealized nature of the model, but in Malaysia simulated yields match very closely. They suggest simulated values are reasonable for other countries and close enough to Ghana [39, 40]. They propose that the low radiation (compared to Malaysia) and recurrent water shortages during the dry season were the causes of the lower yields in Ghana. In their sensitivity analysis, in which 75 of the parameters were adjusted by ±10%, only 4–5 parameter alterations led to a change in yield of ≥5%, suggesting the model is robust to minor parameter choices.

Wageningen University further developed the model, naming it RCASE2, by adding an R wrapper to the original Fortran model, to facilitate future model development and automated simulations [40], and in [23] an important feature was added to CASE2: CO_2 fertilization. The previous version of the model based photosynthesis on light response curves only, so in order to predict yields in the future, [23] needed to add a dependency on CO_2. They updated the model, now CASEJ, to use the Farquhar–von Caemmerer–Berry (FvCB) biochemical model [44] to calculate photosynthesis rates, but do not including the CO_2 acclimation effect, which reduces the benefit of high CO_2 over time. Without experimental field experiments like free-air CO_2 concentration enrichment (FACE) studies on mature cocoa trees, they were unable to validate their CO_2 response function. However, they did ensure that parameters were updated to maintain similar yield calculations to the original configuration of the model.

CASE2 was the first physiological, process-based model for cocoa. It included a number of important plant processes and returned reasonable yields. However, given that yields in Ghana were too high by almost 1500 kg/ha with semi-realistic management, it draws into question the validity of the model, at least in Ghana [23, 40] do not try to validate the model further and simply explain this as a yield gap, suggesting farmers could obtain these yields with better practices. To reflect current yields and management in the region, [23] simply scale the model results by the calculated yield gap in [40]. Ref. [45] argue that CASE is too heavily parameterized to be applied elsewhere. While [39] used a wide range of available data that is not specific to a region or cultivar type, they do attest that most of the experimental data came from Malaysia, as opposed to Ghana or Brazil. This overestimation of yields in Ghana is likely due to (1) the low performance of farms in Ghana, (2) few experimental studies, (3) the model's assumption of no nutrient limitations or pests and disease, (4) the lack of pruning in the management routine, and (5) the model's assumption that the trees do not age. Aging plantations is a large contributor to low yields in Ghana, and a model that assumes maximum yields can be maintained over decades has to overestimate observed and experimental yields.

Given these strengths and limitations of the model in mind, [23] found cocoa yields in West Africa would increase under global warming. They downloaded daily minimum and maximum temperature, precipitation, and solar radiation data from 31 CMIP6 models and selected 5 models that consistently were average, warmer/cooler or wetter/drier than average in each of the four countries considered (Côte d'Ivoire, Ghana, Nigeria, and Cameroon). They calculated the median average temperature and precipitation changes for 19 of the models and then categorized the 5 selected models as Warm/Wet (INM-CM4-8), Hot/Wet (ACCESS-ESM1-5), Mid (GFDL_CM4_GR2), Warm/Dry (BCC-CSM2-MR), Hot/Dry (GISS-E2-1-G). They decided to use SSP5-8.5 as the background scenario but use the middle of the century (2030–2060) where they argue results can still be applicable as emission scenarios diverge mostly at the end of the century. They use monthly CO_2 data from [46] (historical) and [47] (future). They assume a planting density of 1000 trees/ha with 20% shade and trees that are initially 10 years old.

Expectedly, they found a range of precipitation changes, but all five models agreed in a reduction of the dry season duration. Temperature increases (~1–3°C) were fairly uniform with minimum temperature projected to increase more than the mean and maximum in most of the models. When including CO_2 effects, every model resulted in increased yields compared to their historical run with many new suitable areas and higher yields in Nigeria and Cameroon. However, the hot/dry model led to lost suitability in the north of Côte d'Ivoire and Ghana. Without the CO_2 effect, results were much more mixed by region and model. When analyzing the drivers of these changes, they found precipitation (particularly the improved dry season precipitation) was more important than temperature. Just like [18] they found that without the CO_2 effect, the impact of temperature became more negative. When scaling their results down according to the calculated yield gap (86%), total production in Côte d'Ivoire increased by 20 and 2%, with and without the CO_2 effect (**Figure 1**). In Ghana, production increased by 30% and 9%, respectively. Under the high-input scenario (improved management leading to a yield gap of 73%), production approximately doubled. Overall, they found that the increased CO_2 was able to ameliorate the impacts of a warming climate (increasing yields by ~15–21%).

3.3 Almanac

At the time of [17], only one true process-based cocoa model existed, SUCROS-cocoa. But, in Kiniry et al. [24], the Agricultural Land Management Alternative with

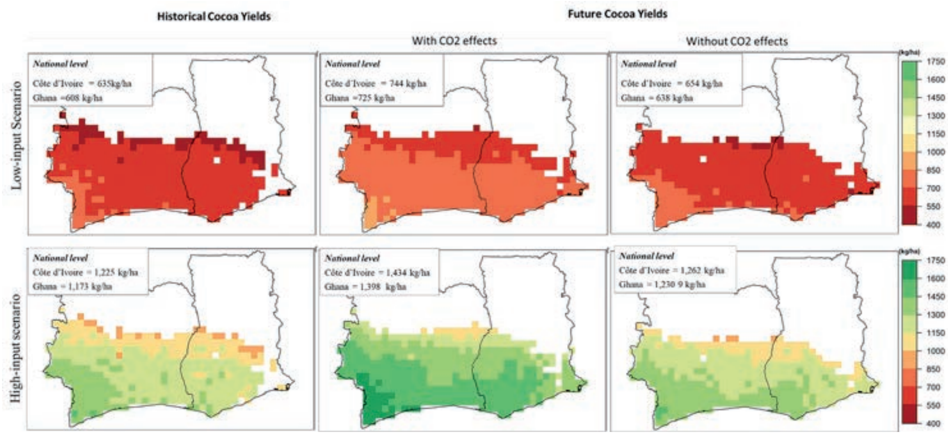

Figure 1.
Reproduced from Asante et al. [23] supplementary materials, ©2025 The Author(s), published by Elsevier B.V., licensed under CC BY 4.0. Maps of cocoa yields under present and future climate (SSP5-8.52030-2060) with yield gaps of 86% (low-input) and 73% (high-input).

Numerical Assessment Criteria (ALMANAC) model [48] was adapted to simulate tree crops. The idea was first proposed 16 years ago as a tool for simulating agroforestry in the tropics. While the model simulates diverse temperate deciduous and evergreen trees [49–54], the model was first applied tropical trees producing economically important seeds in this 2023 study. In that study, the model successfully simulated coffee (*Coffea* species) and cocoa (*Theobroma cacao*).

For cocoa, the physiological model SUCROS [39, 55] represents an important step in simulating the economically important tree crop. Once the various parameters for this complex model have been developed, it is a useful tool to show how various physiological processes interact to produce the seed yield. However, there is a need for a simpler, more easily applied daily timestep model with more accurate soil water balance and nutrient balance components that can be useful at any international site without needing extensive calibration at each site. ALMANAC was designed to fill this role, being complex enough to capture the major plant processes producing biomass and economic yield, but with simple enough parameters that it can be more easily applied.

The ALMANAC model is valuable for tropical trees because of its ability to simulate competition between plant species [48]. This becomes especially important for cocoa, as it is often grown in agroforestry conditions with companion trees much taller than cocoa trees. ALMANAC accurately simulates light competition and competition for water and nutrients among different plant species growing together.

ALMANAC model has been described numerous times [48] and is described at (https://www.ars.usda.gov/plains-area/temple-tx/grassland-soil-and-water-research-laboratory/docs/193226). It is a process-based, daily timestep simulation model that has been parameterized and validated for a wide range of tree species including lodgepole pine (*Pinus contorta* Douglas ex Loudon), white spruce (*Picea glauca* var. glauca), black spruce (*Picea mariana*), and trembling aspen (*Populus tremuloides* Michx.) [50]. ALMANAC uses readily available soils data in the U.S. and soils data for the country of Mexico and readily available daily temperature, solar, and rainfall data. Its use of international soil and weather data was described in [56]. The model simulates plant processes including light interception, dry matter production, and biomass partitioned into plant parts. Biomass is simulated with light interception and species-specific radiation use efficiency (RUE), which is the amount of dry biomass produced per unit of intercepted light [57]. The attributes useful for quantifying potential plant growth are RUE, LAI, and the light extinction coefficient (k) used to calculate the fraction of light intercepted by leaves. LAI has already been shown to be a promising indicator of tropical tree economic yield [58].

This plant growth model simulates crop development throughout the growing season by tracking key physiological processes. The model tracks plant development using growing degree days (GDD), which measure the accumulated heat that plants need to reach maturity. Plant development stages are determined by calculating how much of the total heat requirement has been met, with important events like flowering (anthesis) occurring at specific fractions of this heat accumulation for each plant species. Leaf area development follows an S-shaped growth pattern that captures the natural progression of slow initial growth, rapid mid-season expansion, and declining leaf production as plants shift from building leaves and stems to producing seeds.

The model simulates daily plant growth using radiation use efficiency, which measures how effectively plants convert sunlight into biomass. Each plant species has its own efficiency rating for turning intercepted sunlight into dry matter. The model then divides this growth between different plant parts - initially favoring root development early in the season, then shifting toward above-ground growth, and finally concentrating on seed production after flowering. The harvest index represents the final proportion of total plant weight that ends up as harvestable seeds.

Environmental stresses significantly impact plant performance in the model. Drought stress occurs when soil water cannot meet the plant's evapotranspiration demands, leading to reduced leaf expansion and slower growth. Nutrient stress from insufficient nitrogen or phosphorus is calculated by comparing the plant's optimal nutrient requirements at different growth stages with actual soil availability. Temperature stress affects plants when daily temperatures fall below their base temperature (causing cold stress) or exceed their optimal range (causing heat stress). The model applies whichever stress factor is most severe on any given day, with leaf growth typically being more sensitive to stress than overall biomass accumulation.

Two major strengths of ALMANAC are its ability to specify numerous management choices and its calculation of stress days. The stress day output offers a diagnostic tool for determining which abiotic stressors dominate and reduce yields. In 2023, [17] noted that none of the available cocoa models were able to alter and test management choices to aid in decision support. ALMANAC allows users to specify planting dates and densities, as well as the timing and amount of fertilizer, irrigation, tilling, pruning, harvesting, and more, allowing interested stakeholders to test different management practices virtually. However, two important weaknesses of the model are its use of fixed CO_2 values and its variability in yield. Ref. [24] showed that while ALMANAC captured the average yields well, it did not capture year to year variability.

4. Comparing CASEJ and ALMANAC

Since there are now two models that can simulate cocoa yield under climate change, we can now begin to add uncertainty and bounds on future projections. As such, we now offer a preliminary comparison of the two models based on results in [23, 40]. Due to structural model differences and a lack of access to the CASEJ model and data in time for this publication, we offer only a preliminary comparison and encourage a full-scale study to compare multiple sites and configurations.

4.1 Experiment design

In order to replicate the results of Ref. [23] we downloaded the same datasets, Global Meteorological Forcing Dataset (GMFD) for Land Surface Modeling [59] (1980–2010) for historical and NASA NEX-GDDP data [60] (2030–2060) for the future at the location 6.2°N, 2.33°W (as in Ref. [24]) (see **Figure 2**). However, due to differences in the model structures some alterations had to be made.

Firstly, ALMANAC and CASEJ require different inputs. Available outputs for GMFD and their warm/dry model, BCC-CSM2-MR, only include specific humidity and not relative humidity. While CASEJ utilizes specific humidity, ALMANAC requires relative humidity. For the historical data, we calculate relative humidity using the provided specific humidity, pressure, and temperature. We approximate daily average temperature by averaging maximum and minimum temperature. Unfortunately, without pressure data we could not utilize BCC-CSM2-MR in our comparison. CASEJ also appears to use monthly CO_2 while ALMANAC must use one constant value per simulation. We set CO_2 to 363 for the historical period and 563 ppm for the future.

Ref. [23] were able to select the age of the trees to simulate and how much shade to apply. ALMANAC, however, simulates crops from planting through their juvenile phase, unlike CASEJ, and requires taller trees to be planted to produce shade. Therefore, in order to match their choice of 10-year-old trees with 20% shade, we required 15 years of additional data (1965–1980; 2015–2030) to allow the cocoa trees to grow to 10 years and to plant shade trees 5 years before the cocoa, as done in [23].

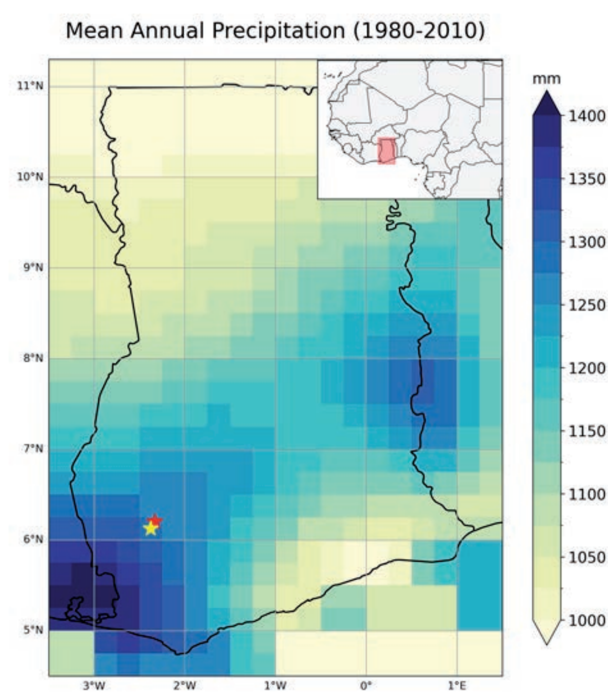

Figure 2.
Average total annual precipitation in Ghana derived from Global Meteorological Forcing Dataset for Land Surface Modeling data. The red star indicates the location of our simulation site. Yellow star indicates the closest cell to our test site. Comparisons to Asante et al. [23] refer to this cell.

We replicate Ref. [23]'s planting density of 1000 trees/ha for cocoa and use a planting density of 90 trees/ha for the shade trees to produce a potential leaf area index (DLAI) of 0.39 and a corresponding interception percentage of 17.8% according to Beer's Law (see [24]). This was the closest we could get to their choice of 20% shade and is still in line with observed shade percentages in mid to wet regions [61]. CASEJ does not have fine-tuned control over the management or its timing. ALMANAC, however, does require certain decisions to be made while other inputs can be automated. ALMANAC was originally parameterized for cocoa with a planting date of Oct 15 and, beginning 4 years later, annual pruning on Apr 15, with double harvests on June 15 and Sep 15. To agree with Figure 4 of [40], we alter the management schedule to the following:

Year 1: plant the shade trees on Mar 15

Year 5: plant the cocoa trees on Oct 15.

Year 8 onward: prune the cocoa trees on Mar 1, harvest on Apr 15 and Nov 1.

4.2 Results

When matching their management choices, ALMANAC simulated yields ranging from 782 to 1373 kg/ha during the historical time period (**Figure 3**). The lower yields were achieved with what [23] might characterize as low input. The harvest dates and planting density were changed from [24] to match [23, 40], but there was no shade, no fertilizer, and includes damage due to pests (40%). Yields of 1373 kg/ha were achieved with no pest damage, automatic nitrogen fertilizer, and ~ 18% shade. These are in range with observed average values reported by Refs. [29, 40, 61], particularly for the mid and wet zones which our test location straddles. Ref. [61] found in a survey of 150 farms, average yields of 211 kg/ha in dry regions, 477 kg/ha in mid

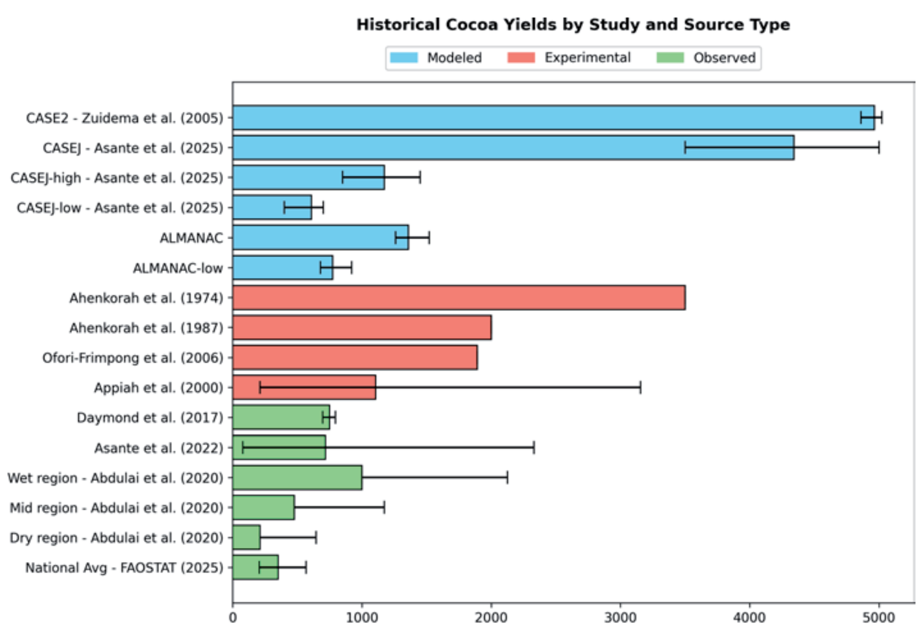

Figure 3.
Reported average yields across observed, experimental, and modeling studies in Ghana. When available, whiskers represent the range of reported values (across years and/or regions) to capture the wide range of possible yields in Ghana.

regions, and 999 kg/ha in wet regions. The highest performing farms in each of those regions had yields of 645 kg/ha (dry), 1174 kg/ha (mid), and 2125 kg/ha (wet) [61]. In another observational study of 96 farms [29], average yields were 717 kg/ha with a range of 78–2331 kg/ha [40]. However, these values are all higher than reported nationally averaged yields of 331 kg/ha from 1980 to 2010 [62]. It is unclear why the observed results of [29, 61] are so much higher than the national average. CASEJ, on the other hand, simulated yields of 4500–5000 kg/ha over the region of our test site, nearly 4 times that of ALMANAC and observations. However, when they apply their yield-gap filters, yields reach 500–700 kg/ha for low-input and 1150–1450 kg/ha for high-input farms. With these filters, values are much closer to national averages and ALMANAC results. However, we argue that the ability of ALMANAC to simulate plausible values without applying a yield gap factor is a strength of the model.

Because their raw model output was so high, we decided to focus on comparing to their high and low input output only. When simulating the future climate (**Figure 4**), we find that after applying their calculated yield gaps to the CASEJ output, the models agree quite well on how yields will change under global warming. Ref. [23] only plotted high and low input yields for the mid scenario, so we scaled the remaining models by the 73% and 86% yield gap factors to produce (**Figure 4**). Under high input farming, yields went up regardless of the climate regime for both CASEJ and

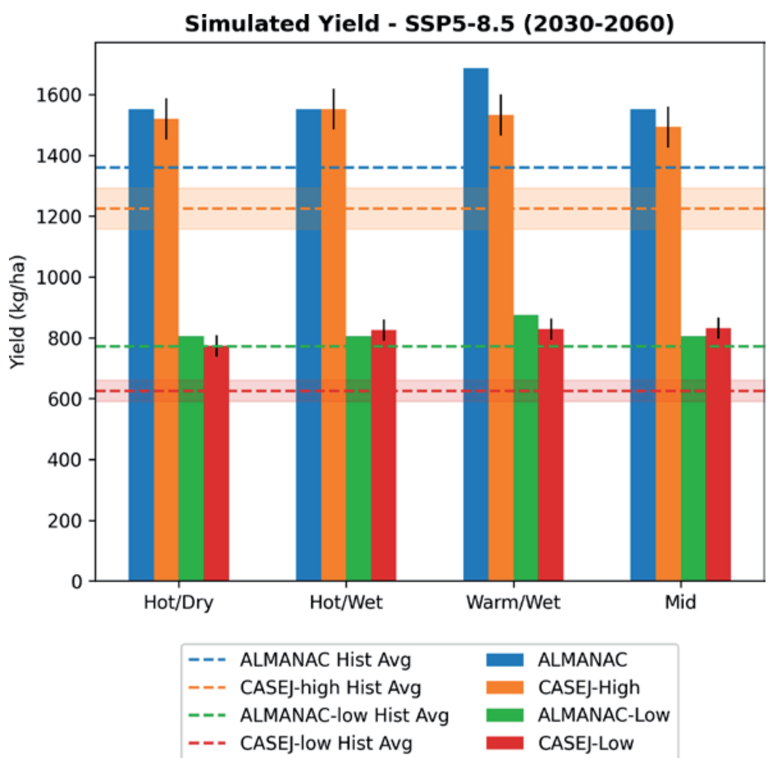

Figure 4.
Simulated cocoa yields in Ghana (6.2°N, 2.33°W) compared to findings in the corresponding grid cell from Asante et al. [23]. ALMANAC and CASEJ-high refer to the high input scenario in which better but still not ideal management is used. ALMANAC-Low and CASEJ-Low refer to the low-input scenario which better characterizes current practices in the region. Dashed lines represent the average yield in each scenario's corresponding historical simulation (with the same management assumptions). Shaded regions and error bars indicate the range of the color bar used in Asante et al. [23].

ALMANAC. ALMANAC increased the most under the warm/wet future, while CASEJ did not show the same sensitivity to climate. However, without the exact values from [23], it is possible there was more variation between models than it seemed. Because the weather does not appear to impact CASEJ-high very much, the increase in CO_2 under SSP5-8.5 are likely the driving factor, which would agree with [18]. Ref. [23] found yields increased by ~15–21% just by including CO_2 effects. While ALMANAC is also sensitive to CO_2 changes, its magnitude appears smaller than CASEJ's. This is supported by the low input scenario, in which CASEJ still improves under each climate forcing but ALMANAC only increases under the Warm/wet condition.

To confirm this, we calculate the CO_2 effect in ALMANAC by running another iteration in which CO_2 is kept at the historical level of 363 ppm. We find a much smaller CO_2 effect than [23]. When averaged across all four models, yields increased by 4.75 and 1.29% with high CO_2, under the high input and low input scenarios respectively. CO_2 had a very small effect in the low-input scenario and appeared to alter the tree's development more than any yield changes, with yields peaking 2–5 years later without CO_2 but declining faster after about 20 years old (**Figure 5**). This means that without improved management in the region, the benefits of the CO_2 fertilization effect would not be realized. This interaction between management and climate is something that cannot be captured through Ref. [23]'s approach of scaling results down afterwards to emulate current practices.

These results confirm Ref. [23]'s findings that under the early years of SSP5-8.5, cocoa yields would increase due to the increased CO_2 and shortened dry season. However, this is only the case with improved management. Under our low-input scenario, only the warm/wet model achieved higher yields (**Figure 4**) and yields fell below or at historical levels by the end of the simulation (**Figure 5**).

There are a few caveats to consider with these results. One shortcoming of ALMANAC is its low yield variability, compared to observations and now CASEJ

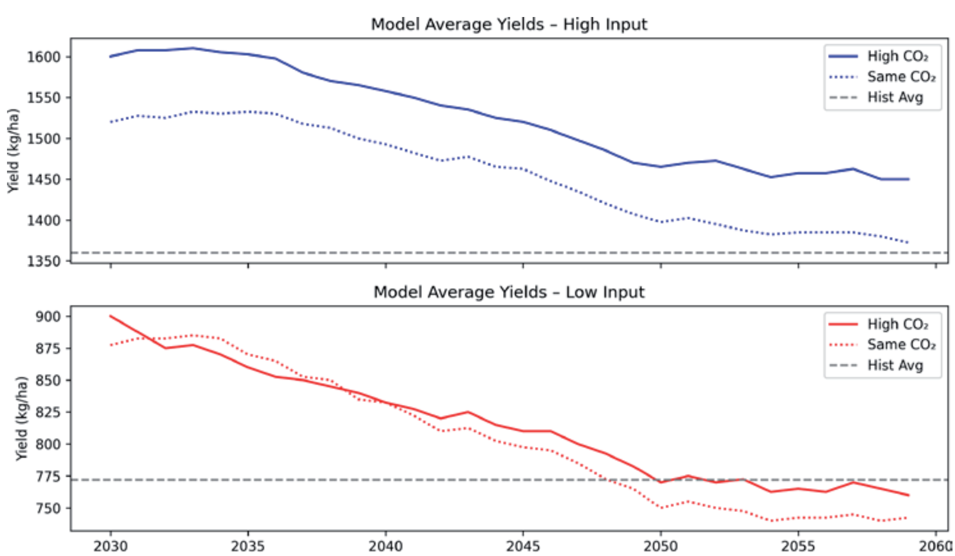

Figure 5.
Time series of yields averaged across all 4 models under the high-input and low-input management scenarios. The dashed lines represent the respective historical average for each management scenario. The blue curves illustrate average yields with CO_2 at 563 ppm and the red curves at 363 ppm.

[24]. While ALMANAC captures the average well, we should assume future yields will be more variable than those predicted. We do not compare yield variability here but encourage future work to explore and correct this. Another important caveat is that CASEJ does not simulate the aging of trees. In ALMANAC both high and low input scenarios approach historical yields by the end of the simulation (**Figure 5**). Maximum yields are usually only maintained for a couple of years before declining. Without the inclusion of tree aging, results in [23] must be an overestimate. Applying the yield gaps over a 30-year period of assumed maximum growth is likely insufficient to recover plausible yields, though it does help to isolate the trends from the changing climate. Aging farms are a major contributor to the low yields in Ghana, so it is important to keep in mind without proper maintenance and renewal, the increases in yield seen here may not be realized.

This model comparison was just the first step toward understanding what cocoa process-based models can and cannot tell us. We encourage future work to apply ALMANAC to the entire cocoa-growing region in West Africa, compare yield variability of the models, and test the sensitivity to crop and management parameter choices.

5. Conclusions

Quantifying and therefore validating cocoa yields is quite difficult. National averages paint one picture but farm level assessments [29, 61] and field experiments, which typically remove yield reducing factors intentionally, paint another. It is apparent that farmers are not realizing the potential yields they could achieve. This is due to a number of factors: access to fertilizers and pesticides, labor, and knowledge of best practices (pruning, planting density, rejuvenation, fungicide and pesticide timing). An ideal model would simulate realistic yields when realistic management is used and higher yields with best practices. ALMANAC was initially parameterized to give realistic yields but with slightly unrealistic management and therefore parameters. Now, with more accurate planting densities, crop calendars, and pest damages, yields are higher than the average observed yields in [29] but still within the range. CASEJ, on the other hand, may be unreasonably optimistic. Even with somewhat realistic parameters (planting density, tree age, no nutrient limitations), yields are still significantly higher even than optimal-condition experimental results [43, 63–65] (**Figure 4**). Labor, pests, and post-harvest losses could explain some of this, since a process-based model would not usually capture how much usable yield a farm ends up with, only what grew. However, experimental studies should reduce most of those factors. Applying some sort of yield gap factor is likely a good approach for now when considering and interpreting CASEJ model estimates until it is more thoroughly understood what drives the low yields in West Africa and the high yields in CASEJ. When considering future impacts on cocoa, for the time being, we recommend more faith be put in the ALMANAC estimates than CASEJ's, but more importantly, readers should consider these results as a range of estimates. It is promising however that after applying the yield gaps, the models offer similar results. This highlights why it is so important that more models be developed, more intercomparison projects be conducted, and more model development be done. Without more models capable of replicating historical yields, there is much uncertainty over the extent climate change will impact cocoa.

The studies that have quantified the future changes for cocoa summarized in this chapter include many crop model approaches, climate scenarios and time periods (**Table 1**). Thankfully, to facilitate comparison, most of the studies have utilized the

Model and Study	Type	# of climate models	Scenario	Time	Output	Prediction
MAXENT [5]	Statistical	19	SRES-A2	2040–2070	Suitability	Decrease
MAXENT [6, 66]	Statistical	19	RCP6.0	2040–2069	Suitability	Decrease
Random Forests [3]	Statistical	10	RCP6.0	2040–2069	Suitability	Decrease
GBM, GAM, GLM, and RF [16]	Statistical	9	SSP1-2.6 SSP5-8.5	2040–2060	Suitability	Increase
EcoCrop [4]	Statistical	1	RCP8.5	2070–2089	Suitability	Decrease
JULES [18]	Process	1	RCP8.5	2070–2100	NPP	Increase
CASEJ [23]	Process	5	SSP5-8.5	2030–2060	Yield	Increase
ALMANAC	Process	4	SSP5-8.5	2030–2060	Yield	Increase

Table 1.
Summary table of studies that have quantified the impacts of global warming on future cocoa yields.

business-as-usual scenario, but we encourage more studies to investigate SSP2-4.5, a more probable pathway. Yet, even with similar climate scenarios, the studies came to different conclusions. For example, [4, 6] found decreased suitability in Nigeria using suitability models but [18, 23] suggested improved yields. This highlights the importance of developing and utilizing process-based models.

However, these models are also only as good as the data given to them. Climate models have errors, so most studies use multiple climate model outputs to account for this. For example, CMIP5 models were known to have faulty representations of the precipitation seasonality in West Africa—missing the bimodal nature of rainfall in the region, but higher resolution models have shown improved skill [18]. Increasing the resolution is often a tool for improving climate variable estimates, especially for precipitation, but the downscaling method is another source of uncertainty. Impact studies prefer downscaled and bias-corrected data when conducting regional or local analyses because all models are imperfect, and the coarse resolution can obscure changes in extremes for temperature, precipitation, wind, etc. Most studies in this review utilized downscaled products but with various downscaling techniques. Ref. [18] used dynamical downscaling by employing a high resolution climate model (UPSCALE). Refs. [3, 5, 6] all use the delta method, a common but simple approach. Ref. [4] used the quantile-quantile method to bias correct but not downscale, and Ref. [23] use NASA NEX-GDDP data which uses a downscaling method not as rigorous as others like ISIMIP [67]. The downscaling method chosen can significantly impact the tails or extremes [67]—the weather most likely to damage crops.

Another source of uncertainty is whether the benefits of CO_2 last or whether the plants eventually acclimate with a diminishing return from the CO_2 fertilization effect. We need more long-term lab and field studies to determine whether we can truly count on the effect to offset the temperature and precipitation changes. Some studies [68, 69] suggest coffee does not acclimate under long-term experiments, but these studies lasted for only a couple of years, and whether cocoa would respond similarly is yet to be determined.

This chapter synthesized the papers that have quantified West African cocoa yields under global warming and revealed a disparity in results depending on the type of model used. While most suitability studies determined that cocoa is threatened by climate change, process-based models that include the CO_2 fertilization effect predicted stable or increased performance. It is also clear that cocoa and other tree crops require more attention from the modeling community. To our knowledge, only two models (CASEJ and ALMANAC) currently exist that can and have been used to simulate cocoa in the future. We also encourage a full-scale model intercomparison and future collaboration between CASEJ and ALMANAC. This study offered an initial comparison, but there are many more questions to be answered. We also encourage the further use and development of other models like [25–28, 45] to see if and how these models might be used for global warming predictions. The model, SIMPLE [70], used in Ref. [45] seems particularly promising given its low RRMSE of 7.2% for yields in Colombia compared to 24.4% for other crops. Machine learning approaches [71, 72] could also be a promising approach.

These new process-based studies show that contrary to past findings, cocoa may, in fact, do well under a global warming scenario like RCP8.5. However, we need more experimental studies to confirm these relationships and more modeling studies that explore a wider range of climate pathways before we can be sure of cocoa's fate.

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