RESEARCH ARTICLE

Climate–yield interactions in West Africa: Machine learning insights for cocoa production in Ghana and Côte d'Ivoire

Salomon Obahoundje[1]*, Seifu A. Tilahun[2], Petra Schmitter[3]

1 Climate Mitigation and Adaptation Pathways (CMAP) Research Group, International Water Management Institute (IWMI), Accra, Ghana, **2** Agricultural Water Management Transformation (AWMT) Research Group, International Water Management Institute (IWMI), Accra, Ghana, **3** Climate Mitigation and Adaptation Pathways (CMAP) Research Group, International Water Management Institute, Colombo, Sri Lanka

* s.obahoundje@cgiar.org, obahoundjes@yahoo.com

Abstract

Cocoa production in Ghana and Côte d'Ivoire is threatened by climate variability and extremes, particularly droughts and excessive rainfall. However, quantitative evidence on the impacts of climate change on cocoa yields remains limited, constraining the development of effective climate-smart adaptation strategies. This study assessed future climate impacts on cocoa production using regridded (~5 km resolution) ensemble projections from 12 Global Climate Models under a low (SSP1-2.6) and a high (SSP5-8.5) SSP scenario. Precipitation and temperature data were bias-corrected using five approaches: Delta Change, CDFt, SDM, EQM, and LOCI. Among these, the Delta Change method best preserved intra-annual climate variability, while temperature corrections outperformed precipitation corrections. A Random Forest model, trained on bias-corrected climate data, simulated and projected cocoa yields with an accuracy exceeding 85%, although performance varied across regions. Future changes were assessed for the near future (2026–2055) and far future (2056–2085) relative to a historical baseline (1985–2014). Ensemble projections indicate a drying trend across cocoa-growing areas, with precipitation declining by 5–10% under SSP5-8.5 and increasing modestly (around 5%) under SSP1-2.6. At the same time, temperatures are projected to rise across all regions, exceeding 3.5°C under SSP5-8.5 by the late century, particularly in central and northern zones. Projected yield responses vary spatially. Southern and coastal cocoa-growing areas are expected to experience yield declines of about 5%, with losses reaching up to 20% under severe drought conditions in highly vulnerable regions such as Dix-Huit Montagnes in Côte d'Ivoire under SSP5-8.5. In contrast, some northern and central regions may maintain or slightly increase yields under SSP1-2.6. Vulnerability is shaped by climatic, biophysical, and socio-economic factors, with regions such as Sud-Comoé (Côte d'Ivoire) and Brong Ahafo (Ghana) identified as at risk. These

OPEN ACCESS

Citation: Obahoundje S, Tilahun SA, Schmitter P (2026) Climate–yield interactions in West Africa: Machine learning insights for cocoa production in Ghana and Côte d'Ivoire. PLOS Clim 5(7): e0000970. https://doi.org/10.1371/journal.pclm.0000970

Editor: Pietro Goglio, University of Perugia, ITALY

Received: December 19, 2025

Accepted: June 2, 2026

Published: July 1, 2026

Data availability statement: All the data used in this study are uploaded as Supporting information.

Funding: This work was supported by the Consortium of International Agricultural Research Centers (CGIAR): Excellence in Agronomy Initiative (EiA) and Sustainable

Farming Program (SFP). Funder's role: The funders had no role in study design, data collection and analysis, decision to publish, or preparation.

Competing interests: The authors have declared that no competing interests exist.

findings highlight the need for targeted adaptation strategies to enhance the resilience of West Africa's cocoa sector.

1. Introduction

Cocoa is the backbone of Ghana's and Côte d'Ivoire's economies, contributing significantly to the national gross domestic product (GDP) and export revenues while supporting the livelihoods of over 800,000 Ghanaian smallholder farmers and nearly one million producers in Côte d'Ivoire [1]. Côte d'Ivoire alone produces about 40% of global cocoa, with the sector accounting for roughly 10% of its GDP, while Ghana's cocoa sector contributes approximately 3.5% of GDP and a quarter of export earnings [2]. Beyond economic contributions, cocoa remains central to employment, household food security, and regional stability [3].

Despite this importance, cocoa farming in both countries is highly vulnerable to climate change and variability [4], primarily because it depends on rainfed systems [4,5]. Rising temperatures, erratic rainfall, and increased frequency of droughts and floods threaten cocoa physiology and yield by reducing flowering, impairing pod development, and increasing tree mortality [6–8]. Climatic stressors also drive shifts in evapotranspiration rates, prolong dry spells, and intensify heat stress, thereby reshaping the climatic suitability of traditional cocoa-growing zones [9–11]. Projections indicate that increasing peak dry-season temperatures may soon become as significant as water scarcity as the primary limiting factor for cocoa cultivation [12]. Similarly, delayed onset and shorter rainy seasons increase drought exposure, thereby undermining seedling establishment, whereas intense rainfall episodes cause nutrient leaching, further reducing productivity. Empirical evidence confirms that both rising temperatures and declining precipitation reduce cocoa output, with lagged climatic effects, such as rainfall from the previous year, exerting a strong influence on yield variability [4].

In addition to direct climate stress, indirect impacts, including pests and diseases, are intensifying. Warmer and more humid conditions increase the risk of black pod disease, caused by Phytophthora species, and cocoa swollen shoot virus, known as CSSV. Together, these diseases account for yield losses ranging from 10–30% in Côte d'Ivoire to 30–50% in Ghana and can lead to widespread tree mortality if not properly managed [3,13]. Furthermore, pollinator decline, associated with habitat loss and climate-related stress, threatens pod set and yield stability [14]. These biophysical stressors are further compounded by socio-economic challenges, such as limited access to irrigation, credit, and climate information services, which constrain farmers' adaptive capacity [15,16].

Projections under high climate change scenarios, specifically SSP5–8.5, indicate significant spatial shifts in cocoa suitability across West Africa [8]. While countries such as Nigeria and Cameroon may benefit from wetter conditions and higher carbon dioxide concentrations, Ghana and Côte d'Ivoire risk losing substantial areas of suitable cocoa land, particularly in transitional agroecological zones. However, regional differences in yield responses remain insufficiently understood, and limited attention has been given to how alternative climate change scenario pathways, especially lower-SSP scenarios such as SSP1 and SSP2, may influence these patterns. This gap in knowledge underscores the urgent need for integrated climate–crop modeling, combined with socioeconomic assessments, to inform adaptive strategies that can help secure the future of cocoa production in West Africa.

Various modelling approaches have been used to assess the impacts of climate change on cocoa productivity, each with distinct strengths and limitations. Process-based models, such as the specialized CASE2, known as the Cacao Simulation Engine for water-limited production, developed by [17], and later modified by [8], simulate cocoa growth based on physiological mechanisms under varying soil and weather conditions. These models provide insights into key yield drivers and help identify knowledge gaps in cocoa tree physiology. Empirical econometric models, such as the transcendental logarithmic production function, referred to as the translog model [4], use historical data to quantify how climatic variables and their interactions influence cocoa output over time. These models have demonstrated that temperature and precipitation trends, together with their lagged effects, significantly affect production in West Africa. More recently, hybrid statistical and machine learning models like MAXEnt have been used to map where cocoa can grow [9], but they often struggle to capture complex, non-linear climate–crop relationships.

Established mechanistic crop models, including the Decision Support System for Agrotechnology Transfer (DSSAT), the Agricultural Production Systems Simulator (APSIM), and AquaCrop, remain essential for simulating crop growth under environmental and management constraints. AquaCrop [18], for instance, is designed to simulate the yield response of herbaceous crops to water while balancing accuracy and simplicity, though it was not originally parameterized for cocoa, and requires adaptation for perennial tree crops [19]. DSSAT and APSIM offer robust frameworks but similarly suffer from limited cocoa-specific phenological parameters, impeding their direct application in cocoa modeling without extensive calibration [20–22].

Conversely, machine learning approaches provide flexibility, scalability, and improved predictive performance when working with incomplete or indirect data. Among these, Random Forest (RF) represents a particularly promising approach [23]. RF models can accommodate high-dimensional, non-linear relationships without relying on strong statistical assumptions, making them well suited to the heterogeneous agroecological zones of Ghana [24] of Ghana [25] and Côte d'Ivoire [5]. They have demonstrated strong performance in crop yield prediction across the national [26], regional and global scales [27]. Unlike traditional statistical models, RF does not rely on assumptions of linearity or normally distributed data and is less sensitive to noise or missing values [26,27]. This makes it particularly valuable in sub-Saharan Africa, where climate and agricultural datasets are often incomplete, inconsistent, or spatially fragmented. As noted d by [28], RF is the most widely applied ML algorithm in climate hazard and yield modeling due to its robustness, scalability across spatial scales, and strong performance in data-scarce and heterogeneous environments.

Despite the increasing adoption of machine learning, its application to cocoa yield research remains limited, particularly in the context of regional climate risk assessments in West Africa, where existing approaches are still largely dominated by process-based models and suitability analyses [8,9]. Moreover, many studies focus on climatic suitability or physiological responses without explicitly linking these to yield outcomes, leading to ambiguity in their interpretation for production forecasting and risk assessment [8]. This study addresses these gaps by integrating bias-corrected CMIP6 climate projections with machine-learning-based yield modelling to quantify region-specific climate sensitivity and future yield responses under defined climate scenarios. Using climate indices, bias adjustment, and Random Forest modelling, it produces spatially explicit, scenario-based yield projections that extend beyond traditional approaches. The outputs are explicitly framed as conditional projections under climate scenarios rather than operational forecasts.

The study applies a Random Forest–based approach to assess cocoa yield responses to future climate change in Ghana and Côte d'Ivoire, focusing on the effects of drought and excessive rainfall. It evaluates key climatic drivers, including precipitation, rainfall indices, and temperature, across multiple SSP pathways, from high-SSP SSP5–8.5 to lower-SSP scenarios such as SSP1–2.6 and SSP2–4.5. By linking climate projections with machine-learning-based yield modelling, the study provides spatially explicit insights into yield risks and resilience strategies, supporting the development of climate-smart adaptation policies for sustainable cocoa production.

2. Data and methodology

2.1. Study area

Côte d'Ivoire and Ghana are the two leading producers of cocoa globally. Cocoa cultivation in both countries is concentrated in the southern and central regions, primarily below latitude 8.5°N, within the forest and transitional zones between forest and savannah [5]. In Côte d'Ivoire, cocoa is mainly grown across 13 regions, ranging from Dix-Huit Montagnes, Moyen-Cavally, and Bas-Sassandra to Moyen-Comoé and Sud-Comoé. In Ghana, production is concentrated in six regions, including Brong-Ahafo, Western, Ashanti, Central, Eastern, and extending to the Volta Region (see Fig 1). The climate conditions are controlled by the West African monsoon, determined by the movement of the intertropical convergence zone (ITCZ). The intra-annual variability of different climate variables is well presented by [5].

The southern zone is characterized by a bimodal rainfall regime, while the central zone exhibits a unimodal pattern, with annual precipitation decreasing from over 1250 mm in the south to about 1000–1250 mm in the central areas. Mean annual temperatures range from 21°C to 32°C, with high humidity during the rainy season, creating generally favorable conditions for cocoa production in Côte d'Ivoire and Ghana [5].

2.2. DataAF

To assess the impacts of future climate changes on cocoa yield, we utilized precipitation and temperature data (minimum, maximum, and mean) from both reanalysis products and climate model projections. For the reanalysis data, precipitation estimates were obtained from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS), which provides

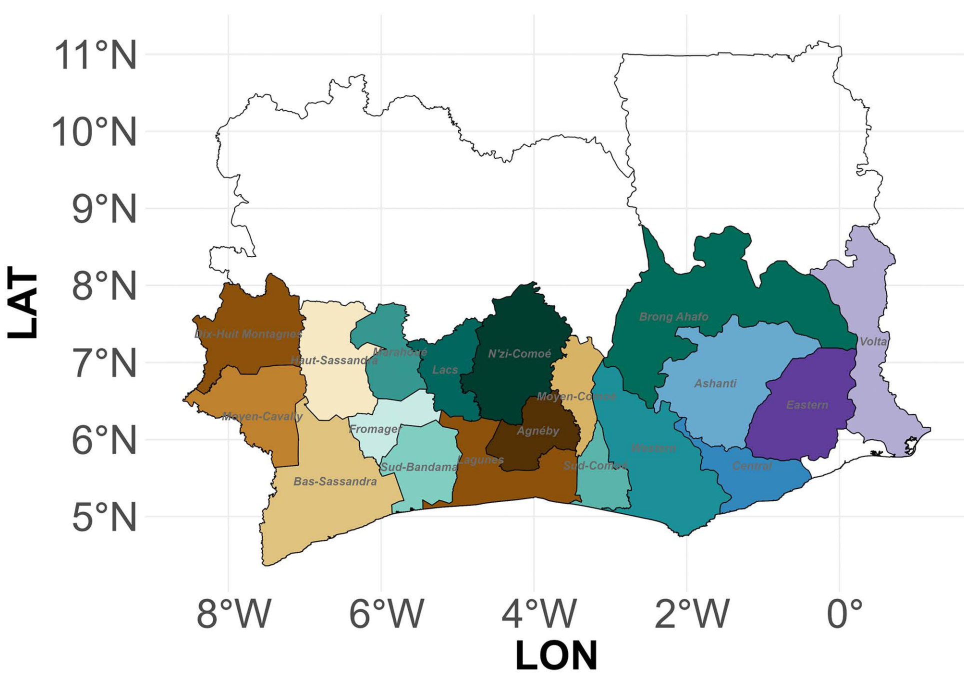

Fig 1. Geographic distribution of Cocoa cultivation in Côte d'Ivoire and Ghana. NB: The shapefiles used to create this image were obtained from the GADM database.

https://doi.org/10.1371/journal.pclm.0000970.g001

daily data at a spatial resolution of 0.05° × 0.05° over the period 1981–2024 for cocoa-growing regions. Temperature data were sourced from the Climate Hazards InfraRed Temperature with Stations (CHIRTS), with the same spatial resolution as CHIRTS, available from 1983 to 2016. Both products are the merger of satellite-based infrared observations with ground-based station measurements, offering reliable climate monitoring and agricultural impact assessment datasets.

These datasets were used to train yield models and to perform bias correction on climate model projections. For future climate projections, outputs from 12 Global Climate Models (GCMs) (Table 1), as presented by [29], were regridded to match the resolution of the CHIRPS and CHIRTS datasets, and subsequently bias-adjusted. The bias-adjusted CMIP6 data variables, namely temperature and precipitation, have shown good performance over West Africa [29].

The Cocoa annual production data was obtained from Ghana COCOBOB (https://cocobod.gh/) for Ghana and from [30] for Côte d'Ivoire. The production data in Ghana covers the period from 2014 to 2022, encompassing the six cocoa-growing regions, namely Brong Ahafo, Western, Ashanti, Central, Eastern, and Volta. For Côte d'Ivoire, it was accessed from three main regions, namely Goh, Marahoue, and Haut-Sassandra, covering 1981–2010. The time series annual yield in tons per ha was derived by dividing the production (tons) by the harvested area (ha) per region accessed from [31]. All datasets were harmonized to ensure consistency in units and spatial aggregation across regions and time periods. Where necessary, production and area data were aligned temporally to ensure that yield estimates correspond to the same reporting year.

2.3. Methodology

2.3.1. Bias-adjustment. Spatial interpolation using bilinear interpolation (remap_bil function in climate data operators) was employed in this study as a cost-effective and computationally efficient approach for bias-adjusting climate data. Statistical relationships were established between local-scale climate variables (precipitation and temperature) and their corresponding large-scale predictors, which were subsequently applied to GCM outputs to generate future regridded projections. Precipitation and temperature data were regridded using the bilinear interpolation method to achieve the same spatial resolution as the CHIRPS and CHIRTS datasets (~5 km). The resulting regridded data were then aggregated at the cocoa farming regional level (see Fig 1) and bias-adjusted to improve accuracy and consistency across the study domain. Five bias-adjustment methods were used, and their performance was compared; the most performed approach was retained. The performance of each bias-correction method was evaluated based on metrics such as mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and correlation coefficients,

Table 1. Selected CMIP6 model descriptions.

Model	Institution	Spatial Resolution	Reference
CMCC-ESM2	Euro-Mediterranean Centre on Climate Change coupled climate model	1.250° × 0.942°	[32]
EC-Earth3	EC-Earth consortium	0.703° × 0.701°	[33]
EC-Earth3-Veg	EC-Earth consortium including interactive dynamic vegetation	0.703° × 0.701°	[34]
FGOALS-g3	Flexible Global Ocean–Atmosphere–Land System Model, Grid-point Version 3	1° × 1°	[35]
INM-CM4–8	Institute of Numerical Mathematics Climate Model version 4–8	2° × 1.5°	[36]
IPSL-CM6A-LR	Institut Pierre-Simon Laplace Climate Model version 6A, Low Resolution	2.5° × 1.25°	[37]
MIROC6	Model for Interdisciplinary Research on Climate version 6	1.4° × 1.4°	[38]
MPI-ESM1–2-LR	Max Planck Institute Earth System Model version 1.2 – Low Resolution	1.875° × 1.875°	[39]
MRI-ESM2–0	Meteorological Research Institute Earth System Model (MRI-ESM), Japan	1.125° × 1.121°	[40]
NESM3	Nanjing University of Information Science and Technology Earth System Model version 3	2.8° × 2.8°	[41]
NorESM2-LM	Norwegian Earth System Model version 2 – Low resolution, Medium atmosphere	1.9° × 2.5°	[42]
TaiESM1	Taiwan Earth System Model	1.250° × 0.942°	[43]

https://doi.org/10.1371/journal.pclm.0000970.t001

comparing observed and bias-adjusted distributions. The best-performing method for each variable was retained and applied to future climate scenarios for impact assessment.

a. **Delta change method**: The delta method [44] was used because it is simple to implement and also preserves the climate trend and signal. To improve its ability to better adjust the distributional characteristics, such as variability and extremes, some modifications were adopted in the initial equation. For temperature, the delta was calculated as the difference between the observed climatology and the GCM historical climatology over the training period. The adjusted future temperature series was obtained by adding this delta to the GCM future simulation. For precipitation, the delta change factor (Delta) was computed as:

$$Delta = Delta = \frac{P}{\langle H \rangle} - 1 \tag{E.1}$$

where $\langle H \rangle$ is the mean precipitation over the historical training period (1983–2002), and P represents the future GCM precipitation. Since this adjustment factor can sometimes result in extreme values (e.g., infinity), it was constrained within a defined range (e.g., between -1 and +3, where +3 represents a 300% increase). The bias-adjusted future precipitation time series was then calculated by scaling the observed climatology $\langle O \rangle$ over the training period using:

$$Adjusted_{prec} = \langle O \rangle \, (1 + Delta) \tag{E.2}$$

b. **Cumulative Distribution Function Transform (CDFt)**: The Cumulative Distribution Function transform (CDFt) [45,46] was applied to bias-correct daily precipitation and temperature series. The precipitation was bias-adjusted through Singularity Stochastic Removal due to the occurrences [46]. The equation used for the bias-adjustment is presented by [47] and [46]. For each variable, we computed the empirical cumulative distribution functions (CDFs) from the historical reference (observations), historical simulations, and future simulations. The simulated distributions were then adjusted by mapping simulated quantiles onto the observed distribution, ensuring correction of biases in both the mean state and higher-order moments. Extreme values and zero-inflated precipitation were explicitly corrected by aligning the tails of the simulated and observed distributions, while preserving the projected climate change signal in the future runs.

c. **Empirical Quantile Mapping (EQM)**: The empirical quantile mapping (EQM) [48] was applied to bias-correct daily precipitation and temperature series. For each variable, empirical cumulative distribution functions (CDFs) were first constructed from observed and simulated historical datasets [48]. Model-simulated values were then mapped onto the observed distribution by replacing each simulated quantile with the corresponding observed quantile. This adjustment corrected biases in both the mean and variability of the simulated climate data. For precipitation, a frequency adaptation step was included to correct for zero-inflation, ensuring a realistic representation of wet and dry day occurrences.

d. **Local Intensity Scaling (LOCI)**: the Local Intensity Scaling (LOCI) [49] was applied to correct precipitation biases by separately adjusting rainfall frequency and intensity. First, a precipitation threshold was determined from observations to distinguish wet and dry days. Model-simulated precipitation was then rescaled so that the frequency of wet days matched the observed threshold. Subsequently, the intensity of simulated wet-day precipitation was adjusted using a linear scaling factor derived from the ratio of observed to simulated mean precipitation.

e. Stochastic Distribution Mapping (SDM): the SDM [50] is applied to bias-correct precipitation and temperature series while preserving higher-order distributional properties. Observed and simulated distributions were first estimated, and correction factors were derived for the mean, variance, and higher-order moments. Unlike EQM, SDM introduces a stochastic perturbation step, where random variability sampled from observed residuals was added to corrected values. This ensured that extremes and overall distribution shapes were preserved in the adjusted dataset.

2.3.2. Derived climate indices. After regridding and bias adjustment, a suite of precipitation-based indicators was derived to comprehensively characterize rainfall variability, intensity, and drought conditions based on ETCCDI (Expert Team on Climate Change Detection and Indices) indices [51], with direct relevance to cocoa production systems. Precipitation total (PRCPTOT) represents the annual or seasonal sum of daily precipitation over wet days (≥ 1 mm) and provides a key measure of overall water availability. PRCPTOT is essential for cocoa growth, pod development, and yield stability due to the crop's high-water demand. The number of rainfall days (RR1) reflects the frequency of rain events and is important for maintaining soil moisture. RR1 reduces plant water stress, as irregular rainfall patterns can disrupt flowering and pod filling. The Simple Daily Intensity Index (SDII), defined as the ratio of PRCPTOT to RR1, indicates the average rainfall intensity on wet days and helps distinguish between frequent light rains and intense rainfall events, with the latter potentially increasing runoff and limiting effective water infiltration in cocoa systems. Threshold-based indices such as Heavy Precipitation Days (R10mm) and Very Heavy Precipitation Days (R20mm) quantify the occurrence of moderate to extreme rainfall events, which are critical for cocoa farming because excessive rainfall can lead to waterlogging, soil erosion, and increased incidence of fungal diseases such as black pod, thereby reducing yields. To assess rainfall persistence, Consecutive Wet Days (CWD) measures the longest sequence of days with precipitation ≥ 1 mm, indicating prolonged wet conditions that may favor disease outbreaks and hinder field operations. Whilst Consecutive Dry Days (CDD) captures the longest dry spells (precipitation < 1 mm), which are particularly detrimental to cocoa as extended dry periods induce water stress, increase cherelle wilt, and reduce productivity. Drought conditions were further evaluated using standardized indices, with the Standardized Precipitation Index (SPI) computed at multiple accumulation periods (1-, 3-, 6-, 9-, and 12-month scales) to quantify precipitation anomalies relative to long-term conditions and identify short- to long-term meteorological droughts affecting cocoa growth cycles. Complementarily, the Standardized Precipitation Evapotranspiration Index (SPEI) incorporates both precipitation and potential evapotranspiration, thereby accounting for temperature-driven evaporative demand [52]. In this study, SPEI was computed from the climatic water balance (P − PET), where potential evapotranspiration (PET) was estimated using the Thornthwaite method [53]. This approach is particularly relevant under climate change, where rising temperatures can intensify moisture deficits even when rainfall remains near normal. Like SPI, SPEI is calculated at multiple time scales (1, 3, 6, 9, and 12 months), providing a more comprehensive assessment of drought stress on cocoa physiology and yield. SPI and SPEI values were then classified into seven categories: extremely wet (≥ 2.0), very wet (1.5 to 1.99), moderately wet (1.0 to 1.49), near normal (−0.99 to 0.99), moderately dry (−1.0 to −1.49), severely dry (−1.5 to −1.99), and extremely dry (≤ −2.0) [54].

2.3.3. Yield modeling. In this study, a Random Forest algorithm was applied to produce accurate, data-driven projections of cocoa yield under two climate scenarios: SSP1-2.6 and SSP5-8.5. A repeated K-fold cross-validation approach was used to reconstruct and predict cocoa yield for Côte d'Ivoire (1981–2010) and Ghana (2014–2022). The bias-adjusted climate variables produced by the best-performing correction method served as input predictors for the Random Forest model. Overall, the dataset consists of 36 observations for Ghana (6 years × 6 regions) and 87 observations for Côte d'Ivoire (29 years × 3 cocoa-producing regions). The repeated k-fold cross-validation method combines the strengths of k-fold cross-validation and repeated random sampling. Specifically, we use K = 5 folds and 20 repetitions (m = 20), with the dataset randomly divided into 5 equal parts. The model is trained in four folds and validated on the remaining one, cycling through all five folds. This full procedure is repeated 20 times with different random splits, resulting in a total of 100 model evaluations. This approach reduces the variance associated with a single data split and yields more robust performance estimates, especially valuable for smaller or variability-sensitive datasets. We extract performance metrics (RMSE, MAE, R^2) from each resample for the historical period. The average and variability of these scores were then used to assess the accuracy and robustness of the Random Forest projections.

The model development follows a three-stage process as shown in Fig 2. In the first stage, all selected predictors from the datasets are used at both monthly and annual time scales. The precipitation [5] and temperature were shown to be the major climate variables affecting cocoa yield [30,55]. Therefore, the precipitation and its derived indicators described above and temperatures (minimal, mean, and maximal) were used as predictors for the model. The second stage narrows the focus to the top 20 predictors (S1 Fig in the supplementary file) based on their importance. The third stage further refines the model by selecting the top 10 predictors (S2 Fig in the supplementary file) along with geographic coordinates (longitude and latitude). A flowchart of the methodology summary is presented in Fig 2.

The projected change in precipitation, expressed as a percentage, was calculated by taking the difference between the average values for the future periods, 2026–2055 (near future) and 2056–2085 (far future), and the reference period (1985–2014), then multiplying by 100 and dividing by the average of the reference period. For temperature, the change was computed as the absolute difference between the average temperatures in the future and reference periods. The potential change in cocoa yield was also estimated using the same percentage-based approach applied to precipitation. In addition, separate analyses were conducted to isolate the impacts of drought conditions and excess rainfall events on cocoa yield, allowing for a more nuanced assessment of climate-driven risks to production. Drought years were considered as years with a standardized precipitation index (SPI) less than or equal to -1, and excess rainfall years were those with an SPI greater than or equal to 1.

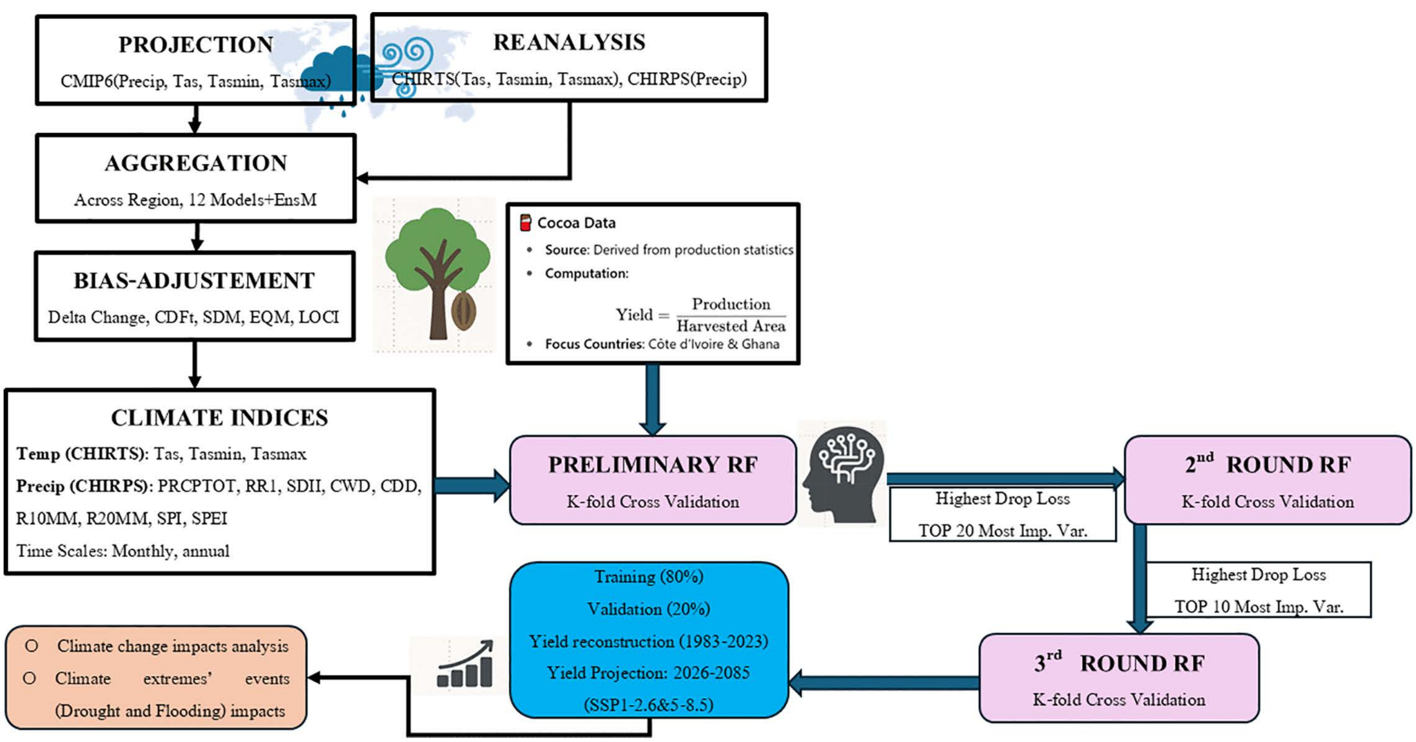

Fig 2. Workflow of the random forest-based Cocoa yield projection model incorporating predictor selection and climate scenario analysis.
NB: Authors' creation.

https://doi.org/10.1371/journal.pclm.0000970.g002

3. Results

3.1. Bias-adjustment performance

The bias-adjusted climate data were aggregated at a monthly time scale, and various performance metrics were computed to evaluate the effectiveness of the adjustment methods (Fig 3). The analysis indicates that all the bias-correction

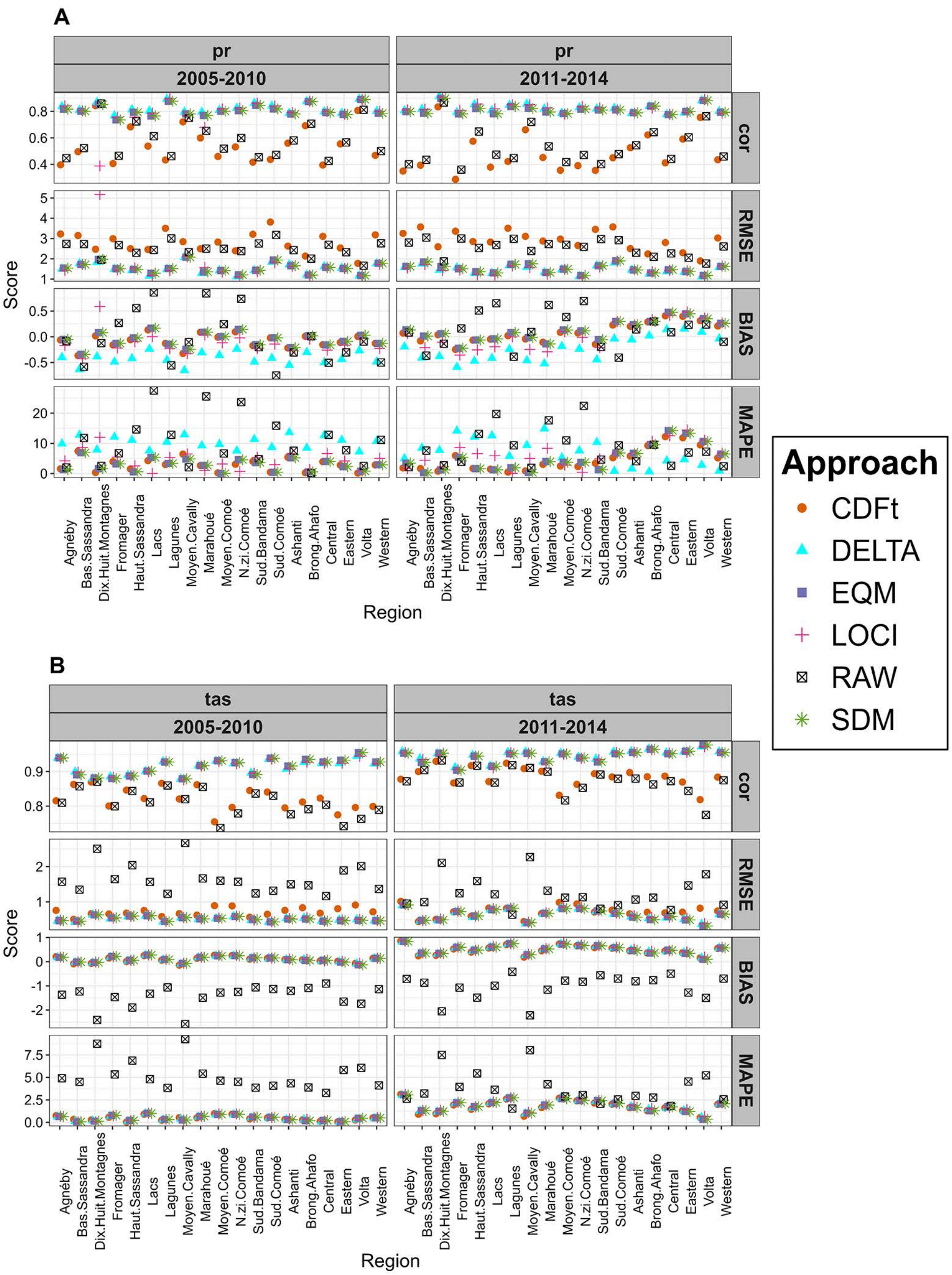

Fig 3. Performance of bias-adjustment techniques for (pr) precipitation and (tas) temperature. Note: The adjusted data were calibrated over the 2005–2010 period and validated over the 2011–2014 period. CDFt = Cumulative Distribution Function transform; DELTA = Delta change method; EQM = Empirical Quantile Mapping; LOCI = Local Intensity Scaling; RAW = uncorrected model output; SDM = Scaled Distribution Mapping.

https://doi.org/10.1371/journal.pclm.0000970.g003

techniques yielded satisfactory results for both precipitation and temperature (Fig 3A and Fig 3B). Among the methods tested, the Delta Change approach demonstrated the most consistent and reliable performance across both variables and climate patterns, leading to its selection for use in the remainder of the study. However, among the methods assessed, CDFt consistently showed the weakest performance. The correlation coefficients for precipitation ranged from 0.8 to 0.9 (Fig 3A), while those for temperature (Fig 3B) were higher, ranging from 0.9 to 0.95. Beyond overall performance, the ability of each approach to capture intra-annual variability was also evaluated (see S3 Fig and S4 Fig for precipitation and temperature in the supplementary file).

3.2. Random forest model performance

The model performance is presented in Fig 4. For instance, Fig 4A illustrates the performance of three rounds of Random Forest models for cocoa yield projection in both countries. Across all metrics, namely the Correlation (Cor), Bias, Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), it is noted that the performance improves progressively from the 1st to the 3rd round, with the 3rd round generally showing the highest correlation and lowest error values in both countries. This indicates that model refinement across rounds enhances predictive accuracy and reduces bias. It is worth noting that the round with the highest correlation and the lowest RMSE has the highest performance. All the round yield correlation >0.7, revealing strong agreement (very satisfactory for all round, see Fig 4A). The final model performance

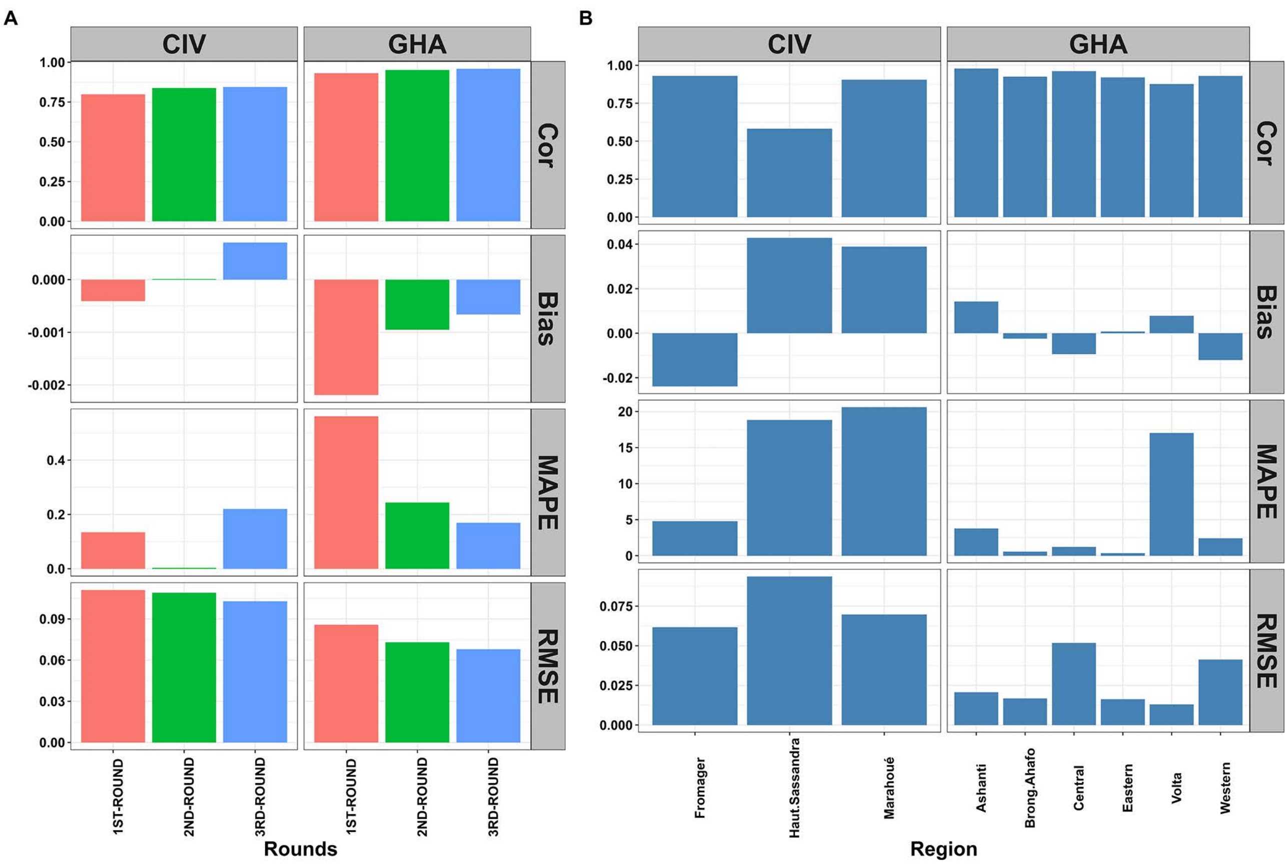

Fig 4. Comparative performance of three Random Forest models. (A) Model results across three rounds of cocoa yield projections for Côte d'Ivoire (CIV) and Ghana (GHA) at the country level. **(B)** Regional validation of the final selected model. Cor denotes correlation, MAPE is Mean Absolute Percentage Error, and RMSE is Root Mean Square Error.

https://doi.org/10.1371/journal.pclm.0000970.g004

across regions is presented in Fig 4B. In Côte d'Ivoire, model accuracy (Cor) varies more significantly across regions, with all > 0.85, except in Haut-Sassandra, indicating more variability in performance. In Ghana, the model exhibits consistently high correlation values across all regions ($R^2 > 0.85$, strong agreement, and very satisfactory). However, regions such as Volta exhibit higher MAPE and RMSE, indicating that while the overall correlation is strong, some areas experience larger absolute and relative projection errors. The time series of reconstructed data is presented in S5 Fig in the supplementary file.

Based on the results of this study, the model achieved its best performance when using the top 10 predictors identified through the feature-importance analysis. However, it is important to note that this does not imply that 10 predictors represent a universally optimal number. The selection reflects a balance between model performance and parsimony within the range of predictors tested (all variables, top 20, and top 10). Reducing the number of predictors below 10 was not explored in this study, and therefore, it cannot be concluded that further reduction would maintain or improve performance.

Figure 5 presents a time series comparison of reconstructed and observed cocoa yields across multiple regions in Ghana and Côte d'Ivoire, highlighting both temporal patterns and the performance of the reconstruction model. Overall,

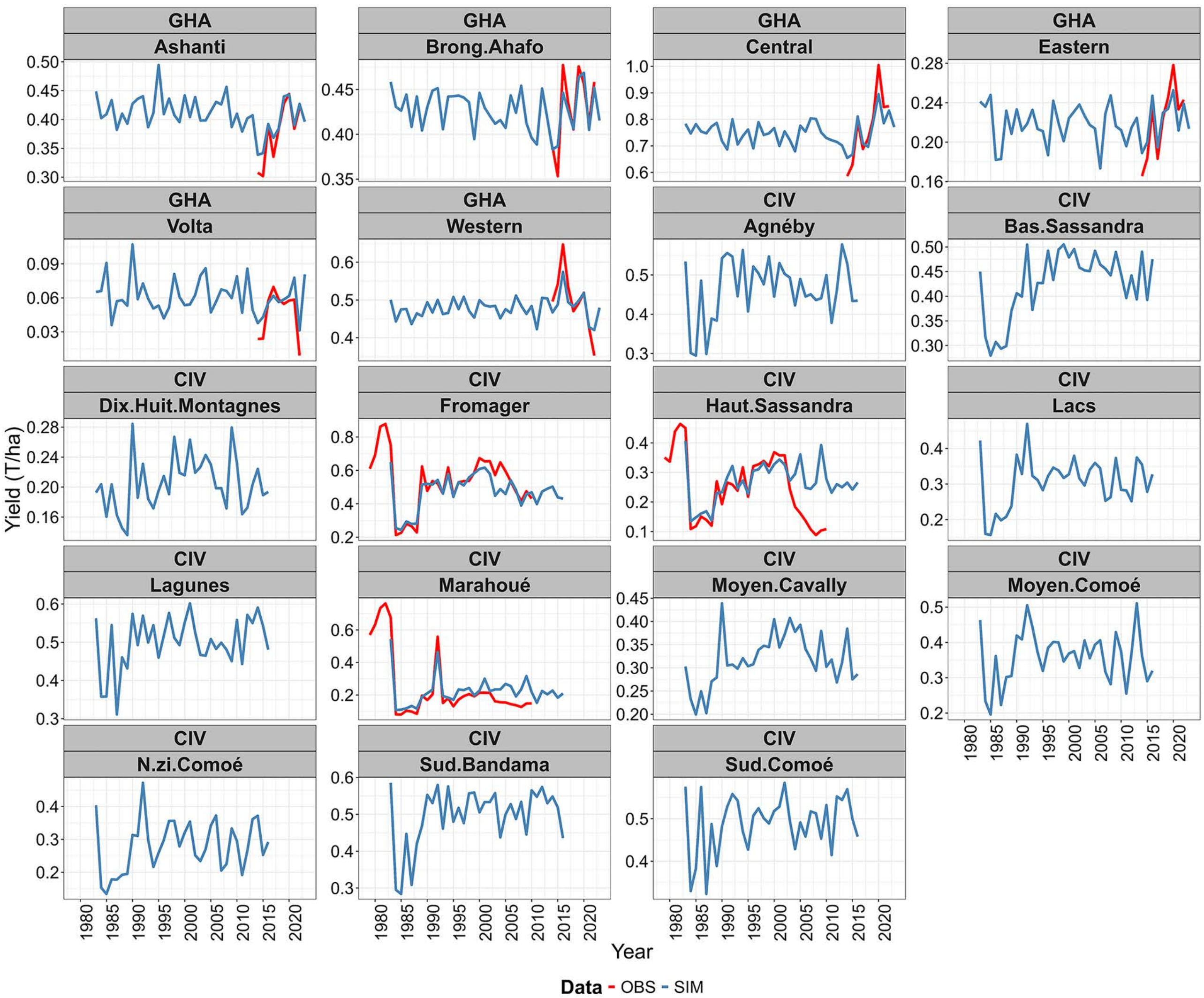

Fig 5. Time series comparison of observed and reconstructed cocoa yields across regions in Ghana (GHA) and Côte d'Ivoire (CIV), highlighting temporal dynamics and model performance. Observations are shown in red, and simulated values in steel blue.

https://doi.org/10.1371/journal.pclm.0000970.g005

the reconstructed yields closely follow the fluctuations and general trends seen in the observed data, demonstrating the model's ability to reproduce regional and country-level variability in cocoa production. The alignment of year-to-year dynamics across regions indicates that the model effectively captures the underlying climatic and agronomic drivers of yield variability. However, a notable limitation is the model's reduced ability to reproduce extreme values; both the highest and lowest yield years tend to be underestimated or smoothed.

3.3. Projected climate and yield responses in cocoa-growing regions of Ghana and Côte d'Ivoire

Climate model outputs consistently reveal a clear warming trend across cocoa-growing regions of Côte d'Ivoire and Ghana, with all 12 models projecting minimum increases (Tasmin), maximum (Tasmax), and mean (Tas) temperatures (S5 Fig for temperature in the supplementary file). The magnitude of warming depends on the model, scenario, region, and time period, but overall ranges from 0.5°C to over 4°C. Near-future projections (2026–2055) suggest increases of 1.0–2.0°C under SSP1-2.6 and 1.5–2.5°C under SSP5-8.5, with central and northern regions warming more than coastal areas. In the far future (2056–2085), warming intensifies under SSP5-8.5, with most regions exceeding 3.5°C and some simulations projecting rises close to or above 4°C. The ensemble mean that inter-model differences are smoothed (Fig 6-Tasmin, Tasmax, and Tas), but the spatial pattern remains consistent, indicating more intense warming inland and relatively moderate increases along coastal zones. The warming could range from 0.5 to 1.5 °C in the near future and 1.5–3.0°C in the far future. Under the low-SSP pathway (SSP1-2.6), projected increases range from 0.5–1.5°C, while under the high-SSP pathway (SSP5-8.5), warming spans from 1.0–3.0°C. Importantly, coastal regions are expected to experience relatively smaller increases compared to inland zones, emphasizing a spatially coherent but uneven warming pattern across all scenarios.

In contrast, precipitation projections are far more uncertain, showing stronger variability across models, regions, and scenarios (see S6 Fig and S7 Fig for precipitation in the supplementary file). About one-third of models' project wetter

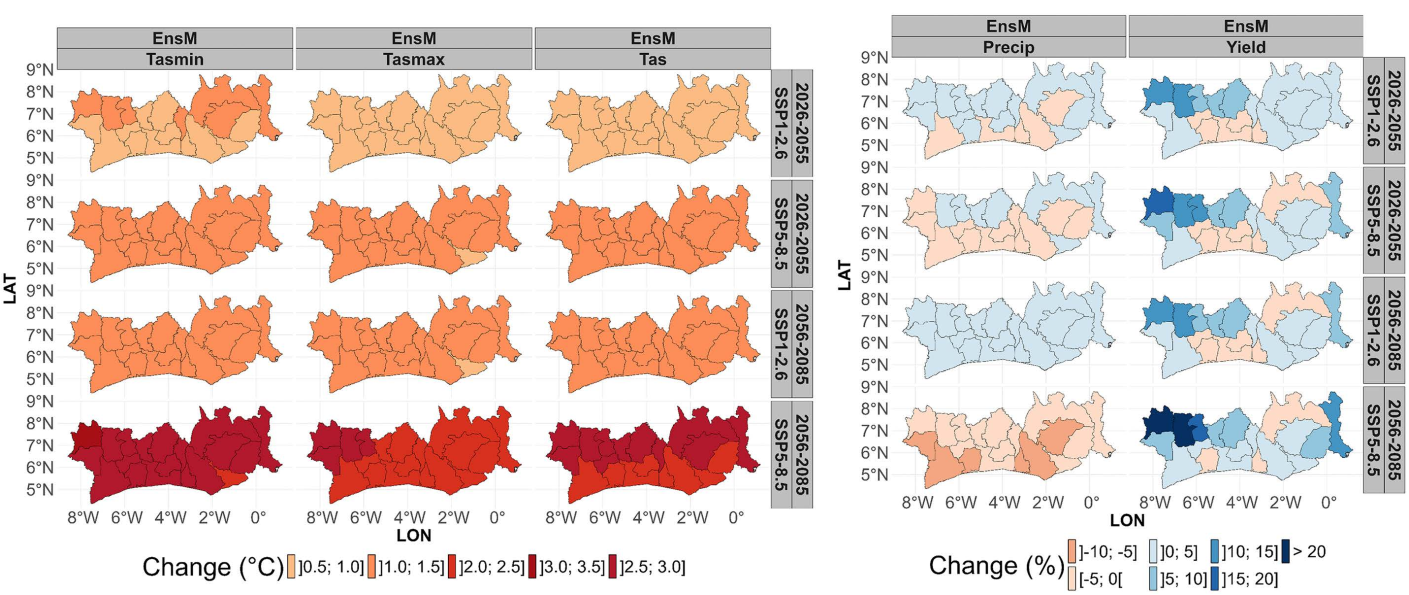

Fig 6. Regional patterns of projected changes in temperature, precipitation, and cocoa yield across Ghana and Côte d'Ivoire under the Shared Socioeconomic Pathways (SSP1-2.6 and SSP5-8.5) for the near future (2026–2055) and far future (2056–2085), relative to the baseline period (1985–2014). EnsM denotes the ensemble mean of the 12 Global Climate Models (GCMs). Tasmin, Tasmax, and Tas represent minimum, maximum, and mean temperature, respectively; Precip refers to precipitation, and Yield to projected cocoa production. The shapefiles used to create this image were obtained from the GADM database.

https://doi.org/10.1371/journal.pclm.0000970.g006

conditions, while nearly half indicate drier futures, with the magnitude and direction of change depending on the climate change scenario, and time horizon. Ensemble means (Fig 6-Precip in the supplementary file) highlight a drying trend, particularly under SSP5-8.5, with modest reductions of around 5% in parts of Ghana and Côte d'Ivoire by mid-century, expanding to widespread declines of 5–10% across most regions by 2056–2085. Under the low SSP scenario (SSP1-2.6), changes are smaller, with some areas even experiencing slight (~5%) increases. Spatial patterns reveal that southern cocoa-growing regions are most exposed to drying, while northern zones show greater variability across models, with some simulations indicating modest rainfall gains or less pronounced declines. This uncertainty contrasts with the robust and consistent warming signal and underscores the complex nature of rainfall responses to climate change. Importantly, such variability in precipitation could affect cocoa development cycles differently across regions, amplifying risks in areas with strong drying trends while creating mixed outcomes where rainfall projections diverge.

Projected cocoa yields across Ghana and Côte d'Ivoire show spatially heterogeneous responses under both SSP1-2.6 and SSP5-8.5 scenarios, with generally slight increases in some regions and relative stability in others (S8–S10 Figs). Uncertainty remains substantial and region-dependent, as reflected by the spread of the 10–90 percentiles and the inter-quartile range (Q1–Q3), highlighting variability across climate model projections. Under the low climate change scenario (SSP1-2.6), yields remain relatively stable (Fig 6-Yield) or improve slightly in central and northern regions, with modest gains of up to 15% in Dix-Huit Montagnes, Haut-Sassandra, Marahoué, Lacs, and N'zi Comoé, while small declines (<5%) are expected in southern and coastal areas such as Fromager, Sud-Bandama, Lagunes, Agnéby, and Sud-Comoé in Côte d'Ivoire. In Ghana, yields show a slight (~5%) increase under both future periods. By contrast, the high climate change scenario (SSP5-8.5) projects larger gains in Côte d'Ivoire, with 10–20% increases in Dix-Huit Montagnes, Haut-Sassandra, and Marahoué, while Ghana shows more modest improvements of about 5–10%, particularly by the far future (2056–2085). The Brong-Ahafo region in Ghana remains consistently at risk of yield decline under both scenarios, though losses are relatively small (~5%). Overall, some northern and western zones retain or improve productivity across scenarios, reflecting shifting climatic suitability despite risks in other regions.

The projected cocoa yield changes in Côte d'Ivoire and Ghana for 2026–2055, based on the EnsM model, show significant regional and scenario-based variability (Fig 7). When comparing the near future to the reference period, cocoa yield changes across Côte d'Ivoire and Ghana show marked regional variability, with some areas experiencing mixed gains and losses. Regions such as Agnéby, Bas-Sassandra, Fromager, Lagunes, Sud-Bandama, Sud-Comoé, and Moyen-Comoé in Côte d'Ivoire, as well as Ashanti, Brong-Ahafo, Central, Volta, Western, and Eastern in Ghana, exhibit both positive and negative shifts depending on the scenario, ranging from small declines (–7.5%) to modest gains (up to +25%). In contrast, several zones in Côte d'Ivoire, including Dix-Huit Montagnes, Haut-Sassandra, Lacs, Marahoué, Moyen-Cavally, and N'Zi Comoé, are projected to achieve consistent yield increases of 2–30% under both SSP1-2.6 and SSP5-8.5, highlighting areas of potential resilience. Conversely, some southern and coastal regions, notably Agnéby, Fromager, Lagunes, Sud-Bandama, and Sud-Comoé, along with Brong-Ahafo in Ghana, show average yield declines of around –0.5% to –4%, pointing to persistent vulnerability despite overall variability.

Decadal projections of cocoa yield changes for 2026–2035, 2036–2045, and 2046–2055 relative to 2005–2014 reveal clear spatial and temporal contrasts across Côte d'Ivoire and Ghana (S11 Fig in the supplementary file). In Côte d'Ivoire, regions such as Dix-Huit Montagnes, Lacs, Haut-Sassandra, and N'Zi-Comoé show consistent median yield increases, particularly under SSP1-2.6, suggesting potential localized benefits from gradual climate shifts. In contrast, southern coastal zones like Sud-Bandama and Sud-Comoé display stagnant or declining yields, especially under SSP5-8.5, highlighting heightened vulnerability. Ghana's response is weaker and more variable, with regions such as Volta, Brong-Ahafo, and Ashanti showing limited or negative changes across all decades, even under low SSP scenario. The wider interquartile ranges under SSP5-8.5 further underscore growing uncertainty and yield instability, emphasizing the need for region-specific adaptation strategies to safeguard cocoa production under changing climate conditions.

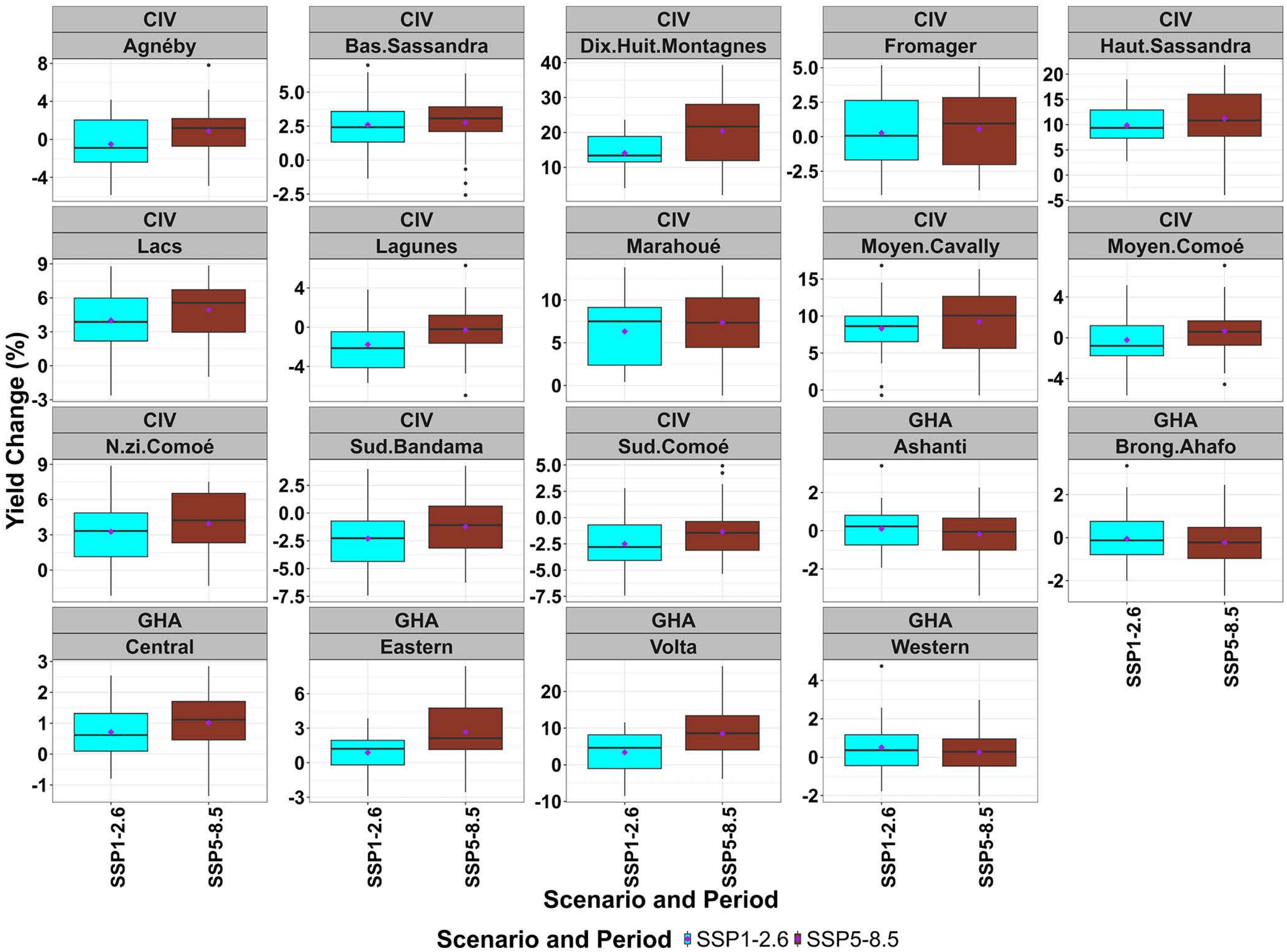

Fig 7. Percentage changes in cocoa yield for the near future (2026–2055) relative to the baseline period (1985–2014) across regions in Côte d'Ivoire (CIV) and Ghana (GHA), under low-(SSP1-2.6) and high-(SSP5-8.5). Shared Socioeconomic Pathways scenarios, based on the ensemble mean (EnsM) of 12 Global Climate Models (GCMs).

https://doi.org/10.1371/journal.pclm.0000970.g007

3.4. Drought and excess rainfall impacts on cocoa yield

Figure 8 presents the potential impacts of drought (Rainfall deficit) and excess rainfall on cocoa yield in the near future for the EnsM model. The multi-model variability is presented in S12 Fig in the supplementary file. It is worth noting that the drought years were considered as years with a standardized precipitation index (SPI) less than or equal to -1 and excess rainfall when SPI greater than or equal to 1. Under drought conditions for the EnsM model, precipitation is projected to decline across cocoa-producing regions in the near future under a low-SSP scenario. In the northern areas of Côte d'Ivoire, including Dix-Huit Montagnes, Haut-Sassandra, Moyen-Cavally, Marahoué, Lacs, Fromager, N'Zi-Comoé, Agnéby, and Moyen-Comoé, the precipitation reductions range between 5% and 10%. In contrast, the southern regions of Côte d'Ivoire, including Bas-Sassandra, Sud-Bandama, Lagunes, and Sud-Comoé, as well as all regions in Ghana, are expected to experience a 10% to 15% decline in precipitation. These changes are likely to be associated with an overall cocoa yield decline of around 5%, except in Marahoué, Lacs (Côte d'Ivoire), and Brong-Ahafo (Ghana), where yields may increase by approximately 5%. However, the contrasting responses observed in Marahoué, Lacs (Côte d'Ivoire), and Brong-Ahafo (Ghana) are likely related to region-specific climate sensitivities captured by the model.

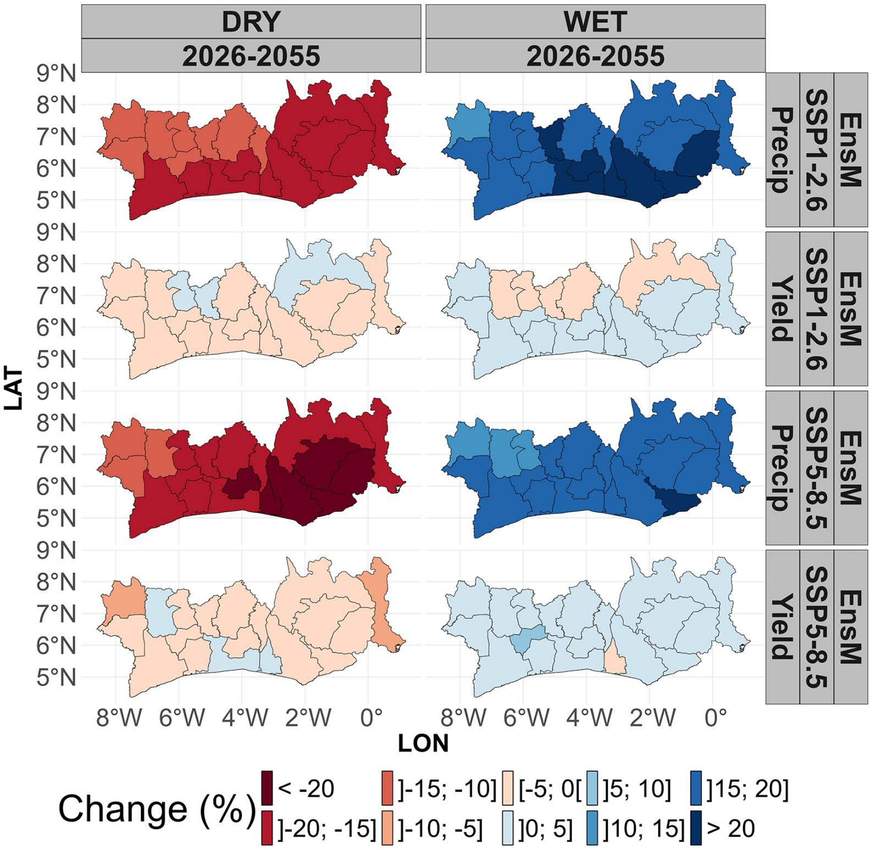

Fig 8. Regional cocoa yield sensitivity to rainfall extremes for the near future (2026–2055) relative to the reference period (1985–2014) under low-(SSP1-2.6) and high-(SSP5-8.5). Shared Socioeconomic Pathways scenarios across Côte d'Ivoire and Ghana, based on the ensemble mean (EnsM) of 12 GCMs (Global Climate Models). The shapefiles used to create this image were obtained from the GADM database.

https://doi.org/10.1371/journal.pclm.0000970.g008

Under a high-SSP scenario of the EnsM model, the expected precipitation declines vary significantly across regions. In Dix-Huit Montagnes, Haut-Sassandra, and Moyen-Cavally, the decrease is projected to be less than 5%. Regions such as Brong-Ahafo, Volta, Marahoué, Lacs, Fromager, N'Zi-Comoé, Agnéby, Moyen-Comoé, Bas-Sassandra, Sud-Bandama, and Lagunes may face a decline of 5% to 10%. In Agnéby (CIV), and the Western, Ashanti, Central, and Eastern regions of Ghana, the precipitation reduction could exceed 20%. These changes are expected to result in a yield decline of less than 5% in most regions but may reach 5% to 10% in Dix-Huit Montagnes (CIV) and Volta (Ghana). Notably, Haut-Sassandra, Lagunes, and Sud-Comoé may not experience significant yield reductions under this scenario.

During excess rainfall, precipitation may increase by 5% to over 20%, particularly under the low-SSP scenario. These wetter conditions could result in a slight relative decrease in cocoa yield (less than 5%) in northern regions (Haut-Sassandra, Marahoué, Lacs, N'Zi-Comoé and Brong Ahafo), while in some southern regions, a slight increase in yield may be observed due to improved soil moisture conditions and reduced water stress.

Under the high-emission SSP scenario, years with excess rainfall are projected to result in a relative yield increase of around 5% across most regions. An exception is observed in Sud-Comoé (Côte d'Ivoire), where yields may slightly decline (less than 5%). These contrasting responses reflect region-specific climate sensitivities captured by the model and should be interpreted as statistical associations rather than direct evidence of processes such as waterlogging or other impacts of excessive rainfall.

The impacts of rainfall deficit and surplus severity on Cocoa Yields in Côte d'Ivoire and Ghana are presented in Fig 9. Under moderately dry conditions, the lowest SSP scenario (SSP1-2.6) results in a precipitation decline ranging from around 5% in regions like Dix-huit Montagnes to up to 10% across most areas, with corresponding cocoa yield reductions of approximately 5%, except in Moyen-Cavally, Haut-Sassandra, and Brong Ahafo, where yields appear less affected. In contrast, under the highest SSP scenario (SSP5-8.5), precipitation declines more sharply, by 10–20%, leading to greater yield losses of up to 10% in vulnerable regions like Dix-huit Montagnes and Volta, while regions such as Haut-Sassandra, Lagunes, and Ashanti show more resilience.

Under severely dry conditions, the lowest SSP scenario indicates precipitation declines between 10% (e.g., Dix-huit Montagnes, Moyen-Cavally) and over 20% (notably in the Central region), resulting in yield losses of around 5% in most regions and up to 10% in Eastern, with exceptions like N'zi-Comoe and Ashanti where yields remain relatively stable. Under the highest SSP scenario, precipitation drops 15–20% or more, causing widespread but moderate yield declines of about 5% in regions such as Marahoue, Fromager, Western, and Ashanti, and 5–10% reductions in Eastern and Volta.

Under extremely dry conditions, precipitation losses exceed 20% almost everywhere under both scenarios, though under SSP1-2.6, yields generally decline around 5%, rising to 10% in areas like Dix-huit Montagnes and Volta, except in Marahoue, Western, and Brong Ahafo. Under SSP5-8.5, the yield losses reach up to 10% in Fromager, Eastern, and Volta, while coastal areas like Bas-Sassandra and Sud-Comoe show slightly smaller losses (~5%), suggesting regional differences in vulnerability and adaptive capacity to future drought intensities.

4. Discussions

4.1. Performance of bias-correction methods

The evaluation showed that all bias-correction techniques enhanced climate projections. However, temperature adjustments were more accurate due to their stable and continuous behavior, compared to the intermittent

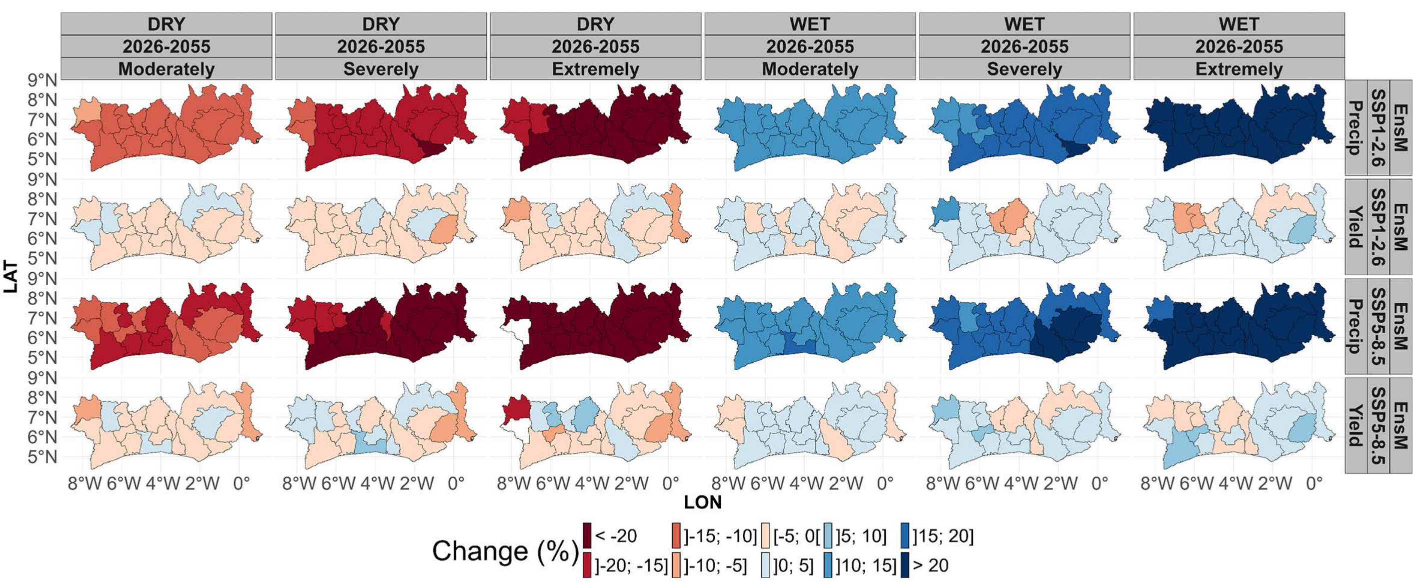

Fig 9. Regional variations in cocoa yield response to different levels of rainfall deficit and excess in the near future (2026–2055), relative to the reference period (1985–2014) under low-(SSP1-2.6) and high-(SSP5-8.5). Shared Socioeconomic Pathways scenarios, across Côte d'Ivoire and Ghana, based on the ensemble mean of 12 GCMs (Global Climate Models). The shapefiles used to create this image were obtained from the GADM database.

https://doi.org/10.1371/journal.pclm.0000970.g009

variability of precipitation. The modified Delta Change approach performed most consistently, particularly in preserving intra-annual variability and maintaining the climate change signal (CCS). Its simplicity, robustness, and transparency make it particularly suitable for data-sparse regions, outperforming complex techniques such as CDFt, LOCI, SDM, and EQM, which may distort extremes if non-stationarity is ignored. This finding aligns with [56] and [57], who noted that Delta Change approaches preserve long-term climatic trends essential for impact modeling.

Given the large uncertainties and substantial inter-model divergence characterizing CMIP6 precipitation projections over West Africa [58,59]. The ability of the Delta method to produce stable corrections without excessively modifying extreme values becomes particularly valuable. Studies such as [45,46] have warned that quantile-based bias-correction techniques, including CDFt and EQM, may artificially alter rainfall occurrence frequencies or exaggerate tail behavior when the relationship between historical and future distributions shifts significantly [45,46]. The present study's finding that temperature correction accuracy exceeds precipitation accuracy is also consistent with established understanding. This is because temperature fields are more spatially and temporally homogeneous than precipitation, making them inherently easier to bias-adjust with high fidelity [48,49].

Overall, these methodological insights reinforce a growing consensus in literature. The delta change approach is a simple, trend-preserving bias-correction method that often provides more robust and reliable inputs for climate impact assessments in tropical, data-limited environments. This conclusion is especially relevant for cocoa–climate modeling applications, where crop yields are highly sensitive to precipitation extremes and distributional characteristics. By avoiding unnecessary manipulation of rainfall statistics while maintaining key climatic signals, the Delta Change method offers a pragmatic and scientifically defensible pathway for generating bias-adjusted datasets that support resilient and accurate impact modelling.

4.2. Machine learning and spatial variability in cocoa yield projection

Subsequent Random Forest (RF) models for cocoa yield projection progressively improved over three iterations, achieving higher accuracy and reduced bias. This improvement is primarily due to the progressive selection of the most informative predictors and the removal of less relevant variables, thereby enhancing model parsimony and explanatory power. Each iteration allowed the model to better learn the nonlinear interactions among climate variables, enhancing its ability to generalize across regions [26,60]. Nonetheless, even the best-performing RF model did not fully explain the total variability in cocoa yield. A substantial share of the unexplained variance remains, ranging from 10–35% in Côte d'Ivoire and 5–20% in Ghana, depending on the region. This reflects the influence of non-climatic factors such as soil characteristics, farm management, tree age, and socio-economic conditions that are not captured by climate-only predictors. Addressing these limitations will require more detailed datasets and integrated modelling approaches to better isolate climate-driven yield responses.

Despite the overall strong performance, the results also reveal marked spatial differences in model accuracy. Regions such as Volta in Ghana and Haut-Sassandra in Côte d'Ivoire exhibited higher projection errors, potentially beacuse these regions are characterized by noisier and more variable observational datasets, which can reduce the model's ability to learn stable climate–yield relationships. This pattern is consistent with findings from [55], which shows that cocoa's sensitivity to climate is highly region-specific, driven by variations in soil moisture regimes and temperature thresholds. Recent work by [5] similarly demonstrates that changing water stress patterns and precipitation extremes affect cocoa production differently across ecological zones in Côte d'Ivoire and Ghana. Study [10] further highlights the influence of local microclimates, particularly in agroforestry systems, where variations in shade, humidity, and canopy structure modify the crop's climatic response. Earlier ecological studies, including [13] and [14], also show that factors such as pollination dynamics, shade configuration, and disease susceptibility (e.g., black pod) can either amplify or dampen cocoa yield responses to climate variability.

The findings of this study show that Random Forest is a powerful method for capturing nonlinear climatic influences on cocoa yield. However, climatic predictors alone cannot fully explain yield variability. A significant portion of the variance remains unexplained. This suggests the need to integrate additional data layers [27]. These include socio-economic conditions such as access to inputs, extension services, and credit. Biological factors such as tree age and cultivar are also important. Ecological conditions, including shade cover and pest and disease pressures, should also be considered. Incorporating such variables, as recommended by recent machine-learning applications in West African agriculture, would enhance the granularity and predictive robustness of future cocoa–climate modeling frameworks [5,26]. Ultimately, the combination of bias-corrected climate data and machine-learning approaches provides a strong foundation for spatially explicit cocoa yield forecasting, but further integration of multi-sectoral drivers is essential for achieving truly location-specific accuracy [27].

4.3. Climate change impacts, vulnerability, and adaptation

Climate projections indicate significant spatial and temporal variability across Ghana and Côte d'Ivoire. Under high SSP scenarios (SSP5-8.5), rainfall is expected to decline by up to 20%, while temperatures rise by over 3.5°C by 2085, which is consistent with results reported in [58,59]. The combination of intensified heat stress and reduced rainfall could pose substantial risks to rainfed cocoa systems, particularly in the humid forest and coastal zones, where our analysis indicates potential yield reductions of 10–20%, as compound drought and heat events have been shown to substantially amplify crop yield losses compared to individual stresses [61]. In contrast, under low-SSP scenarios (SSP1-2.6), certain northern and central regions are projected to experience relative yield stability or modest increases. This spatial divergence is primarily driven by consistent increases in temperature across all scenarios, while precipitation projections remain highly variable, increasing uncertainty in rainfall-dependent regions.

These regional differences are well supported by existing literature. Studies [12] and [9] identify southern Côte d'Ivoire and Ghana as long-term climate "hotspots" where rising vapor-pressure deficits and heat stress increasingly undermine cocoa suitability. Similarly, study [8] shows that projected mid-century suitability losses are concentrated in the humid forest belt, consistent with the yield declines observed in this study. Conversely, the relative stability or emerging potential in the northern and central zones under lower SSP scenarios is consistent with [62], which highlights opportunities for cocoa expansion in these areas, provided that effective shade management, agroforestry practices, and soil moisture conservation are implemented.

Drought conditions ($SPI \leq -1$) were associated with amplified yield losses due to reduced precipitation and increased water stress, consistent with evidence that drought can significantly reduce crop yields and that combined heat and drought extremes further exacerbate losses [61]. In contrast, years with excess rainfall ($SPI \geq 1$) were associated with modest yield gains in some regions. However, these responses vary spatially and reflect statistical relationships captured by the model rather than direct evidence of processes such as waterlogging. Overall, cocoa appears more sensitive to water deficits than to excess moisture, suggesting that regions exposed to prolonged drought conditions may experience comparatively greater impacts [5–7]. Overall, these results highlight the location-specific nature of climate change impacts on cocoa productivity and underscore the need for targeted adaptation strategies, particularly in vulnerable southern and coastal production zones.

To mitigate the growing risks of climate change, targeted adaptation strategies in highly vulnerable cocoa-growing regions such as Sud-Comoé, Sud-Bandama in Côte d'Ivoire, Volta, and Brong Ahafo in Ghana should combine ecological, technological, and institutional approaches to enhance resilience. Ecological interventions, including agroforestry systems and shade management, can reduce heat stress, improve soil structure, and promote biodiversity [63–65], though their effectiveness may be constrained by root competition for water in already-dry environments. Supplemental irrigation can help stabilize yields during dry spells [8,66], but its implementation requires substantial investment in infrastructure and reliable water access [67]. Developing and disseminating drought- and flood-tolerant cocoa varieties [7] can further enhance crop resilience and sustain productivity under increasingly variable climatic conditions.

Enhanced climate information services, such as localized forecasts and seasonal outlooks [68–70], are critical for timely decision-making and risk reduction. Integrating Internet of Things (IoT) technologies, machine learning, and citizen science can strengthen local data collection, improve climate monitoring, and enable early warning systems for extreme events [71–73]. These digital innovations support proactive, data-driven adaptation planning and enhance regional capacity to manage climate risks. Ultimately, aligning adaptation strategies with local agroecological conditions and socio-economic realities is essential for ensuring the long-term sustainability and productivity of cocoa farming in West Africa.

4.4. Limitations

This study's projections of climate change impacts on cocoa production in Côte d'Ivoire and Ghana are subject to several methodological and data-related limitations. The use of Global Climate Models (GCMs) introduces inherent uncertainties due to variations in model structures, parameterizations, and climate change scenario assumptions. While spatial interpolation and bias correction improve local relevance, they cannot fully capture microclimatic processes, localized feedback, or extreme weather variability that significantly affect cocoa productivity. The spatial resolution (~5 km) may overlook fine-scale heterogeneity in soil properties, topography, and farm-level management practices that influence cocoa growth.

The reliability of rainfed cocoa production is further undermined by persistent uncertainty in rainfall projections and the significant warming expected across both near- and far-future periods, as variable precipitation patterns reduce the predictability and stability of yields [5]. Climate change may also drive a northward contraction of suitable cocoa-growing areas, particularly through the expansion of the Savanna zone [62], leading to region-specific losses or gains in production potential. Collectively, these factors interact across spatial and temporal scales, resulting in uneven vulnerability and highlighting the need for regionally tailored adaptation strategies.

The Random Forest model used for yield projection, though robust, relies on available historical data that may not fully represent future physiological or ecological responses to compound climate stressors such as prolonged drought or heatwaves. Moreover, this study did not explicitly integrate socio-economic, institutional, and technological factors that shape farmers' adaptive capacity and decision-making. Key influences such as input access, financial constraints, crop age structure, pest and disease dynamics, and land-use change were not modeled, potentially oversimplifying real-world vulnerability [7,8]. The analysis assumes static management conditions and does not account for adaptive shifts in cropping systems, irrigation practices, or cultivar selection that could alter future outcomes. Similarly, the treatment of extreme climate events, such as floods or multi-year droughts, was limited to general yield impacts, without dynamic modeling of event frequency, intensity, or recovery periods. These limitations highlight the need for coupled climate–crop–socioeconomic modeling frameworks and finer-scale observational data to improve the accuracy, interpretability, and policy relevance of future projections for West Africa's cocoa sector.

Future research should focus on filling key knowledge gaps to strengthen the resilience of cocoa production under climate change. Priorities include developing high-resolution suitability maps that integrate biophysical and socio-economic data, examining how farm management practices and farmer characteristics influence climate impacts, and assessing the socio-economic consequences of yield variability on livelihoods and food security. Further studies should also isolate the effects of extreme events such as heatwaves, droughts, and heavy rainfall on yield fluctuations, and produce region-specific, seasonal productivity assessments to support risk-based adaptation and targeted policy interventions across West Africa.

5. Conclusions

This study rigorously evaluates bias-correction methods for climate projections and their application in predicting cocoa yields across Côte d'Ivoire and Ghana, finding that the simpler modified Delta Change approach consistently outperforms more complex techniques due to its robustness and ability to preserve climate signals, especially for precipitation. By integrating bias-corrected climate data with Random Forest models, the study achieves improved cocoa yield projections.

However, spatial differences in model accuracy highlight the need to consider local factors, such as soil, tree age, and management practices, to refine forecasts.

Projected climate change impacts exhibit significant variation across regions and time under both low- and high-SSP scenarios. Drying trends, especially in southern cocoa-growing areas, are expected to worsen by mid- to late-century under high SSP scenario, with rainfall drops of over 20% and sharp temperature rises. These changes may threat rain-fed cocoa production, with yields potentially stable or slightly improved in northern and central zones under low climate change scenario but declining sharply in southern and coastal areas under high SSP scenario. Droughts intensify these losses, highlighting the need for targeted, region-specific adaptation strategies.

The severity of extreme climate events, such as dry-warm and wet-warm conditions, poses additional threats to cocoa sustainability by increasing vulnerability in the most sensitive regions. To mitigate these impacts, adaptation strategies that combine ecological, technological, and institutional measures, like agroforestry, supplemental irrigation, climate-resilient cocoa varieties, and advanced climate information services, are crucial. Furthermore, harnessing machine learning and IoT technologies for early warning systems and adaptive management can enhance local resilience.

For long-term sustainability, future research should prioritize high-resolution suitability mapping that integrates both biophysical and socioeconomic factors, in-depth analysis of management practices and socioeconomic drivers of yield variability, and assessment of the socioeconomic impacts of climate change. Additionally, isolating the effects of specific extreme weather events on cocoa productivity and performing regionally detailed seasonal assessments will refine risk modeling and guide the development of more effective, equitable adaptation policies.

Supporting information

S1 Fig. Top 20 variables ranked by importance in round two modelling.
(TIF)

S2 Fig. Top 10 variables ranked by importance in round three modelling.
(TIF)

S3 Fig. Performance of bias correction methods in representing precipitation seasonality.
(PNG)

S4 Fig. Performance of bias correction methods in representing mean temperature seasonality.
(PNG)

S5 Fig. Regional patterns of mean annual temperature change under ssp1-2.6 and ssp5-8.5 scenarios (2026–2085). NB: The shapefiles used to create this image were obtained from the GADM database.
(PNG)

S6 Fig. Regional patterns of annual precipitation change under ssp1-2.6 and ssp5-8.5 scenarios (2026–2085). NB: The shapefiles used to create this image were obtained from the GADM database.
(PNG)

S7 Fig. Model agreement on projected changes in precipitation and predicted yield for the near future. NB: POS refers to positive change, while NEG stands for negative change. The shapefiles used to create this image were obtained from the GADM database.
(TIF)

S8 Fig. Statistical summary of projected cocoa yields across regions based on the ensemble of 12 models, showing the median along with the 10th and 90th percentile ranges.
(TIF)

S9 Fig. Statistical summary of projected cocoa yields across regions based on the ensemble of 12 models, showing the median and interquartile range (Q1–Q3).
(TIF)

S10 Fig. Regional variations in cocoa yield response to climate change in Côte d'Ivoire and Ghana. The shapefiles used to create this image were obtained from the GADM database.
(PNG)

S11 Fig. Decadal variability in projected cocoa yield change (2026–2055) across climate scenarios in Côte d'Ivoire and Ghana.
(PNG)

S12 Fig. Projected rainfall and yield changes averaged over the dry years for the near future. The shapefiles used to create this image were obtained from the GADM database.
(PNG)

S1 Data. Supporting dataset containing the data used in this study for statistical analyses, model development, and the generation of figures and tables presented in the manuscript.
(ZIP)

Author contributions

Conceptualization: Salomon Obahoundje, Seifu A. Tilahun, Petra Schmitter.

Data curation: Salomon Obahoundje.

Formal analysis: Salomon Obahoundje.

Funding acquisition: Petra Schmitter.

Investigation: Salomon Obahoundje, Seifu A. Tilahun.

Methodology: Salomon Obahoundje, Seifu A. Tilahun.

Project administration: Petra Schmitter.

Resources: Petra Schmitter.

Supervision: Seifu A. Tilahun.

Validation: Seifu A. Tilahun, Petra Schmitter.

Visualization: Salomon Obahoundje.

Writing – original draft: Salomon Obahoundje.

Writing – review & editing: Salomon Obahoundje, Seifu A. Tilahun, Petra Schmitter.

References

1. ClientEarth. A legal pathway to sustainable cocoa in Ghana and Côte d' Ivoire. ClientEarth; 2022. Available from: https://www.clientearth.org
2. World Bank. Au pays du cacao comment transformer la Côte d'Ivoire. 2019. Available from: http://documents.worldbank.org/curated/en/277191561741906355/Cote-dIvoire-Economic-Update
3. Kongor JE, Owusu M, Oduro-Yeboah C. Cocoa production in the 2020s: challenges and solutions. CABI Agric Biosci. 2024. https://doi.org/10.1186/s43170-024-00310-6
4. Ofori-Boateng K, Insah B. The impact of climate change on cocoa production in West Africa. Int J Clim Chang Strateg Manag. 2014;6(3):296–314. https://doi.org/10.1108/ijccsm-01-2013-0007
5. Obahoundje S, Akpoti K, Zwart SJ, Tilahun SA, Cofie O. Implications of changes in water stress and precipitation extremes for cocoa production in Côte D'ivoire and Ghana. Intl Journal of Climatology. 2025;45(9). https://doi.org/10.1002/joc.8872

6. Daymond AJ, Hadley P. Differential effects of temperature on fruit development and bean quality of contrasting genotypes of cacao (Theobroma cacao). Ann Appl Biol. 2008;153(2):175–85. https://doi.org/10.1111/j.1744-7348.2008.00246.x
7. Lahive F, Hadley P, Daymond AJ. The physiological responses of cacao to the environment and the implications for climate change resilience. A review. Agron Sustain Dev. 2018;39(1). https://doi.org/10.1007/s13593-018-0552-0
8. Asante PA, Rahn E, Anten NPR, Zuidema PA, Morales A, Rozendaal DMA. Climate change impacts on cocoa production in the major producing countries of West and Central Africa by mid-century. Agric For Meteorol. 2025;362:110393. https://doi.org/10.1016/j.agrformet.2025.110393
9. Schroth G, Läderach P, Martinez-Valle AI, Bunn C, Jassogne L. Vulnerability to climate change of cocoa in West Africa: patterns, opportunities and limits to adaptation. Sci Total Environ. 2016;556:231–41. https://doi.org/10.1016/j.scitotenv.2016.03.024 PMID: 26974571
10. Asitoakor BK, Asare R, Ræbild A, Ravn HP, Eziah VY, Owusu K, et al. Influences of climate variability on cocoa health and productivity in agroforestry systems in Ghana. Agric For Meteorol. 2022;327:109199. https://doi.org/10.1016/j.agrformet.2022.109199
11. Anning AK, Ofori-Yeboah A, Baffour-Ata F, Owusu G. Climate change manifestations and adaptations in cocoa farms: perspectives of smallholder farmers in the Adansi South District, Ghana. Curr Res Environ Sustain. 2022;4:100196. https://doi.org/10.1016/j.crsust.2022.100196
12. Läderach P, Martinez-Valle A, Schroth G, Castro N. Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire. Clim Change. 2013;119(3–4):841–54. https://doi.org/10.1007/s10584-013-0774-8
13. Duguma B, Gockowski J, Bakala J. Smallholder cacao (Theobroma cacao Linn.) cultivation in agroforestry systems of West and Central Africa: challenges and opportunities. Agrofor Syst. 2001;51(3):177–88. https://doi.org/10.1023/a:1010747224249
14. Groeneveld JH, Tscharntke T, Moser G, Clough Y. Experimental evidence for stronger cacao yield limitation by pollination than by plant resources. Perspect Plant Ecol Evol Syst. 2010;12(3):183–91. https://doi.org/10.1016/j.ppees.2010.02.005
15. Maguire-Rajpaul VA, Khatun K, Hirons MA. Agricultural information's impact on the adaptive capacity of Ghana's smallholder cocoa farmers. Front Sustain Food Syst. 2020;4. https://doi.org/10.3389/fsufs.2020.00028
16. Baffour-Ata F, Antwi-Agyei P, Boakye L, Tettey LSNA, Forson MNEF, Abiwu AE, et al. Assessing the adaptive capacity of smallholder cocoa farmers to climate variability in the Adansi South District of the Ashanti Region, Ghana. Heliyon. 2023;9:e13994. https://doi.org/10.1016/j.heliyon.2023.e13994
17. Zuidema G, Gerritsma M, Mommer L, Leffelaar PF. A physiological production model for cacao: Model description and technical program manual of CASE2 version 2.2. 2003. Available from: http://edepot.wur.nl/16613
18. Cao J, Zhang Z, Luo Y, Zhang L, Zhang J, Li Z, et al. Wheat yield predictions at a county and field scale with deep learning, machine learning, and google earth engine. Eur J Agron. 2021;123:126204. https://doi.org/10.1016/j.eja.2020.126204
19. Vanuytrecht E, Raes D, Steduto P, Hsiao TC, Fereres E, Heng LK, et al. AquaCrop: FAO's crop water productivity and yield response model. Environ Model Softw. 2014;62:351–60. https://doi.org/10.1016/j.envsoft.2014.08.005
20. Kipkulei HK, Bellingrath-Kimura SD, Lana M, Ghazaryan G, Baatz R, Boitt M, et al. Assessment of maize yield response to agricultural management strategies using the DSSAT–CERES-maize model in trans Nzoia County in Kenya. Int J Plant Prod. 2022;16(4):557–77. https://doi.org/10.1007/s42106-022-00220-5
21. Luetkemeier R, Stein L, Drees L, Müller H, Liehr S. Uncertainty of rainfall products: impact on modelling household nutrition from rain-fed agriculture in Southern Africa. Water. 2018;10(4):499. https://doi.org/10.3390/w10040499
22. Akinseye FM, Ajeigbe HA, Kamara AY, Omotayo AO, Tofa AI, Whitbread AM. Establishing optimal planting windows for contrasting sorghum cultivars across diverse agro-ecologies of North-Eastern Nigeria: a modelling approach. Agronomy. 2023;13(3):727. https://doi.org/10.3390/agronomy13030727
23. Breiman L. Random forests. Machine Learning. 2001;10: 5–32. https://doi.org/10.3390/rs10060911
24. Crane-Droesch A. Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. Environ Res Lett. 2018;13(11):114003. https://doi.org/10.1088/1748-9326/aae159
25. Olofintuyi SS, Olajubu EA, Olanike D. An ensemble deep learning approach for predicting cocoa yield. Heliyon. 2023;9(4):e15245. https://doi.org/10.1016/j.heliyon.2023.e15245 PMID: 37089327
26. Asamoah E, Heuvelink GBM, Chairi I, Bindraban PS, Logah V. Random forest machine learning for maize yield and agronomic efficiency prediction in Ghana. Heliyon. 2024;10(17):e37065. https://doi.org/10.1016/j.heliyon.2024.e37065 PMID: 39286064
27. Jeong JH, Resop JP, Mueller ND, Fleisher DH, Yun K, Butler EE, et al. Random forests for global and regional crop yield predictions. PLoS One. 2016;11(6):e0156571. https://doi.org/10.1371/journal.pone.0156571 PMID: 27257967
28. Obahoundje S, Tilahun SA, Birhanu BZ, Schmitter P e t r a. A critical synthesis of remote sensing and machine learning approaches for climate hazard impact on crop yield. Environ Res Commun. 2025;7:102001. https://doi.org/10.1088/2515-7620/ae1099
29. Obahoundje S, Diedhiou A, Troccoli A, Boorman P, Alabi TAF, Anquetin S, et al. Teal-WCA: a climate services platform for planning solar photovoltaic and wind energy resources in West and Central Africa in the context of climate change. Data. 2024;9(12):148. https://doi.org/10.3390/data9120148
30. Yoroba F, Kouadio K, Kouassi BK, Doumbia M, Diawara A, Dje BK, et al. Evaluating the impacts of climate variability on cocoa production in the western centre of Cote d'Ivoire during 1979-2010. ACS. 2023;13(02):201–24. https://doi.org/10.4236/acs.2023.132012

31. Abu I-O, Szantoi Z, Brink A, Robuchon M, Thiel M. Detecting cocoa plantations in Côte d'Ivoire and Ghana and their implications on protected areas. Ecol Indic. 2021;129:107863. https://doi.org/10.1016/j.ecolind.2021.107863 PMID: 34602863
32. Lovato T, Peano D, Butenschön M, Materia S, Iovino D, Scoccimarro E, et al. CMIP6 simulations with the CMCC Earth System Model (CMCC-ESM2). J Adv Model Earth Syst. 2022;14(3). https://doi.org/10.1029/2021ms002814
33. Döscher R, Acosta M, Alessandri A, Anthoni P, Arsouze T, Bergmann T, et al. The EC-Earth3 earth system model for the climate model intercomparison project 6. 2022. https://doi.org/hal-03451376
34. Wyser K, Kjellström E, Koenigk T, Martins H, Döscher R. Warmer climate projections in EC-Earth3-Veg: the role of changes in the greenhouse gas concentrations from CMIP5 to CMIP6. Environ Res Lett. 2020;15(5):054020. https://doi.org/10.1088/1748-9326/ab81c2
35. Wang Y, Yu Z, Lin P, Liu H, Jin J, Li L, et al. FGOALS-g3 Model Datasets for CMIP6 flux-anomaly-forced model intercomparison project. Adv Atmos Sci. 2020;37(10):1093–101. https://doi.org/10.1007/s00376-020-2045-8
36. Volodin E, Mortikov E, Gritsun A, Lykossov V, Galin V, Diansky N. INM INM-CM4-8 model output prepared for CMIP6 CMIP. World Data Center for Climate (WDCC) at DKRZ; 2023. Available from: https://www.wdc-climate.de/ui/entry?acronym=C6_4405689
37. Lurton T, Balkanski Y, Bastrikov V, Bekki S, Bopp L, Braconnot P, et al. Implementation of the CMIP6 forcing data in the IPSL-CM6A-LR Model. J Adv Model Earth Syst. 2020;12(4). https://doi.org/10.1029/2019ms001940
38. Tatebe H, Ogura T, Nitta T, Komuro Y, Ogochi K, Takemura T, et al. Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. Geosci Model Dev. 2019;12(7):2727–65. https://doi.org/10.5194/gmd-12-2727-2019
39. Mauritsen T, Bader J, Becker T, Behrens J, Bittner M, Brokopf R, et al. Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and its response to increasing CO2. J Adv Model Earth Syst. 2019;11(4):998–1038. https://doi.org/10.1029/2018MS001400 PMID: 32742553
40. Yukimoto S, Kawai H, Koshiro T, Oshima N, Yoshida K, Urakawa S, et al. The meteorological research institute earth system model version 2.0, MRI-ESM2.0: description and basic evaluation of the physical component. J Meteorol Soc Jpn. 2019;97(5):931–65. https://doi.org/10.2151/jmsj.2019-051
41. Cao J, Ma L, Liu F, Chai J, Zhao H, He Q, et al. NUIST ESM v3 data submission to CMIP6. Adv Atmos Sci. 2021;38:268–84. https://doi.org/10.1007/s00376-020-0173-9
42. Seland Ø, Bentsen M, Olivié D, Toniazzo T, Gjermundsen A, Graff LS, et al. Overview of the Norwegian Earth System Model (NorESM2) and key climate response of CMIP6 DECK, historical, and scenario simulations. Geosci Model Dev. 2020;13(12):6165–200. https://doi.org/10.5194/gmd-13-6165-2020
43. Lee WL, Liang HC. AS-RCEC TaiESM1.0 model output prepared for CMIP6 CMIP 1pctCO2. Earth Syst Grid Fed. 2020;6:4–7. https://doi.org/10.22033/ESGF/CMIP6.9702
44. Navarro-Racines C, Tarapues J, Thornton P, Jarvis A, Ramirez-Villegas J. High-resolution and bias-corrected CMIP5 projections for climate change impact assessments. Sci Data. 2020;7(1):7. https://doi.org/10.1038/s41597-019-0343-8 PMID: 31959765
45. Famien AM, Janicot S, Ochou AD, Vrac M, Defrance D, Sultan B, et al. A bias-corrected CMIP5 dataset for Africa using the CDF-t method – a contribution to agricultural impact studies. Earth Syst Dynam. 2018;9(1):313–38. https://doi.org/10.5194/esd-9-313-2018
46. Vrac M, Noël T, Vautard R. Bias correction of precipitation through singularity stochastic removal: because occurrences matter. J Geophys Res Atmospheres. 2016;121(10):5237–58. https://doi.org/10.1002/2015jd024511
47. Michelangeli P -A., Vrac M, Loukos H. Probabilistic downscaling approaches: application to wind cumulative distribution functions. Geophys Res Lett. 2009;36(11). https://doi.org/10.1029/2009gl038401
48. Maraun D. Bias correcting climate change simulations - a critical review. Curr Clim Change Rep. 2016;2(4):211–20. https://doi.org/10.1007/s40641-016-0050-x
49. Schmidli J, Frei C, Vidale PL. Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. Int J Climatol. 2006;26(5):679–89. https://doi.org/10.1002/joc.1287
50. Switanek MB, Troch PA, Castro CL, Leuprecht A, Chang H-I, Mukherjee R, et al. Scaled distribution mapping: a bias correction method that preserves raw climate model projected changes. Hydrol Earth Syst Sci. 2017;21(6):2649–66. https://doi.org/10.5194/hess-21-2649-2017
51. Alexander L, Zhang X. Global observed changes in daily climate extremes of temperature and precipitation. J Geophys Res Atmospheres. 2006. Available: http://onlinelibrary.wiley.com/doi/10.1029/2005JD006290/full
52. Vicente-Serrano SM, Beguería S, López-Moreno JI. A Multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim. 2010;23(7):1696–718. https://doi.org/10.1175/2009jcli2909.1
53. Thornthwaite CW. On the deformation mechanisms in sap single crystals. Geogr Rev. 1948;38:55–94. https://doi.org/10.1016/0022-3115(71)90076-6
54. WMO. Standardized precipitation index user guide. Geneva, Switzerland: WMO; 2012. Available from: https://digitalcommons.unl.edu/droughtfacpub
55. Yoroba F, Kouassi BK, Diawara A, Yapo LAM, Kouadio K, Tiemoko DT. Evaluation of rainfall and temperature conditions for a perennial crop in tropical wetland: a case study of cocoa in Côte d'Ivoire. Adv Meteorol. 2019. https://doi.org/10.1155/2019/9405939
56. Räty O, Räisänen J, Ylhäisi JS. Evaluation of delta change and bias correction methods for future daily precipitation: intermodel cross-validation using ENSEMBLES simulations. Clim Dyn. 2014;42(9–10):2287–303. https://doi.org/10.1007/s00382-014-2130-8

57. Cannon AJ, Sobie SR, Murdock TQ. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? J Clim. 2015;28(17):6938–59. https://doi.org/10.1175/jcli-d-14-00754.1
58. Quenum GMLD, Nkrumah F, Klutse NAB, Sylla MB. Spatiotemporal Changes in temperature and precipitation in West Africa. Part I: analysis with the CMIP6 historical dataset. Water. 2021;13(24):3506. https://doi.org/10.3390/w13243506
59. Almazroui M, Saeed F, Saeed S, Nazrul Islam M, Ismail M, Klutse NAB, et al. Projected change in temperature and precipitation over Africa from CMIP6. Earth Syst Environ. 2020;4(3):455–75. https://doi.org/10.1007/s41748-020-00161-x
60. Talero-Sarmiento L, Roa-Prada S, Caicedo-Chacon L, Gavanzo-Cardenas O. A data-driven approach to improve cocoa crop establishment in Colombia: insights and agricultural practice recommendations from an ensemble machine learning model. AgriEngineering. 2024;7(1):6. https://doi.org/10.3390/agriengineering7010006
61. Sutanto SJ, Zarzoza Mora SB, Supit I, Wang M. Compound and cascading droughts and heatwaves decrease maize yields by nearly half in Sinaloa, Mexico. npj Nat Hazards. 2024;1(1). https://doi.org/10.1038/s44304-024-00026-7
62. Bunn C, Läderach P, Quaye A, Muilerman S, Noponen MRA, Lundy M. Recommendation domains to scale out climate change adaptation in cocoa production in Ghana. Clim Serv. 2019;16:100123. https://doi.org/10.1016/j.cliser.2019.100123
63. Dumas Y, Ubacht J, van Andel E, Keledorme LA. Exploring the transition to agroforestry for smallholder farmers: a feasibility study for the Ashanti region of Ghana. Front Sustain Food Syst. 2025;8. https://doi.org/10.3389/fsufs.2024.1493753
64. Asare-Nuamah P, Botchway E, Nuamah NJ, Anane-Aboagye M. Beyond cocoa agroforestry in Ghana: agroforestry knowledge, practices and adoption among smallholder food crop farmers in rural Ghana. Agroforest Syst. 2025;99(5). https://doi.org/10.1007/s10457-025-01212-w
65. Mills O, Sarfo A, Simon A. Cocoa-agroforestry in Ghana: practices, determinants and constraints faced by farmers. Afr J Agric Res. 2024;20(4):312–22. https://doi.org/10.5897/ajar2023.16560
66. Tilahun SA, Amponsah AK, Atampugre G, Birhanu BZ, Dembélé M, Darko S, et al. Insight for sustainable supplemental irrigation development for Cocoa in changing Ghana's agroforestry landscapes. Discov Sustain. 2025;6(1). https://doi.org/10.1007/s43621-025-01794-6
67. Gbodji KK, Quarmine W, Minh TT. Effective demand for climate-smart adaptation: a case of solar technologies for cocoa irrigation in Ghana. Sustain Environ. 2023;9(1). https://doi.org/10.1080/27658511.2023.2258472
68. Hansen JW, Vaughan C, Kagabo DM, Dinku T, Carr ER, Körner J, et al. Climate services can support African farmers' context-specific adaptation needs at scale. Front Sustain Food Syst. 2019;3. https://doi.org/10.3389/fsufs.2019.00021
69. Mwangi M, Kituyi E, Ouma G. A systematic review of the literature on the contribution of past climate information services pilot projects in climate risk management. Sci Afr. 2021;14:e01005. https://doi.org/10.1016/j.sciaf.2021.e01005
70. Carr ER, Goble R, Rosko HM, Vaughan C, Hansen J. Identifying climate information services users and their needs in Sub-Saharan Africa: a review and learning agenda. Clim Dev. 2019;12(1):23–41. https://doi.org/10.1080/17565529.2019.1596061
71. Kumar V, Sharma KV, Kedam N, Patel A, Kate TR, Rathnayake U. A comprehensive review on smart and sustainable agriculture using IoT technologies. Smart Agric Technol. 2024;8:100487. https://doi.org/10.1016/j.atech.2024.100487
72. Mourad KA, Hosseini SH, Avery H. The role of citizen science in sustainable agriculture. Sustainability. 2020;12(24):10375. https://doi.org/10.3390/su122410375
73. Vaughan C, Hansen J, Roudier P, Watkiss P, Carr E. Evaluating agricultural weather and climate services in Africa: evidence, methods, and a learning agenda. WIREs Climate Change. 2019;10(4). https://doi.org/10.1002/wcc.586