Earth's Future

RESEARCH ARTICLE
10.1029/2026EF008409

Key Points:
- Climate change will reduce maize grain yields but increase grain protein concentration
- Grain yield, protein content, and protein concentration reduces by −5.7%, −4.8% and +4.6% by mid-century under SSP3-RCP7
- Most studies are yield-focused and might underestimate climate risks to food security and hidden malnutrition in West Africa

Supporting Information:
Supporting Information may be found in the online version of this article.

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Citation:
Abigaba, D., Schauberger, B., Chemura, A., & Gornott, C. (2026). Climate change shows inverse effects on grain yield and protein concentration in West Africa. *Earth's Future*, *14*, e2026EF008409. https://doi.org/10.1029/2026EF008409

Received 24 FEB 2026
Accepted 17 JUL 2026

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Climate Change Shows Inverse Effects on Grain Yield and Protein Concentration in West Africa

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Abstract Climate change driven shifts in temperature, precipitation patterns, and atmospheric CO_2 concentrations threaten both productivity and nutritional quality of maize, a staple crop that underpins daily energy and protein intake for millions of households in Africa and beyond. While several studies focus on yield, impacts on maize grain nutrient composition remain less assessed. Here, we use the Agricultural Production Systems simulator (APSIM) crop model to estimate climate impacts on maize yield and grain protein levels across 16 West African countries under two contrasting shared socioeconomic pathways (SSP1-RCP2.6 and SSP3-RCP7.0). Our model results show spatially heterogeneous climate impacts across the region, with a mean reduction of −5.7% (range: −43.7%–49.7%) for yield and −4.8% (range: −42.6%–54.3%) for protein content under the high-emission scenario by mid-century. Spatially, protein concentration shows an inverse trend with yield: areas that experience yield and protein content gains show reductions in protein concentration, and vice versa. Across the region, protein concentration shows a mean increase of 4.6% (range: −4.9%–19.3%). Northern regions exhibit larger percentage yield increases, driven by higher projected precipitation and comparatively low baseline yields. By jointly evaluating productivity and nutritional quality at subcontinental scale, we demonstrate that yield-only assessments may underestimate future food system vulnerability and thus a potential trade-off between yield and protein concentration. Since adaptation measures that aim to stabilize or increase maize grain yield may jeopardize improvements in grain quality, further research on region-specific measures that optimize grain yield and quality are warranted and discussed in this study.

Plain Language Summary Climate change is altering temperature, precipitation patterns, and atmospheric CO_2 concentrations, all of which affect maize production, a staple crop across Africa. Currently, most studies focus on how climate change will affect maize yield, but place less emphasis on grain quality. In this study, we use a crop model to estimate climate impacts on maize yield and grain protein levels across 16 West African countries until the end of the century. Our results show that, overall, maize yields and protein production are likely to decline across all emission scenarios, while protein concentration increases. However, an increase in protein concentration alone does not guarantee increased nutritional value, as the total protein harvested per area declines. By jointly evaluating productivity and nutritional quality, we demonstrate that yield-only assessments may obscure nutritional aspects that are relevant for food security and the design of future food systems. Adaptation measures that aim to increase maize grain yields may, in some cases, reduce grain quality. Therefore, there is a need for region-specific strategies that improve both yield and nutritional quality under climate change.

1. Introduction

Climate change continues to reshape the earth system (Rockstrom et al., 2023), while directly affecting vital sectors such as agriculture thereby posing challenges for food production amidst growing population (Hatfield et al., 2011; Hultgren et al., 2025; Jagermeyr et al., 2021). Rising temperatures, shifting precipitation regimes, and increasing atmospheric CO_2 concentration are exacerbating and accelerating existing food and nutritional insecurity. Climate risks to agriculture are more pronounced in sub-Saharan Africa, which is dominated by smallholder farms with less adaptive capacity (Kraklow et al., 2025; Onyeaka et al., 2024). This pressure threatens to reverse efforts to combat hunger and malnutrition as stipulated in the Sustainable Development Goals (Akombi et al., 2017; Willett et al., 2019). Importantly, the impacts of climate change on food security are mediated not only by total food availability but also by the composition and diversity (FAO, 2008; Guiné et al., 2021). Diets across sub-Saharan Africa are dominated by cereal-based staples, which constitute the primary sources of dietary

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energy and protein (Schonfeldt & Gibson Hall, 2012; White & Gleason, 2022). In many countries, cereals account for more than 50% of daily food intake, far exceeding the recommended 15% and contributing to low dietary diversity. While cereals ensure caloric adequacy, their limited protein quality and micronutrient density increase the risk of protein-energy malnutrition and hidden hunger (Cockx & Boti, 2024; Schonfeldt & Gibson Hall, 2012; Temba et al., 2016).

In addition to the already low protein concentrations in cereals, current and projected shifts in weather patterns are expected to reduce crop yields (J. Wang et al., 2018) and alter crop nutrient composition (Asseng et al., 2019). Cereals are particularly sensitive to temperature extremes, with elevated temperatures during reproductive stages exerting pronounced negative effects on yield (Fatima et al., 2020; Hatfield & Prueger, 2015). For instance, maize grain yield has been shown to decline by approximately 7.1% for each 1°C increase in temperature above optimal levels during the reproductive phase (Bassu et al., 2014). Elevated atmospheric CO_2 concentrations further complicate these dynamics by differentially affecting crop yield and nutrient composition. Under nitrogen-sufficient conditions, C_3 crops generally exhibit greater yield gains in response to elevated CO_2 levels due to enhanced carbon assimilation compared to their counterpart C_4 plants whose more efficient photosynthesis starts to saturate at ambient CO_2 levels (Rezaei et al., 2023; Toreti et al., 2020). In terms of nutrient concentrations, increasing CO_2 concentrations have been associated with reductions in macronutrients such as protein in C_3 plants, whereas the effect in C_4 plants is comparatively smaller (Myers et al., 2014; Toreti et al., 2020). Although CO_2 fertilization could offset climate-related yield losses through enhanced crop growth and subsequently yield, the overall effect could be undermined by reductions in the nutritional composition of the edible components of the crop (Müller et al., 2014). Therefore, efforts to match food production with the growing population and food demand in a changing climate could compromise the grain quality of cereals with important implications for food and nutrition security (Asseng et al., 2019; Mueller et al., 2019).

Maize (*Zea mays* L.) is a cornerstone of food systems across Africa, serving as a major staple and primary source of dietary energy for millions of people. Notably, many sub-Saharan African diets comprise more than 20% of maize products as an energy source, underscoring its central role in food and nutrition security (Nuss & Tanumihardjo, 2011). On the other hand, maize is highly susceptible to environmental changes (Cairns et al., 2013; Shi & Tao, 2014; Tigchelaar et al., 2018). The interplay between rising temperatures, altered rainfall patterns and elevated atmospheric CO_2 could significantly affect maize growth at different development stages. Generally, extreme temperatures beyond the optimal thresholds during the critical reproductive stages (flowering and grain filling) affect pollen viability, disrupt assimilate allocation, and ultimately reduce grain yield (Hatfield & Prueger, 2015; Zhai et al., 2021). Consistent with these physiological sensitivities, recent multi-model projections show a potential mean maize yield reduction of mostly 20%–30% across Africa by end of the century with some areas showing yield gains, though results differ depending on the choice of climate and crop model (Jagermeyr et al., 2021). While numerous studies have assessed climate impacts on maize yield across spatial and temporal scales (Cairns et al., 2012; Ocwa et al., 2023), less attention has been paid on understanding the potential impacts on the grain composition, despite its vital impact on nutrition security and ensuring human health (Myers et al., 2014; Wu, 2016). Moreover, heat stress associated with high growing-season temperatures may disrupt physiological and biochemical cycles, including nutrient uptake, transport, and remobilization from vegetative tissues to developing grains, affecting grain quality (Sehgal et al., 2018). In addition, changes in weather patterns during the reproductive stage alter nitrogen mobilisation across the crop, thereby altering grain nitrogen accumulation (Mueller et al., 2019). Understanding these complex interactions and how they shape maize production beyond yields requires integrative modelling approaches that capture system interactions, including atmospheric processes, soil dynamics, and agricultural management practices.

Process-based crop models, which have demonstrated strong capability in simulating crop development, yield formation, and nutrient partitioning, provide a robust framework for quantifying the impacts of climate change on crop production across spatial and temporal scales. Moreover, process-based models are widely used to project future changes in agricultural productivity under different climate trajectories, thereby supporting the evaluation of adaptation strategies and long-term food system resilience (Gavasso-Rita et al., 2024). In this study we use the Agricultural Production Systems sIMulator (APSIM) Next Generation -version 2024.3.7415.0; hereafter APSIM (Holzworth et al., 2018) to assess the impacts of climate change on maize production across 16 Western African countries. Specifically, we evaluate changes in yield amount, protein content, and protein concentration (as an indicator for nutritional quality). A multifaceted understanding of how climate change will affect protein content and concentration alongside grain yield is vital, especially in regions where cereal-based foods constitute the

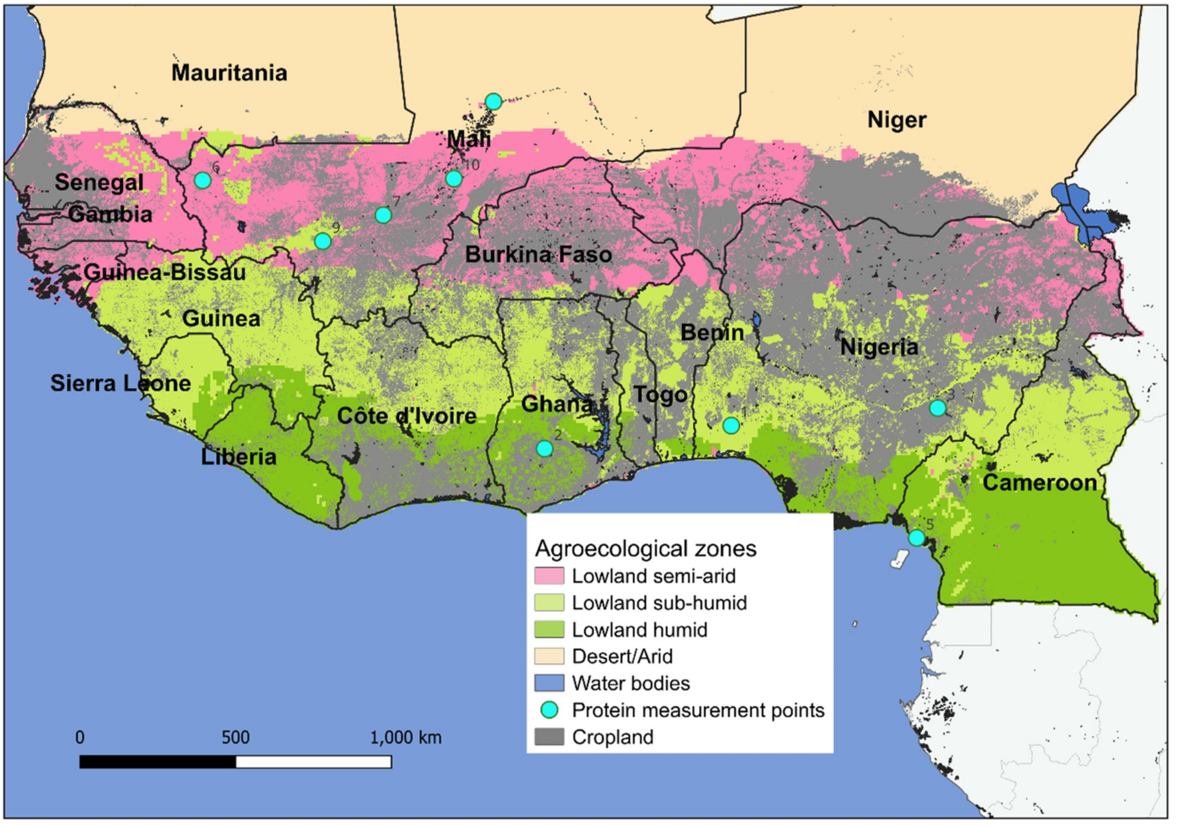

Figure 1. Study area map showing countries covered by the simulation, along with the agroecological zones according to the Food and Agricultural Organization (FAO). The cropland layer from the Anomaly Hotspots for Agricultural Production database, used for masking cropland and grid-level weighted averaging, is superimposed on the map to show the crop areas considered in the simulation. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

primary source of dietary energy and protein, as in sub-Saharan Africa. To our best knowledge, there is no previous study comparable in scale and scope. By integrating production and nutritional dimensions, this work advances current understanding of how climate change may simultaneously affect food quantity and quality in cereal-dependent regions.

2. Methodology

2.1. Study Area and Data

In this study, we simulate maize yields, protein content and concentration across 16 West African countries (Figure 1) using the APSIM model. We limit the model to crop land by applying a crop mask from the Anomaly Hotspots for Agricultural production database of the Joint Research Centre-European Commission (JRC-EC) (Fritz et al., 2024).

2.2. Model Description and Input Data

The crop model APSIM has been applied across a wide range of environments to simulate crop growth, soil dynamics, on-farm management practices, climate change risk assessments, and possible adaptation measures (Gavasso-Rita et al., 2024; Holzworth et al., 2014, 2018). In addition to final yield and biomass, the APSIM model is capable of simulating grain components such as nitrogen through partitioning of nutrients at different phenological stages considering the balance between the nutrients supplied and those demanded by the plant (Verburg et al., 2025). Such grain components can be used to derive important grain macronutrients such as protein content and concentration which are indicators of the nutritive value of grain crops. The APSIM model requires detailed inputs on crop management practices (e.g., sowing dates, plant density, and fertilization), cultivar-specific parameters, soil physical and chemical properties, and daily weather variables, including temperature, precipitation, and solar radiation.

2.2.1. Crop Management Information

Crop management practices such as sowing dates, fertilizer application and sowing densities vary across countries and agroecological zones. To capture this spatial heterogeneity, management information was first defined at the country level and subsequently disaggregated according to the FAO agroecological zoning framework (FAO & IIASA, 2025) (see Figure 1). Planting windows were obtained primarily from the FAO sowing calendars (FAO, 2024) and, where available, synchronised with country-level crop management calendars using the median date of the sowing period. Country-level planting windows were obtained from the literature (Adu et al., 2014; Akossou et al., 2016; Wolf et al., 2015). Agroecological zones within the study area differ markedly in their rainfall regimes and cropping patterns. Most areas under the lowland humid agroecological zone have a bimodal rainfall pattern, warranting two growing seasons, while the lowland sub-humid and semi-arid areas are characterized by a single growing season (Kpanou et al., 2021; Tano et al., 2022). To define the two distinct seasons in APSIM, we used the start and end dates specified in the cropping calendars and configured the management modules accordingly. For each year, crop simulation was set to trigger planting when 20 mm of rain is received over the previous 6 days and at least 30 mm of extractable soil water in the top layer within the planting window is reached (Seyoum et al., 2018). In cases where the above sowing rule is not met, sowing was triggered at the last day of the sowing window.

There are many maize varieties cultivated in West Africa. However, most are localized to specific regions with no documented variety-specific information. To ensure comparability across the region, we chose to model the variety "Obatanpa," an open-pollinated variety grown across many regions of sub-Saharan Africa (Abate et al., 2017). The variety is cultivated across most West African countries and has been parametrized for APSIM considering different experimental studies (Fosu-Mensah et al., 2019; MacCarthy et al., 2015) (see Table S1 in Supporting Information S1). By focusing on a broadly adopted, high-protein variety, our approach isolates the effects of climate variability and change from confounding differences in genetic traits, while still maintaining relevance to prevailing production systems.

2.2.2. Soil Data

Gridded soil data with a 1 km^2 resolution were derived from the International Soil Reference and Information Center (ISRIC) database (Poggio et al., 2021). The soils were aggregated to a 50 km resolution to match the climate data by selecting the most dominant soil type per grid using the ISRIC soil classification as the reference. The ISRIC database contains soil parameters such as bulk density, cation exchange capacity, nitrogen, water retention capacity, soil pH, soil organic carbon, and percentages of silt, sand, and clay. Other soil parameters were calculated and processed using pedotransfer functions (Miguez, 2022) to produce gridded APSIM-compatible soil profiles.

2.2.3. Daily Weather Data

APSIM requires daily minimum and maximum temperature, solar radiation and precipitation as climate input data. Historical daily precipitation, temperature, and solar radiation data were obtained from the gridded W5E5 v2.0 reanalysis product (Lange & Büchner, 2021) at a resolution of 50 km. For future scenarios, we use bias-adjusted daily data from the Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP3b) (Lange & Büchner, 2021). For future projections, we use two contrasting representative concentration pathways, SSP1-RCP2.6 and SSP3-RCP7.0, hereafter referred to as the low-emission and high-emission scenarios, respectively, with five primary GCMs: UKESM1-0-LL, MRI-ESM2-0, MPI-ESM1-2-HR, IPSL-CM6A-LR, and GFDL-ESM4.

2.2.4. Maize Yield and Protein Data

Observed yield data sets for 2010–2018 (i = 1,577 grids) were obtained from numerous sources. First, we prioritize national agricultural yield statistics from individual countries collected at different administrative levels. Although maize is an important staple crop in West Africa, some countries lack publicly available yield data sets; hence, we use other yield data sources to fill this gap. These data sets are the Spatial Production Allocation Model

(SPAM) (International Food Policy Research Institute, 2019) and the Famine and Early Warning System Network (FEWS NET) (Lee et al., 2024) (details are provided in Table S2 in Supporting Information S1). There was no data for Liberia and Sierra Leone, therefore the two countries were not considered in the validation.

For validation of the protein concentration and content, we use measured grain protein data from nine grain sample measurement studies (Ahenkora et al., 1999; Barikmo et al., 2004; Bello et al., 2014; Ibirinde et al., 2020; Ngone et al., 2023) (Figure 1 and Table S3 in Supporting Information S1) to compare modeled and observed protein concentration across countries. We assume experimentally derived protein contents to be representative of the grid cells in which the experiment was performed and compare them with the simulated protein concentrations in those same cells.

Grain protein synthesis is related to the rates of carbon and nitrogen assimilation and transport across the plant, as determined by genetic, environmental, and soil characteristics (Z. Wang et al., 2021). Protein contains amino acids with nitrogen as the key element. APSIM produces grain nitrogen as one of the final outputs, therefore protein content—that is the amount of protein that can be harvested from a given area was derived by multiplying the grain nitrogen content by a nitrogen to protein conversion factor of 5.6 (Mariotti et al., 2008) (Equation 1). Grain nitrogen is simulated using a dynamic nitrogen supply-demand framework, in which grain N demand is determined by potential grain growth and target N concentration, while N supply arises from soil uptake and remobilization from vegetative tissues. These physiological rules ensure that simulated grain nitrogen reflects the balance between yield potential and available nitrogen supply. Protein concentration, different from harvestable amounts (protein content), refers to the ratio of protein content to the overall grain weight expressed as a percentage (Equation 2).

$$\text{Protein Content}\left(\text{g/m}^2\right) = \text{Grain } N\left(\frac{\text{g}}{\text{m}^2}\right) \times 5.6 \tag{1}$$

$$\text{Protein Concentration } (\%) = \left(\frac{\text{Protein Content}\left(\frac{\text{g}}{\text{m}^2}\right)}{\text{Grain Weight }\left(\frac{\text{g}}{\text{m}^2}\right)}\right) \times 100 \tag{2}$$

2.3. Model Calibration and Validation

We performed separate calibration and validation steps. For model calibration, we aimed to achieve maximum congruence between simulated and observed maize yields (kg/ha). Grain protein concentrations were not used for model calibration but were used only for validation as extensive phenological specific data were missing. We systematically tested different combinations of management practices, namely fertilizer application rates, sowing densities and sowing windows based on the literature. We use a fully factorial combination of these key parameters: planting date adjustments (either ±30 days from the baseline), fertilizer application rates (0–100 kg/ha at 20 kg level intervals), and sowing density of 2, 3, 4, and 5 plants m^{-2}, to evaluate their combined effects and identify the best-performing simulation against observed yield data. The tested key parameter ranges were derived from the literature (Ajayo et al., 2021; Bello et al., 2014; MacCarthy et al., 2023). For fertilizer application rates, we use NO_3^-N applied 30 days from crop emergence. Since agriculture in West Africa is predominantly rain-fed (Biazin et al., 2012), we set up the model without additional irrigation.

Model performance assessment was done by comparing the goodness of fit between observed and simulated yields/protein concentration using the coefficient of determination (R^2), percent bias (Pbias) and index of agreement (Willmott's d). R^2 and d range from 0 to 1, where 1 represents a perfect agreement between the observed and simulated data, while Pbias measures the percentage tendency of simulated values to be higher or lower than the observed values. Therefore, a Pbias of 0 represents a perfect match, positive values indicate model underestimation, and negative values show model overestimation.

To identify associations among variables relevant to crop growth and grain protein dynamics, we performed two additional steps: First, pairwise Pearson correlations were calculated among grain-related variables, including grain yield, protein concentration, protein content, grain size (GS), aboveground biomass (AGB), and leaf area index (LAI), to explore their internal relationships. Second, we applied linear mixed-effects regression models fitted using restricted maximum likelihood to quantify the effects of soil variables (plant-available water, soil nitrogen) and climate variables (mean temperature, precipitation, solar radiation, maximum temperature, minimum temperature) on yield and protein components. Predictor variables were assessed for multicollinearity using the variance inflation factor and variables with VIFs above 10 were iteratively removed. The model incorporated random intercepts for country and gridID, to account for unobserved, hierarchical spatial heterogeneity at both national and grid-cell levels (Equation 3) (Mohammadi et al., 2023; Tran et al., 2025). Predictor variables were normalized prior to model construction using the min-max normalization method and the model was implemented in R (R Studio Team, 2020) using the lme4 package.

$$Y_{it} = \boldsymbol{X}_{it}\boldsymbol{\beta} + Z_{it}\boldsymbol{b}_i + \varepsilon_{it} \tag{3}$$

where:

Y_{it} is the response (yield, protein content or protein concentration) in year t,
X_{it} contains the fixed-effect covariates (PAW, SoilN, Prec, Tmean, Rad),
$\boldsymbol{\beta}$ is the corresponding vector of fixed-effect coefficients,
Z_{it} is the random-effect design matrix for Country and GridID,
b_i is the vector of random intercepts for Country and GridID,
ε_{it} is the residual error vector.

2.4. Climate Change Impact Assessment

The impact of climate change on maize yield and grain protein was determined by simulating maize production under historical and future conditions. We use the period 1990–2014 as the baseline, while the future is represented by three 25-year time frames—early century (2020–2044), mid-century (2045–2069) and late century (2070–2100). The climate change effect is calculated as the difference between the baseline and the future yields and protein levels. To minimize the influence of legacy effects from prior management and soil nutrient carryover across simulation years, soil nutrient states were reset at the beginning of each simulation following an initial 10-year spin-up period. This approach facilitates a clear isolation of climate change impacts and is consistent with established APSIM applications focused on climate sensitivity analyses (Chisanga et al., 2020; Huang et al., 2020; Saddique et al., 2025). To study the long-term soil impacts, including cumulative nutrient depletion, we additionally conducted continuous simulations without resetting the soil nutrient pools and the results are shown in Figure S5 in Supporting Information S1. This option allows for cumulative changes in soil nutrient pools over time providing a more realistic but less controlled representation of actual field conditions.

3. Results

3.1. Historical Simulated Maize Yields and Protein Content Across West Africa

At the regional scale, spatially aggregated evaluation shows a good agreement between modeled and observed yields with a coefficient of determination (R^2) of 0.51, a percent bias (Pbias) of 24.2 and a d of 0.76 (Figure 2a). Simulated grain protein concentration is within the range of reported protein contents from site-specific studies and national averages across West Africa with an R^2 of 0.55 and a d of 0.75 (Figure 2b). The model satisfactorily reproduces the spatial pattern of average reported maize yield across the region as shown in Figure 2c. Across individual countries, we obtained stronger differences in model accuracy between observed and simulated maize yields with coefficients of determination (R^2) ranging from 0.01 to 0.62, and an index of agreement (d) ranging between 0.25 and 0.81 (Figure S1 in Supporting Information S1).

Historical simulated maize yields vary across countries and subnational regions and range from approximately 200 to 4,500 kg/ha, with an average yield of about 1,500 kg/ha. Though there is no pristine gradient across the region, yields are generally lower in the upper lowland semi-arid and arid areas of West Africa, specifically Mali and Niger (Figure 3). Maize yields are higher in Cameroon, Côte d'Ivoire, central Nigeria, and the southern parts of Mali and Ghana. The simulated maize protein content follows a similar spatial pattern as yield amounts, with a minimum of 1.2 g/m^2 and a maximum of 27.6 g/m^2. On the other hand, protein concentration shows an opposite trend to yield and protein content, with areas with low yields having higher protein concentration. The simulated protein concentration ranges from a minimum of 4.9% to an isolated maximum of 15.7%, with an overall mean of 6.7% (Figure 3).

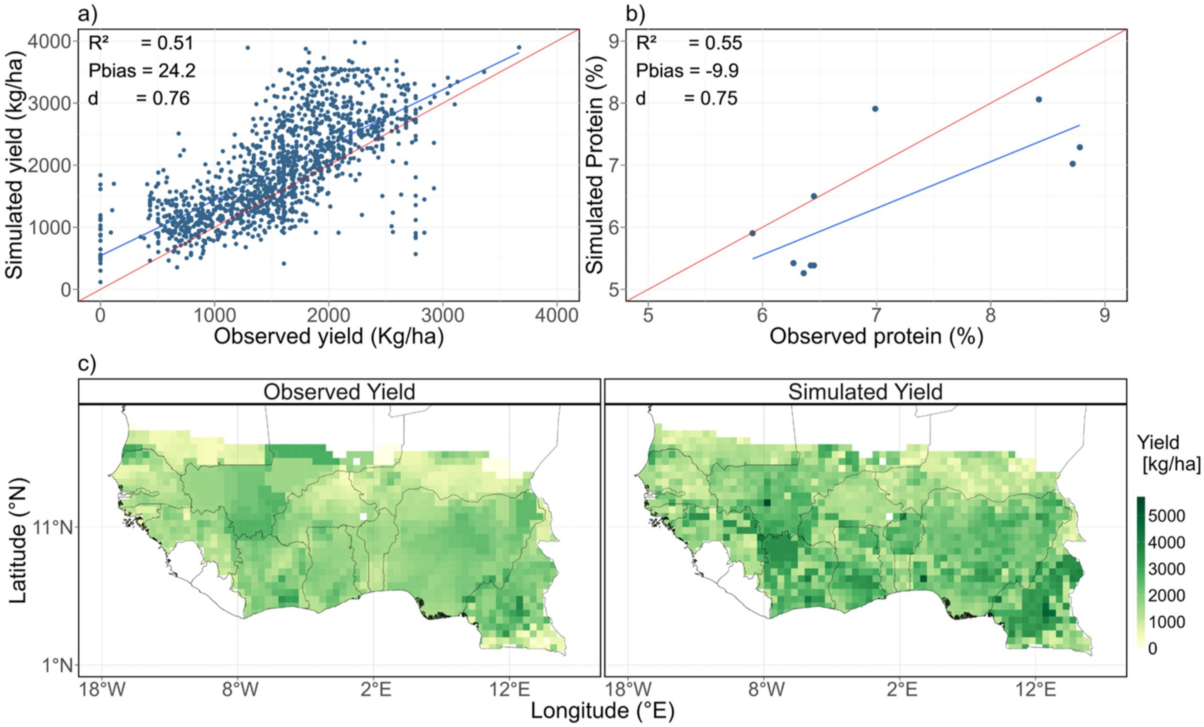

Figure 2. Regional level evaluation of yield (a) and protein concentration (b) across West Africa. Observed and simulated yields represent 9-year averages (2010–2018) while protein concentration values are taken from experimental measurements across the region. The red 1:1 line represents perfect agreement between observed and predicted values, while the blue line shows the fitted linear regression line, indicating the actual relationship between the observed and predicted values. Panel (c) shows the spatial distribution of observed (left) and APSIM simulated (right) average maize yields for 2010–2018.

While maize protein content is highly positively correlated with yield (0.96), above ground biomass (0.79), and grain size (0.77), protein concentration is negatively correlated with yield (−0.54) and grain size (−0.56), but positively correlated with LAI (0.58) (Figure S2 in Supporting Information S1). Across phenological stages, linear mixed effect models reveal strong, stage-specific and trait-specific sensitivities of yield and grain quality to climate and soil drivers. During the vegetative phase, effects are generally modest: soil mineral nitrogen consistently exerts a positive influence, while precipitation shows small but significant negative effects on yield and protein content, but a positive effect on protein concentration. In contrast, responses during the reproductive phase are markedly stronger and more contrasting. Grain yield and protein content are positively associated with precipitation and soil mineral nitrogen, but negatively affected by plant-available water. Grain protein concentration exhibits pronounced trade-offs, where precipitation and soil nitrogen strongly reduce protein concentration, whereas plant available water and mean temperature increase it, highlighting a classical yield–protein antagonism intensified during grain filling (Figure 4, Table S4 in Supporting Information S1).

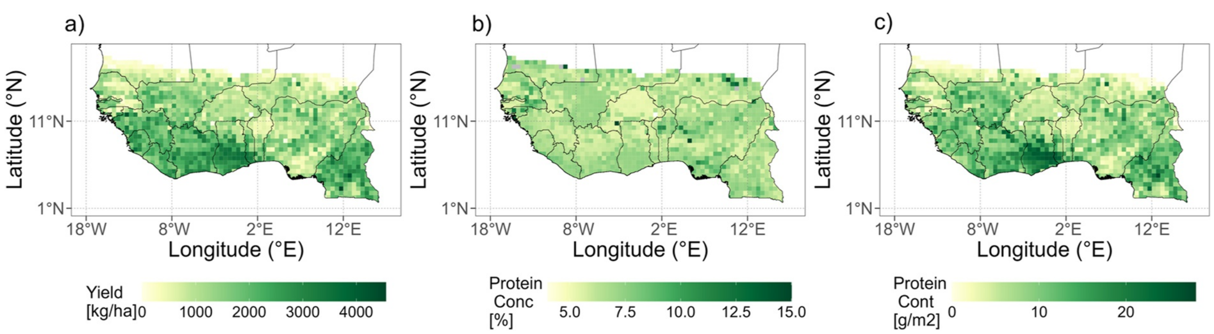

Figure 3. (a) Historical (1990–2014) simulated spatial patterns of maize grain yield, (b) protein concentration and (c) protein content across West Africa. The figures represent the mean ensemble data from the five ISIMIP global climate models.

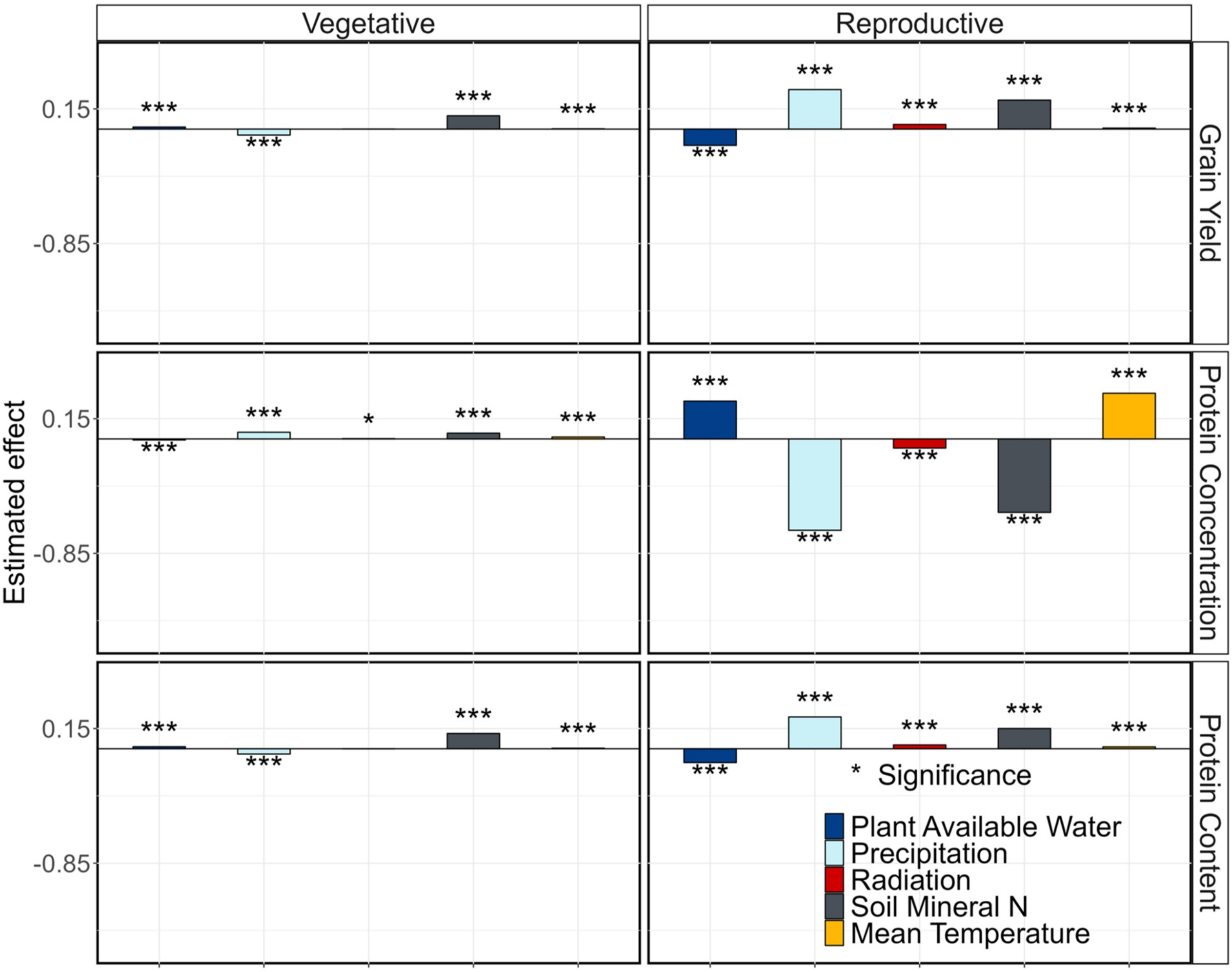

Figure 4. Estimated normalized effects of soil nitrogen, mean temperature, solar radiation, precipitation, and plant available water across vegetative and reproductive stages on final grain yield (upper row), protein concentration (middle row), and protein content (bottom row) using linear mixed regression models. Bars represent the estimated effects (β coefficients) from the mixed-effects model, with positive and negative values indicating the direction of the effect. Stars indicate statistical significance of the estimates: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. No stars indicate non-significant effects ($p \geq 0.05$).

3.2. Projected Climate Impacts on Yield and Protein

Our model results show substantial projected climate impacts on both grain yield and protein content across West Africa, having substantial spatial heterogeneity across the region. Across most countries, there is a projected general mean reduction in maize grain yield and protein content across all climate scenarios. This pattern indicates that warming-induced heat and water stress progressively outweigh the benefits of CO_2 fertilization, leading to net yield penalties under sustained high-emission conditions. The models show percentage gains in northern-region yield and protein content, especially under the high-emission scenario at the end of the century, primarily driven by projected rainfall increases and low baseline yields. Protein concentration mostly shows an opposing trend: regions with yield decreases show an increase in protein concentration (Figure 5; Figures S3 and S6 in Supporting Information S1). The impacts on yield and protein content increase across different time periods, with greater negative impacts by the end of the century. Regionally aggregated impacts are shown in Figure 6. Projected grain yield changes show large and increasing uncertainty across GCMs, time periods, and scenarios, especially under higher emissions across early, mid, and late century. The uncertainty is dominated by inter-model variability among GCMs, with scenario differences becoming increasingly important toward the end of the century (Figure S7 in Supporting Information S1). Here, we present the mean change across the region, while values in brackets denote the average gains and losses calculated from grid cells that show increases or decreases.

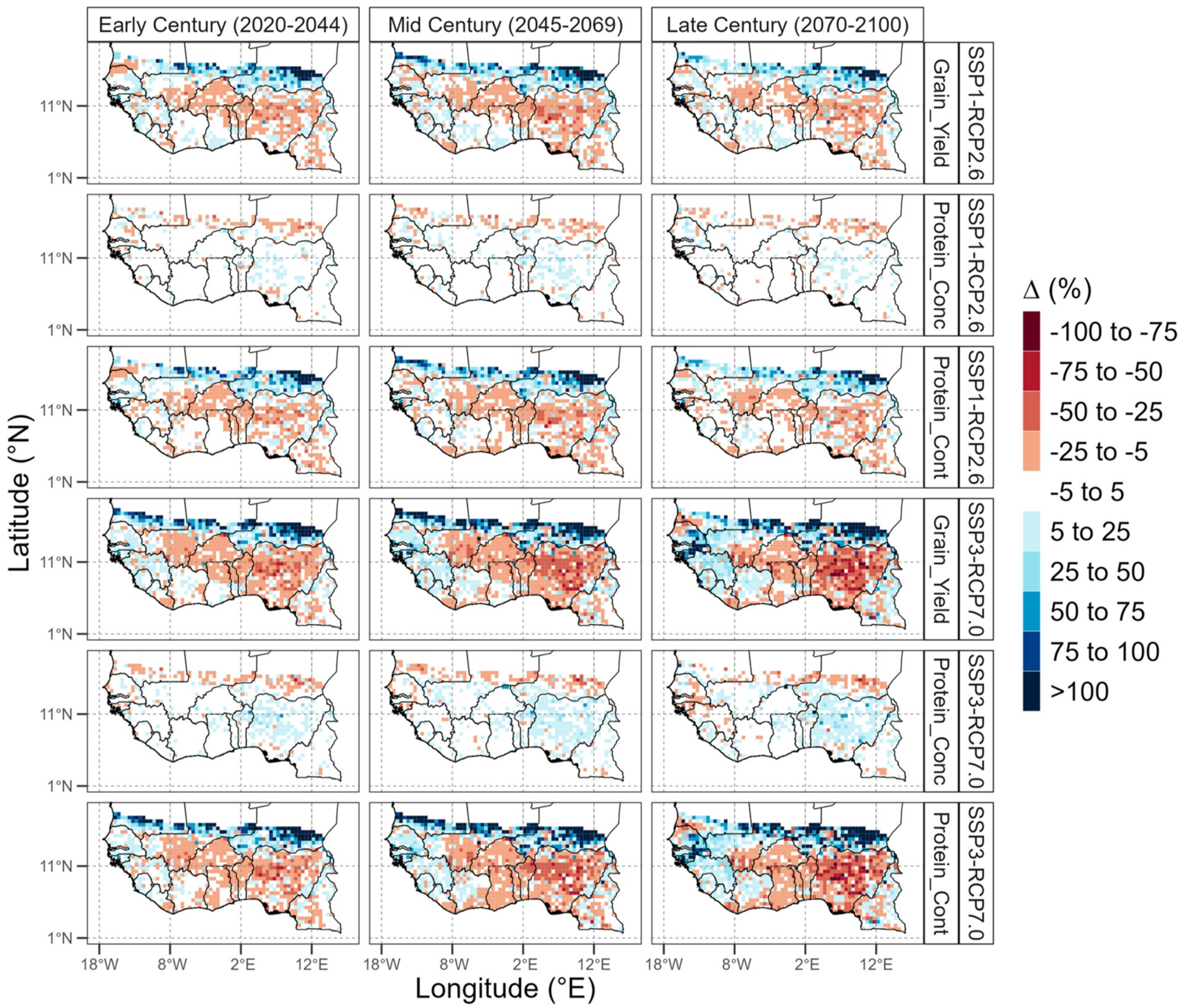

Figure 5. Projected changes in maize yield, protein concentration and protein content across West Africa as simulated under two Shared Socioeconomic Pathways for different time frames until 2100. Results represent the mean ensemble from five Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) global climate models. The changes are relative to the baseline/historical yields (1990–2014).

When averaged over the entire region under the low emission scenario, mean grain yield shows small negative changes across the century, with a mean loss of −0.8% during the early century (range: −21.3 to +30.5%), −1.7% during mid-century (−25.8 to +30.2%), and −1.1% in the late century (−23.4 to +27.8%). Protein content follows a similar pattern, with mean changes of −0.6% (−21.4 to +29.4%), −1.6% (−25.0 to +32.2%), and −1.1% (−22.5 to +29.4%) for the early, mid, and late century periods, respectively. In contrast, protein concentration increases slightly under SSP1–RCP2.6, with mean changes of +1.2% in the early century (−4,6 to +7.3%), +1.7% in mid-century (−4.5 to +10.4%), and +1.1% in the late century (−4.7 to +8.1%).

Compared to the low-emission scenario, mean changes in grain yield and protein content under the high-emission scenario are substantially higher. Mean grain yield changes are −4.1% in the early century (−31.9 to +34.7%), −5.7% in mid-century (−43.7 to +49.7%), and −4.4% in the late century (−57.3 to +68.5%). Changes in protein content mirror these yield responses, with mean reductions of −3.4% (−31.2 to +34.1%), −4.8% (−42.6 to +54.3%), and −3.6% (−56.6 to +74.3%) across the respective periods. Overall, the trend in mean protein loss is relatively similar to the yield losses across scenarios, with slight deviations among countries. Burkina Faso, Benin, and Nigeria show the highest decline in both yield and protein content across both timeframes and scenarios. Conversely, protein concentration shows consistent increases, with mean changes of +2.7% in the early century (−4.4 to +11.6%), +4.6% in mid-century (−4.9 to +19.3%), and +5.5% in the late century (−5.3 to

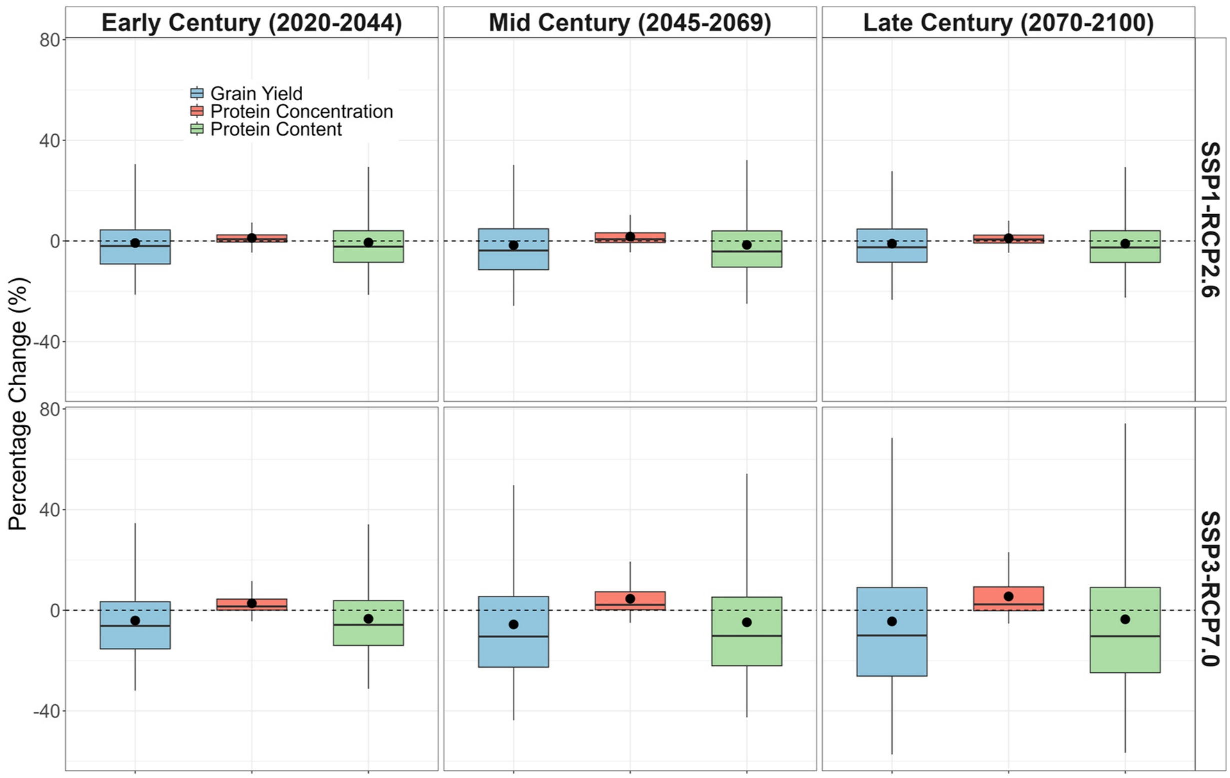

Figure 6. Cropland area-weighted box plots showing percentage changes in grain yield, protein content and protein concentration across scenarios and time frames until the end of the century. The middle line indicates the median, while the black points indicate weighted mean changes. The dashed horizontal line marks zero change.

+23.1%). In all cases, mean increases outweighed mean decreases, indicating a net positive impact on protein concentration despite climate-related stress on yields (Figure 6).

The regional averages mask strong spatial contrasts, yet disaggregating these regional means into areas of increase and decrease reveals much stronger responses (Figure S3 in Supporting Information S1). Given the substantial spatial heterogeneity in projected impacts, country or subnational level evaluations are essential to disentangle the net effects masked by regional averages. Aggregate statistics obscure the divergent responses between northern zones, where relative gains are amplified by low baseline productivity and the more productive southern regions (Figure S4 in Supporting Information S1), which experience comparatively smaller increases or greater vulnerability to losses. In a scenario without resetting soil parameters, our model projects substantial reductions in yield and protein content across the region starting from mid-century under both emission scenarios. Still, grain yield and protein increases in the northern region are projected, though not as pronounced as in the option with soil nutrient reset (Figure S5 in Supporting Information S1).

4. Discussion

Understanding how climate change will shape the future of food systems requires assessments capable of capturing the complex interactions among atmospheric processes, soil dynamics, and agricultural management on diverse food and nutrition security-related outcome indicators. Process-based crop models such as APSIM provide a critical bridge between Earth system change and food system outcomes by mechanistically simulating how crops respond to evolving environmental conditions. In this context, integrating climate projections with soil-plant-management interactions is essential for anticipating future food production risks and identifying adaptation pathways that enhance resilience. In this study, we use APSIM to spatially simulate the impacts of climate change on maize yield, protein content and protein concentration, demonstrating the potential effects on maize nutritive content. Whereas studies have explored impacts on cereal grain protein, especially wheat (Asseng et al., 2019; Kashyap et al., 2024; Zahra et al., 2023; D. Zhang et al., 2023; Zhou et al., 2021) and rice (Yulong et al., 2021), maize, a key staple crop in sub-Saharan Africa and beyond remains unstudied. In this study, we demonstrate that APSIM can be calibrated to reproduce measured maize grain protein concentration from field trials. Despite the scarce protein concentration measurement data, the model satisfactorily reproduced measured grain protein across different regions. To the best of our knowledge, this is the first regional study in sub-Saharan Africa to explore the effects of climate change beyond yield levels and to assess the nutritive content of maize grains. Across a few grids, the model predicts isolated anomalies in protein concentration of up to 15%, which are above values reported in the literature. These anomalies could be attributed to inconsistencies in data sets, including upscaling and grid-level soil aggregation, which can misrepresent soil nutrient levels. Although instances of protein overestimation are limited to a few grid cells, this underscores the importance of using precise, accurate input data wherever possible, an option often constrained by the scarcity of high-quality, publicly available data sets in West Africa. Overall, this modeling approach provides a proof of concept for linking crop simulation outputs to nutritional quality metrics, thereby expanding APSIM's applicability beyond traditional yield-focused studies. The study therefore, provides a valuable basis for assessing maize nutritional characteristics while offering important insights into the mechanisms underlying starch-protein divergence in cereals (Cao et al., 2024). This improved regional understanding can help guide future research and breeding strategies aimed at optimizing both yield and grain quality.

Overall, model findings suggest that climate change does not affect yield and protein aspects independently. Instead, it appears to impose a systematic trade-off: conditions that support biomass or yield can simultaneously reduce protein concentration, likely through altered carbon-nitrogen partitioning and a dilution of nitrogen in the harvested product. There is a general decreasing trend in grain yield and protein content, especially across the southern region, and a positive correlation between the two variables. This finding is particularly important for communities that depend on maize as a staple crop because reductions in calories and protein necessitate additional sources of protein and starch. Given the complex biophysical mechanisms that underlie crop growth, understanding the relative contributions of variables to final yield and protein amounts requires more than regression models, instead, it is well explained by process-based models that clearly capture stage-wise processes. Our range of climate impacts on grain yield under the high-emission scenario aligns with those reported by Ahmed et al. (2015), Freduah et al. (2019), Jansen et al. (2025), Traore et al. (2017), and Zhai et al. (2021) who predict yield losses of up to 67% by mid-century. Similar to Parkes et al. (2018), our model shows an increased probability of crop failure, with high yield losses starting in 2075 under the high-emission scenario. On the other hand, the model shows some increase in yields especially in the northern parts of West Africa similar to results of Parkes et al. (2018); and Sultan et al. (2023). This increase can be partly attributed to low baseline yields and increased precipitation across this region (Figure S6 in Supporting Information S1), though there is substantial uncertainty in climate model precipitation projections (Monerie et al., 2020). Projected increases in precipitation amounts do not necessarily benefit crops, as they enhance nitrogen loss through leaching, exacerbating the already low N input and soil N content in the region (Falconnier et al., 2020; Yameogo et al., 2021). Warmer conditions typical in the tropics and projected to increase in the future may increase nutrient release through enhanced decomposition, but could also lead to nutrient depletion in the long run (Falconnier et al., 2020; Robinson et al., 2022).

Without resetting soil nutrients, our model shows a substantial decline in yields and protein content across the region beginning from mid-century (Figure S5 in Supporting Information S1). In agreement with Couedel et al. (2026), the large yield losses observed in simulations without resetting soil dynamics suggest significant nutrient depletion over time (Falconnier et al., 2020). These results indicate that beyond the direct impacts of climate change such as heat and drought stress, long-term nutrient exhaustion could become a major yield-limiting factor across West Africa. The interaction between soil nutrient depletion and climate stress could exacerbate maize production losses warranting tailored measures that address both causes. The two approaches used (resetting soil nutrients and no reset) together provide a plausible range of crop responses to changing weather conditions and the possible effects on grain nutrient content across the region.

The reproductive stage exhibits stronger and more contrasting environmental sensitivities than the vegetative stage, indicating that grain yield and quality formation are particularly responsive to late-season conditions. These findings are consistent with the physiological understanding of maize development, where soil moisture and nutrients at the reproductive stages highly influence the kernel number, weight and resource (nitrogen) remobilization (Alam et al., 2021; Bheemanahalli et al., 2022; Lizaso et al., 2018; Melchiori & Caviglia, 2008), which together control yield and grain nitrogen accumulation. Conditions that enhance grain yield and protein content - particularly increased precipitation and nitrogen availability can simultaneously reduce protein concentration, highlighting important trade-offs relevant for both production and nutritional quality under future climate scenarios. This pattern is consistent with a dilution effect, where favorable moisture and nitrogen conditions enhance carbohydrate accumulation more than nitrogen deposition in the grain, reducing protein concentration despite higher yields (Mueller et al., 2019). This divergence explains why protein concentration cannot be inferred directly from yield responses and reinforces the need to assess multiple grain quality metrics simultaneously. Despite statistical significance, the predictor variables in the regression model capture only a fraction of the factors influencing grain yield, protein content, and concentration, as shown by the low explanatory power (low R^2). Crop growth and grain composition are governed by complex, multistage biophysical processes, such as resource remobilization and developmental dynamics, that a limited set of predictors cannot fully represent within a single regression framework.

The contrasting responses of protein concentration versus grain yield and protein content highlight a fundamental physiological trade-off. Despite the reduction in grain yield and protein content, protein concentration shows an inverse trend, in line with other experimental studies (Bogard et al., 2010; Lugoi et al., 2022; Mueller et al., 2019; L. Zhang et al., 2020) that show protein and amino acid dilution when grain yield is enhanced and vice versa. These results indicate a clear dilution effect, whereby increases in grain yield are associated with reductions in protein and amino acid concentrations, and vice versa. This trade-off reflects a complex physiological response in which changes in grain protein concentration are driven primarily by altered carbon -nitrogen partitioning, with reduced starch accumulation playing a stronger role than enhanced nitrogen uptake or assimilation. The strength of this trade-off depends critically on soil nutrient availability. Under nutrient-replete conditions (soil reset configuration), higher yields intensify protein dilution as carbon assimilation outpaces nitrogen allocation to the grain. In contrast, under nutrient-depleted conditions (no soil reset configuration), protein concentration tends to increase because carbon assimilation is more strongly constrained than nitrogen remobilization, leading to relative protein enrichment. This contrast arises from fundamentally different nutrient trajectories: nutrient-replete soils promote yield-driven protein dilution, whereas nutrient-depleted soils favor relative protein enrichment as carbon assimilation is more strongly constrained than nitrogen allocation to the grain. Collectively, these contrasting responses highlight the strong sensitivity of simulated grain protein dynamics to assumptions about soil nutrient carryover and emphasize the importance of representing realistic nutrient cycling in climate-impact assessments.

Although protein concentrations may increase in some regions, these gains do not compensate for the overall decline in total protein production, as reductions in grain yield lead to lower protein content per unit area. From a food and nutrition security perspective, regional increases in protein concentration alone should be interpreted with caution, because in particular nutrition security depends on both nutritional quality and the total protein quantity available within a region (FAO, 2008; Guiné et al., 2021). Quantity is primarily driven by yield per unit area, which determines how much protein is physically produced. Reductions in yield therefore decreases overall protein produced, which can worsen food insecurity even if nutrient density, that is, protein concentration, improves. Thus, total protein harvested per unit area is a more relevant metric than protein concentration alone, and our projections show that overall protein supply may decline in future periods. Protein concentration, on the other hand, is particularly relevant in the context of nutrient-dense end-use products, as the number of calories a person can consume per day is limited. Consequently, the protein concentration of food plays an important role in determining daily protein intake. This is especially relevant for children and other nutritionally vulnerable population groups, for whom adequate protein intake is critical for health, growth, and development.

For C_3 crops such as wheat, a similar trend is observed, with increased grain yield projected in major wheat-growing regions due to higher temperatures and elevated CO_2. However, protein content does not increase by the same magnitude, resulting in a lower protein concentration (Asseng et al., 2019; Nuttall et al., 2017; D. Zhang et al., 2023). As illustrated by Mueller et al. (2019), breeding programs in the US have been successful in producing nitrogen-use-efficient varieties with higher yields, but at the expense on grain nitrogen concentrations. The reasons, however, are beyond nitrogen dilution, including internal nitrogen mobilization from stems and leaves during grain filling. The regional divergence of climate impacts highlights the need for region-specific implementation of adaptation measures to maintain a balance between grain yield and total protein content, the latter defined by yield and protein concentration. Tailoring strategies to local environmental conditions will be essential to avoid trade-offs and ensure both productivity and nutritional quality are sustained. Possible adaptation measures have been studied and recommended to counter climate impacts on maize across West Africa, including changes in varieties, irrigation, and fertilizer management (Sultan & Gaetani, 2016). Given the negative

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association between maize grain yield and protein concentration, current breeding efforts ought to be more careful and holistic not to compromise the nutritive value of maize in an effort to increase yield in regions where maize serves as a staple crop and primary protein source. Such targeted breeding efforts are already in place, for example, the breeding of high-yielding Quality Protein Maize (QPM) (Abate et al., 2017; Mbuya et al., 2011; Tandzi et al., 2017; Vivek, 2008). Targeting breeds with higher nitrogen remobilization efficiency from stems and leaves could be an option, especially in systems with low nitrogen input. Such breeding technologies are however cost intensive and therefore potentially less scalable in low-income countries (Tandzi et al., 2017). Beyond genetic improvement, agronomic interventions, particularly improved nitrogen management, offer resource-efficient means to sustain or enhance yield and grain nutritive traits (L. Zhang et al., 2020), though this may be hampered by in-season weather variability. To overcome the potential protein energy malnutrition, legume cereal intercropping or diversification should be promoted (Chimonyo et al., 2023). Consequently, these adaptation mechanisms ought not to be treated independently, but rather find a possible area specific combination. For example, shifting planting dates could mean shifting the amounts and timing of fertilizer application to target the most efficient nutrient assimilation stage and avoid leaching (Abebe & Feyisa, 2017; Mosisa et al., 2022). Proper timing of fertilizer application can also enhance the balance between nitrogen supply and demand—a major determinant of protein accumulation in grains (L. Zhang et al., 2020).

Projections of crop productivity under climate change have several limitations, including limitations in climate data, assumptions about management practices, and model calibration (Asseng et al., 2013; Chapagain et al., 2022; Di Paola et al., 2016; Durand et al., 2018; Muller, 2013). These uncertainties propagate into the final yield projections. Climate models do not agree on the general spatial trends of precipitation patterns and intensity which could influence crop model projections as shown in the uncertainties in Figure S7 in Supporting Information S1. In West Africa in particular, the representation of the Western monsoon shows systematic biases in precipitation, with some models projecting opposing changes between wetter and drier conditions (Klutse et al., 2021; Monerie et al., 2020; Romanovska et al., 2023). The use of a single crop model (APSIM) reduces the ability to capture structural uncertainties related to representation of key processes such as phenology, photosynthesis, water/nutrient uptake, and yield formation. Ensemble models have proven to capture a wide range of uncertainties compared to single-crop models (Asseng et al., 2013; Chapagain et al., 2022; Jagermeyr et al., 2021; Wallach & Thorburn, 2017). Together, these sources of uncertainty reduce confidence in the magnitude and spatial distribution of projected changes, particularly toward the end of the century. While there is some agreement on general tendencies, such as increasing variability over time, the combined uncertainties imply that projections should be interpreted as indicative ranges rather than precise outcomes. Second, in this study, we use a single commonly cultivated maize variety across the entire region, despite a mix of varieties known to be cultivated in West Africa (Abate et al., 2017), allowing us to compare climate impacts across the region. However, given the agroecological diversity in West Africa, using a single variety may skew results due to limitations in capturing genotypic-by-environment interactions, biotic stress adaptation, and local social-cultural preferences. This may also partly explain the variation in model performance across countries relative to reported yields and protein concentrations. Breeding programs in West Africa have consistently developed new crop varieties that are more drought-resistant (Badu-Apraku et al., 2013; Menkir et al., 2024), protein-rich (Abate et al., 2017; Mbuya et al., 2011; Tandzi et al., 2017; Vivek, 2008), and early-maturing (Abate et al., 2017; Badu-Apraku et al., 2013). The projections presented here do not account for these ongoing genetic improvements and may therefore overestimate the adverse impacts of climate change relative to the adaptive capacity already achieved through existing breeding efforts. Due to data constraints, only grain yield and selected measured grain protein concentration were considered for model calibration and validation at a spatial scale; however, the model would benefit more from phenological-level calibration, including biomass accumulation and leaf and flower development. Despite the uncertainty, the direction of change in yield and total protein content is consistently negative across most models and scenarios, indicating a robust signal of declining protein availability.

5. Conclusion

The impact of climate change on cereal grain components, specifically maize, has been little explored, despite its vital contribution to local nutritional security. This study assessed the impacts of climate change on grain yield, protein content, and protein concentration across West Africa using the APSIM crop model. On average across the region, our model results show a general decrease in grain yield and protein content, but a divergent response in protein concentration. The study further highlights yield protein concentration trade-off which necessitates targeted adaptation measures such as breeding for nitrogen-efficient as well as high-quality protein varieties. Mean climate effects mask substantial spatial and temporal variability, with impacts differing across countries and becoming more adverse toward the end of the century. Further research should target effects beyond grain yield and also integrate grain quality components to achieve both food and nutritional security. In addition, identifying genotype-by-environment-by-management interactions that synergize grain yield and protein traits remains a priority for identifying optimal adaptation strategies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The input data and scripts used to run the APSIM model in the study are available at Zenodo (Abigaba, 2026).

Acknowledgments
This work has been funded by the PACO, ClimaKid, and CC&H PI3 project. PACO is part of the International Climate Initiative (IKI). The Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) supports this initiative on the basis of a decision adopted by the German Bundestag. ClimaKid is financed by the Wellcome Trust and CC&H PI3 is financed by the German Research Foundation (DFG). Open Access funding enabled and organized by Projekt DEAL.

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