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ORIGINAL ARTICLE

Adaptation potential of alternate varieties and fertilization strategies for peanut and maize in Senegal under climate change

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Abstract

In Senegal, rising temperatures are projected to reduce maize yields due to a shortened growth duration, while elevated CO_2 fertilization may increase peanut yields under climate change. However, there is limited evidence on climate change impacts if crop cultivars change and systems intensify, which is expected to occur in parallel with climate change. For climate-adapted agriculture, the performance of improved agronomy and varieties should be evaluated under current and future climate scenarios. This study assesses the impact of climate change on crop yields of two varieties of peanut and maize at each under current and intensified fertilization. Simulations were performed for mid-century (2045–2074) and end-century (2070–2099) relative to a baseline (1981–2010) using the SIMPLACE modeling framework at 0.5° resolution. Climate projections from nine global climate models (GCMs) were used under SSP2-4.5 and SSP5-8.5 scenarios. Soil data was derived from the Harmonized World Soil Database. The results indicate that the impacts of climate change on crop yields differed by crop. Peanut showed an increase in yield of up to 45% and a decrease for maize of up to 25% by the end of the century. Peanut yield gains were higher under the intensification fertilization case compared to the current fertilization case, whereas for maize, losses were high in the intensification case. Furthermore, yield losses are more substantial in the southern and western parts of the country for both crops. Additionally, for maize, yield losses were higher for the short cycle variety than the long cycle variety; there was little difference between varieties for peanut.

Keywords Crop yields · Intensification · Climate change · SIMPLACE · Senegal

Introduction

Climate change is projected to negatively impact crop yields in sub-Saharan Africa due to increased temperatures and high interannual and intra-annual rainfall variability. The impacts are expected to be further exacerbated under climate change, particularly for rainfed cropping systems, which predominate in the region and are inherently more vulnerable than irrigated systems. Negative impacts are expected for the production of the main cereals such as maize, pearl millet, and sorghum (Alimagham et al. 2024; Sultan et al. 2023), while legumes such as peanut are projected to benefit from

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climate change due to their positive response to elevated CO_2 concentration (Faye et al 2018a).

Maize and peanut are important crops in sub-Saharan Africa, particularly in Senegal, where rainfed cropping systems account for more than 90% of cultivated land (Noblet et al. 2018). The agricultural sector employs approximately 70% of the active population (CIAT et BFS/USAID 2016; Zougmoré et al. 2016) and contributes around 13% to the national GDP in 2019. Given this economic reliance on agriculture, understanding how climate change will impact the sector is critically important.

Despite their importance, current yield levels of maize and peanut remain low due to several factors, including poor soil fertility, limited input use, and low adaptive capacity (MacCarthy et al. 2021a). In addition to these challenges, the country faces rapid population growth, estimated at 2.5% per year (ANSD 2013; Van Ittersum et al. 2016). This is projected to increase the production gap for national food sufficiency to nearly 40,000 ton for maize and an additional 70,000 ton for imported wheat (Compact senegal 2023).

However, little evidence has evaluated how changes in varieties and nutrient management to address challenges of low yields will perform under climate change. Indeed, the majority of studies assessing climate change impacts on cropping systems in the region have relied on a single, currently adopted cultivar, without accounting for the potential yield benefits of improved varieties better suited to future climatic scenarios (Amouzou et al. 2019; MacCarthy et al. 2021b; Roudier et al. 2011). Few studies considered the adaptation of the growing cycle duration potentially leading to overly pessimistic crop yield projections in most countries in West Africa. Additionally, increased temperature caused by climate change contributes to heat stress which can drastically reduce crop yields regardless of the elevated CO_2 concentration (Gérardeaux et al. 2021). While some crop-climate models include CO_2 fertilization effects, they often neglect the offsetting impact of heat stress, especially during flowering and grain-filling stages critical for maize (Gabaldón-Leal et al. 2016). Cultivar adaptation can compensate for the negative impact of climate change in West Africa by up to 67% and 43% of the potential production in 2050 and 2090 respectively (Alimagham et al. 2024). Ndour et al. (2017) suggested testing short-cycle varieties of cotton to reduce yield losses caused by rainfall deficits, even though none of the cultivars used were adapted to water stress. Despite the increasing urgency, evidence remains scarce on how cultivar selection, growing cycle adjustments, and nutrient management can collectively contribute to climate change adaptation in Senegal's peanut and maize systems.

Nutrient management, particularly nitrogen and phosphorus application, is known to significantly improve crop yield levels in West Africa. To meet future food demands while minimizing agricultural land expansion, it is essential to focus on yield increases through sustainable intensification. This can be achieved by maintaining high nitrogen use efficiency, thereby optimizing input use and reducing environmental impacts (Holden 2018). In this context, promoting sustainable intensification strategies not only addresses the growing demand for food but also contributes to the protection of natural resources (Droppelmann et al. 2017; Franke et al. 2018).

While nitrogen-fixing peanut typically responds only to phosphorus application (Naab et al. 2015), maize shows a strong yield response to both nitrogen and phosphorus. In fact, nitrogen fertilization alone has been shown to more than double maize yields (Faye et al. 2018b) and, in some cases, even triple them compared to current levels (Folberth et al. 2013). However, despite these gains, increased fertilization is associated with greater yield variability (Danso et al. 2018) and may amplify the negative impacts of climate change (Faye et al. 2018b), making increasing yield levels through fertilization more risky under climate change. Nevertheless, emerging evidence from other regions suggests that improved nutrient management could serve as a viable adaptation strategy to climate change, offering a pathway to maintain productivity while reducing vulnerability (Carr et al. 2022; Rezaei et al. 2023).

To comprehensively assess the impacts of climate change on crop yield under intensification strategies, this study employs a process-based crop modeling approach using the SIMPLACE modeling framework (Enders et al. 2023). The analysis is conducted for maize and peanut across Senegal at a spatial resolution of 0.5°.

The study is structured in two main steps: first, we evaluate the projected impacts of climate change on maize and peanut yields under current nutrient management practices. Second, we assess how these impacts may change under intensification strategies, specifically under conditions of non-limiting nutrient availability and the use of adapted crop varieties.

Materials and methods

Study area

This study is focused on Senegal, a country located in West Africa along the Atlantic coast, between latitudes 12° and 16°N and longitudes 11° and 17°W. The country is characterized by a tropical climate with a distinct rainy season (typically from June to October) and a dry season, with rainfall decreasing from south to north. Annual cumulative rainfall ranges from 200 to 400 mm $year^{-1}$ in the north, 400 to 800 mm $year^{-1}$ in the central region, and 800 to 1100 mm $year^{-1}$ in the south of the country (Salack et al. 2011). Average annual temperatures range between 25 and

30 °C, with higher temperatures typically recorded in the northern and inland areas. Agriculture in Senegal is highly vulnerable to climate change, primarily because of its reliance on rainfed farming systems, the increasing frequency and severity of droughts, and shifting rainfall patterns. In response to these challenges, we conducted a study examining the impacts of climate change on maize and peanut, with a particular focus on evaluating intensification strategies that mitigate these adverse effects. Senegal was selected due to the availability of climate data, as well as the prior calibration of these two crops. Although several climate change studies have been conducted in Senegal, they often overlook intensification strategies. Our study addresses this gap by explicitly examining intensification as an adaptive response.

Climate data

The study used daily climate data at 0.5° spatial resolution derived from the new projections of the Coupled Model Intercomparison Project 6th Phase (CMIP6) including daily minimum and maximum air temperature, precipitation, global radiation, and wind speed. Nine global circulation models (GCMs) were selected with five models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) climate input datasets used in Jägermeyr et al. (2021) and four models (BCC-CSM2-MR, CanESM5, INM-CM5-0, MIROC-ES2L) from the study conducted by Sultan et al. (2023). The climate data were bias-corrected using reanalyzed forcing data as the reference dataset Sultan et al. 2023). The simulations were conducted for the baseline period (1981–2010) and the future periods 2045–2074 (2060) and 2070–2099 (2100). Two shared socio-economic pathways scenarios (SSP2-4.5 and SSP5-8.5) were used over the two future periods.

These two scenarios were chosen that allow us to assess a range of potential future impacts on crop yields under both moderate and extreme climate change conditions (Riahi et al. 2017), which is particularly relevant for sub-Saharan Africa, a region widely recognized as being highly vulnerable to climate change due to its high exposure and low adaptive capacity (Niang et al. 2015; Serdeczny et al. 2017). For long-term agricultural planning, infrastructure investment, and the development of adaptation policies in Senegal, both mid-century (2045–2074) and end-century (2070–2099) periods were adopted to assess the projected impacts of climate change on the two selected crops. These timeframes align with common planning horizons used in climate impact assessments and policy frameworks, allowing for the evaluation of distant challenges and opportunities.

Soil data

Soil data was derived from the Harmonized World Soil Database (HWSD); https://www.fao. org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). The original data had a resolution of 30 arc seconds by 30 arc seconds (1-km resolution). The physical and chemical characteristics of topsoil (0–30 cm) and subsoil (30–100 cm) were selected for clay, silt, sand, bulk density, organic carbon, and available water capacity. Data were aggregated to the 0.5° grid of the climate data by selecting the soil class having the largest area in each simulation unit. Parameters such as soil water at field capacity, wilting point, and saturation were calculated using a pedotransfer function (Saxton and Rawls, 2006) with the Van Genuchten parameters determined based on texture class, which was required for the process-based crop model.

Crop selection and varieties

These two crops were selected based on their high economic importance in Senegal, as well as their widespread cultivation. Maize is a staple crop in Senegal, grown mainly under rainfed conditions and is particularly sensitive to climate change compared to other cereals such as sorghum and millet. It plays a key role in household food security and is increasingly promoted by national programs such as the Program to Accelerate the Pace of Senegalese Agriculture (PRACAS) to reduce dependence on cereal imports. Several studies have shown that maize experiences larger yield reductions under warming and drought conditions (Zhao et al. 2017). Crop modeling studies in Senegal and the broader Sahel region also project significantly greater yield declines for maize under future climate scenarios, while millet shows more stable or even slightly positive responses depending on the scenario (MacCarthy et al. 2021b). While peanut has long been a key cash crop in Senegal and also serves as an important source of dietary protein and vegetable oil for local populations, it plays a critical role in rural livelihoods, contributing significantly to household income, food security, and national export revenues (World Bank 2017). In addition to its economic value, peanut residues are commonly used as fodder, enhancing its multifunctional role in smallholder farming systems (Ayantunde et al. 2007). Both crops are thus central to food security and rural livelihoods. Additionally, they represent different photosynthetic pathways allowing for the exploration of contrasting physiological responses to elevated CO_2, temperature, and rainfall stress.

Crop cultivars were selected based on expert knowledge for maize, considering both short-season (90 days to maturity) and long-season (120 days to maturity) varieties, following the approach adopted in Sultan et al. (2023). The short-season variety was calibrated using parameters from EVDT97-SPR, while the long-season variety calibration was based on the Obatanpa parameters as described in the study by Faye et al. (2018b). Rainfed maize is grown in the peanut basin with a growing season of 90 to 100 days and in the Eastern and South of Senegal where the growing season lasts from mid-June to mid-October. The selection of peanut cultivars is based on the study of Faye et al. (2018a). The two peanut cultivars Fleur11 (90 days) and 73–33 (105 to 110 days) are calibrated and validated in three different agroecological zones (Bambey, Nioro, and Sinthiou Malem) in Senegal and are widely sown by farmers. Peanut cultivars were tested in both irrigated and rainfed conditions from 2014 to 2015.

Fertilizer scenarios

Two fertilization scenarios were considered in this study: current and intensification fertilization case. For the current fertilization case, fertilizer application rates for both crops were derived from previous studies. Maize received for all grids a uniform rate of 15 kg N ha^{-1} (Faye et al. 2018b; Vanlauwe and Dobermann, 2020), while for peanut, the recommended fertilizer rate of 9 kg N 14 kg P ha^{-1} was applied based on agronomic recommendations from the Institut Sénégalais de Recherches Agricoles (ISRA) (Faye et al. 2016). The timing of nitrogen application was at sowing for both crops. For the intensification fertilization case, a crop-specific approach was adopted. For maize, nitrogen limitation was turned off to simulate optimal nutrient availability. For peanut, both nitrogen and phosphorus limitations were turned off, based on previous findings indicating that peanut, as a legume crop, is generally less responsive to nitrogen fertilization due to its ability to fix atmospheric nitrogen (Faye et al 2016).

Modeling framework

In this study, we used the SIMPLACE (Scientific Impact Assessment and Modelling Platform for Advanced Crop and Ecosystem Management) modeling framework (www.simplace.net). SIMPLACE is a flexible, modular simulation environment designed for advanced assessment of crop and ecosystem management. It allows researchers to integrate various biophysical process models relevant to crop growth, soil dynamics, and environmental interactions (Enders et al. 2023; Gaiser et al. 2013). It has been widely used in the West African context (Adelesi et al. 2023, 2024; Faye et al. 2018a, 2018b; Sultan et al. 2023).

In our configuration, we used the LINTUL5 model (Wolf, 2012) which calculates crop growth and yields under potential, water-limited, and nutrient-limited (nitrogen, phosphorous and potassium) conditions. Simulated potential yields were based on optimal conditions, determined by factors such as maximum and minimum temperatures, solar radiation, crop characteristics, and CO_2 concentration. Phenology and subsequent development stages are simulated with the accumulation of thermal time which is used to determine the occurrence of emergence, anthesis and maturity, with photoperiodism potentially slowing the time from emergence to anthesis. Crop development stages (DVS) are simulated as a function of daily temperature sums (thermal time) and crop-specific thermal time requirements, TSUM1 and TSUM2, to develop from emergence to anthesis and from anthesis to maturity, respectively. Biomass crop growth rate and biomass production are determined by intercepted radiation and allocated to different crop organs based on developmental stage. New assimilate is calculated daily using intercepted light, which is a function of leaf area index, and radiation use efficiency.

The photoperiod sensitivity is simulated using the correction factor of development rate as function of day length (PHOTTB) from emergence to flowering. The value of PHOTTB ranges from 0 (no flowering) to 1 (maximum development) and it is cultivar specific.

The combined model used a modified version of the soil water balance Slimwater (Addiscott et al. 1986; Addiscott et Whitmore, 1991) model and the FAO-56 dual crop coefficient procedure for calculating crop evapotranspiration (Allen et al. 1998).

The NPKDemandSlimNitrogen module calculates the daily demand and uptake of N, P, and K stress factors and movement in the soil profile into multiple layers together with leaching of soil mineral nitrogen (Addiscott et al. 1986; Addiscott et Whitmore, 1991; Jamieson et al. 1998; Porter 1993). The turnover and leaching of nitrate and ammonium are closely related to the soil water dynamics where input data related to daily changes in soil water content and soil water fluxes are provided by SlimwaterModified. Daily total mineral N is an input to the module provided by the SoilCN module, an hourly canopy temperature module (Webber et al. 2016) to simulate canopy temperature and a heat stress module (Gabaldón-Leal et al. 2016) to simulate heat stress with input from the canopy temperature module.

The soilCN module (Corbeels et al. 2005) simulates soil organic carbon and soil nitrogen dynamics using multiple soil layers. The soilCN model used in this study was validated at a regional scale with different crop types and management options (Faye et al. 2023).

Simulation setup

This study is conducted in Senegal a country in West Africa with an annual average rainfall of 300 mm in the northern part (arid zones) and about 1200 mm in the southern part (humid zones) with a unimodal distribution (Ndione et al. 2017). Simulations were conducted for two crops, maize and peanut assuming rainfed conditions. Simulations were conducted on a gridded basis with input climate and soil data at 0.5° resolution. For each crop, two varieties were simulated as described in the "Crop selection and varieties" section. Additionally, all simulations were conducted for two intensification cases: current fertilizer use and intensification fertilization case (unlimited nutrient supply and availability). For maize, current fertilizer use was limited to nitrogen only, whereas for peanut simulations in the current fertilizer use case, both nitrogen and phosphorus limitations were simulated. It was assumed that the varieties were not adapted between the baseline and climate change scenarios, and the same sowing dates were used for both periods. The simulations were performed under ambient (results not shown) and elevated CO_2 concentrations for all periods and all scenarios. Simulations for the current fertilization case were performed for both the baseline and future scenarios, and the same approach was applied to simulations under the intensification fertilization case.

The CO_2 concentration for the ambient scenario across all periods was 362 ppm, while for the elevated scenario, it was set to 534 ppm and 593 ppm for the mid- and long-term under SSP2-4.5, respectively. For SSP5-8.5, it was set to 646 ppm and 958 ppm (Table S1).

The model was reinitialized each year to allow a simplification of the setting and to reduce uncertainties due to the carryover effects in the continuous simulations. These simplifications would not have an impact on the climate change signal as shown in (Faye et al. 2023).

Data analysis

The simulations were conducted for each of the 99 simulation units for the whole country at 0.5° resolution. Final grain yields were both mapped at the simulation unit level as well as aggregated to the country level using the Spatial Production Allocation Model (SPAM) by averaging yields for each period and scenario. The SPAM dataset at 10-km resolution, SPAM version 2017 (Yu et al. 2020), was used to select the harvested areas for the two crops. As simulations were performed only under rainfed conditions, aggregated yields at the country level did not consider weighting by current production areas. Production areas with rainfall all from the SPAM dataset were used for data aggregation. Yield distributions were plotted by aggregating yields over years and simulation units and considering any given GCMs × SSPs × Period × Crops × intensification case combination.

To evaluate the performance of the SIMPLACE crop model for maize, simulations were performed for the historical period using the reanalyzed EWEMBI datasets from 1979 to 2013 (Lange 2016) available at ISIMIP (https://www.isimip.org/). Simulated historical yields were compared with observed yield data from the FAOSTAT dataset as described in greater details in Sultan et al. (2023). For peanut, parameters were derived for both model calibration and evaluation following the study of Faye et al. (2018a).

The statistical analysis was conducted using two indices to evaluate the accuracy of the model by comparing the FAOSTAT dataset with the simulated yield data.

The coefficient of determination (R^2), slope, and intercept of the linear regression between observed and simulated values were established. It can be interpreted as the variance in the observed values that is attributable to the variance in the simulated values.

The root mean squared error (RMSE) was used to quantify the difference between the simulated grain yields predicted by the model and the observed grain yield. It is used to evaluate the model's accuracy and is expressed in the same units as the target variable (grain yield).

$$\textit{Root mean squared error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2}$$

where O_i and S_i are the observed and simulated values, respectively, and n is the sample size.

Relative yield change (ΔYield) was calculated to evaluate the impact of climate change on crop production. It was determined by averaging over the years for a given combination.

$$\Delta\text{Yield}\ (\%) = \frac{\text{Yield}_{\text{scenario}} - \text{Yield}_{\text{baseline}}}{\text{Yield}_{\text{baseline}}} * 100$$

where $\text{Yield}_{\text{scenario}}$ is the simulated yields under the future scenario, and $\text{Yield}_{\text{baseline}}$ is the simulated yields under de baseline scenario.

Results

Crop model evaluation

Model evaluation was conducted differently between peanut and maize, primarily due to differences in the availability of input data, as well as distinct calibration and evaluation datasets used for each crop. For peanut, the model was calibrated and validated using field data from Faye et al. (2018a) at two different sites in Senegal. In contrast, for maize, calibration relied on parameters from Faye et al. (2018b), and evaluation was done by comparing simulated yield anomalies with national-level anomalies from FAOSTAT.

The model performance of peanut for both calibration and evaluation was consistent, with a good correlation (R^2 = 0.54). Even though, the model performance maintained

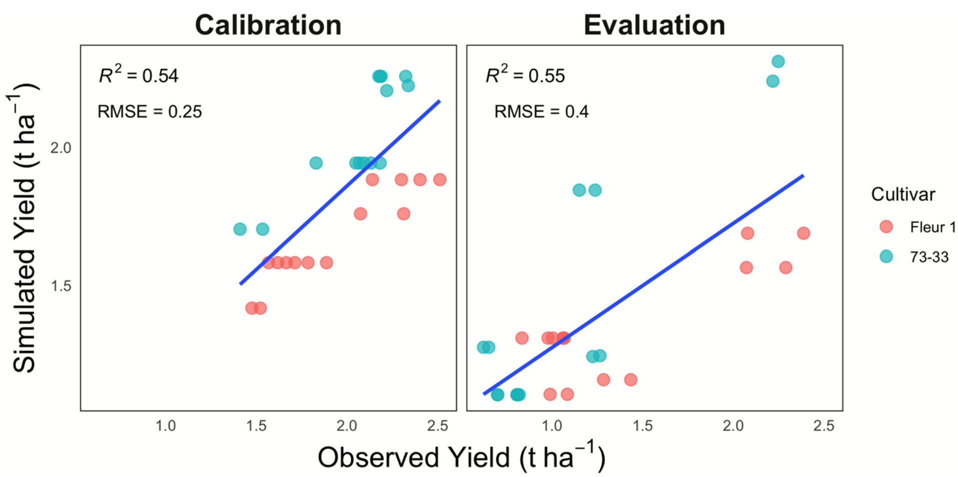

Fig. 1 Calibration and evaluation of the peanut crop model for two cultivars at two experimental sites in Senegal. Model calibration was performed at the Nioro site and evaluation at the Bambey site. Results are shown for the peanut cultivar Fleur 11 (green circles) and 73–33 (red circles)

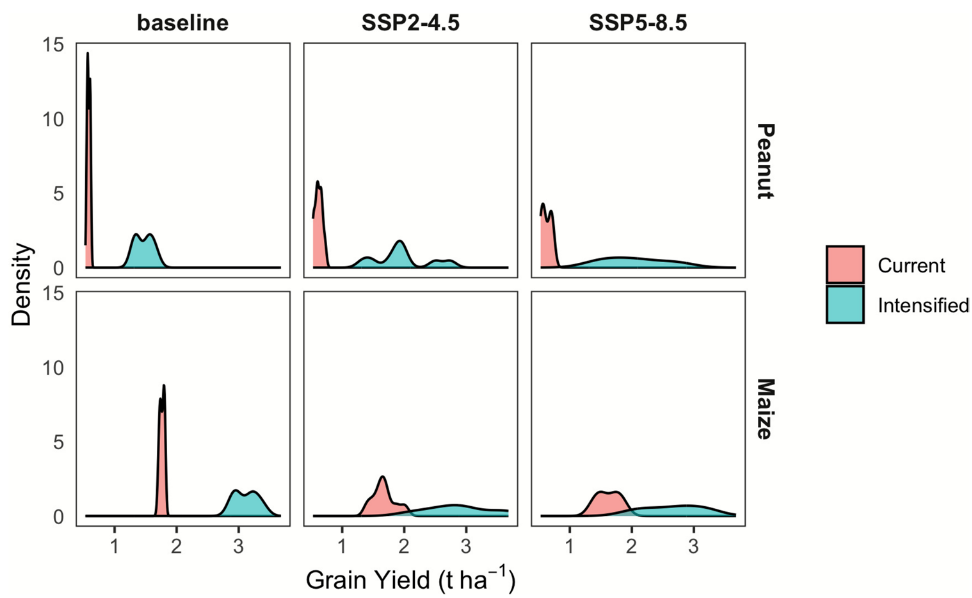

Fig. 2 Distribution of grain yields simulated for peanut (top row) and maize (bottom row) under the current fertilization (orange color) and the intensification fertilization case (green color). The columns show the combination of three scenarios (baseline, SSP2-4.5 and SSP5-8.5), centered on the mid-century period (2045–2074). Distribution is shown for the nine general circulation models (GCMs) under elevated (CO_2). Yield values are averaged across years and aggregated at the national scale

the predictive strength, RMSE increased during the evaluation, which may reduce the overall accuracy (Fig. 1). Among cultivars, Fleur11 exhibited stronger calibration performance (R^2 = 0.87) compared to 73–33 (R^2 = 0.68). Interestingly, this relationship reversed during evaluation, where 73–33 slightly outperformed Fleur11 (R^2 = 0.79 vs. 0.71), suggesting cultivar-specific sensitivities across sites (Fig. S1).

For maize, model performance was moderately low with a correlation of R^2 = 0.29 when comparing the simulated yield anomalies with FAO yield anomalies at the country level, indicating the variability in yield (Fig. S2). The use of yield anomalies, rather than absolute yield values, served to minimize the influence of outliers and reduce uncertainties associated with measurement errors in reported yield data.

Absolute yield simulations

Under baseline conditions, average peanut yield levels were approximately 1.0 t ha^{-1} for the current fertilization case (Fig. 2). For maize, the two cultivars had distinct simulated yields for the current fertilization case, with 1.5 t ha^{-1} for the short season variety and 2 t ha^{-1} for the long season variety (Fig. S3). In the intensification case, simulated yields were twice as high as yields simulated under the current fertilization case for both peanut and maize. However, yield variability was notably higher under the intensification fertilization cases (Fig. 2). This yield variability tended to be higher when considering the scenarios of SSPs and in the far future period for both crops. Among the SSP scenarios, SSP5-8.5 exhibited the highest yield

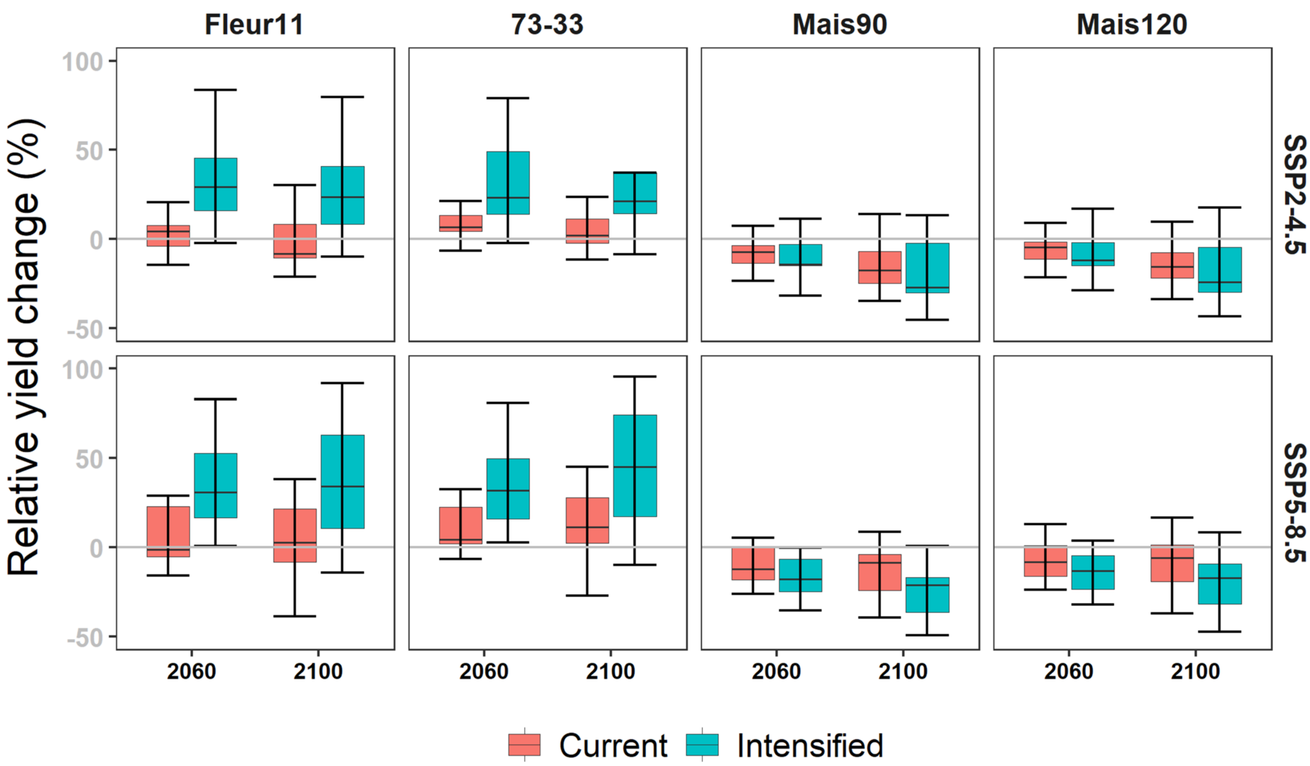

Fig. 3 Relative yield change of two peanut (Fleur 11 and 73–33) and two maize cultivars (Mais90 and Mais120) for the future periods 2045–2074 and 2070–2099 relative to the baseline 1981–2010. Box-and-whisker plots depict the distribution across GCMs for the 25th and 75th percentiles; the median is shown as a horizontal bar in each box and whiskers extend to the maximum/minimum value within 1.5 times the interquartile range. Orange and green bars depict the current and intensification fertilization cases, respectively. Results are displayed for two shared socioeconomic pathways (SSPs): SSP2-4.5 (top row) and SSP5-8.5 (bottom row)

variability particularly under the intensification fertilization cases (Fig. S2).

Changes in mean yields

Across all intensification cases, the relative change in yields was negative for maize and positive for peanut irrespective of the considered scenario SSPs (Fig. 3). Yield losses for maize ranged between −23% and −5% for the intensification and the current fertilization cases (Tables S2 and S3), respectively. On the other hand, peanut yield increased under climate change, between 2% for the SSP2-4.5 in the long term to 8% for the SSP5-8.5 in the mid term, all assuming the current fertilization case. Under the intensification case, yield gains for peanut were higher with 32% and 38% in the near term for SSP2-4.5 and SSP5-8.5, respectively. In the long term, peanut exhibited yield increases of 34% for SSP2-4.5 and 56% for SSP5-8.5 for the intensification fertilization case (Tables S2 and S3). However, when considering nitrogen limitation alone as the current fertilization case, peanut yield gains were similar under both the current and intensification cases (Fig. S5).

Irrespective of the scenarios and the periods, it was evident that climate change impacts were generally more negative under the intensification fertilization case for maize, including all cultivars of each crop. The relative changes in yield were higher for SSP5-8.5 and in the long term (2070–2099) than in the mid term (2045–2074) for peanut under the intensified fertilization scenario. Comparing crops, there was less uncertainty across GCMs for the SSP2-4.5 scenario except for the short cycle variety of maize for the period 2070–2099. However, there was much greater uncertainty across GCMs in the simulated yield impacts with the intensification fertilization case and for the SSP5-8.5 scenario. For all crops, the uncertainty across GCMs was generally much greater than any signal from the period, the scenario or the intensification fertilization case.

These aggregate results hide much information about the spatial variation of simulated yield changes, shown as in Fig. 4, for both peanut and maize cultivars. Regardless of the intensification cases, simulated yield changes were generally positive in peanut everywhere in the country. In contrast, maize yield losses were concentrated in the south and east, especially for the short-cycle variety (Mais90), where

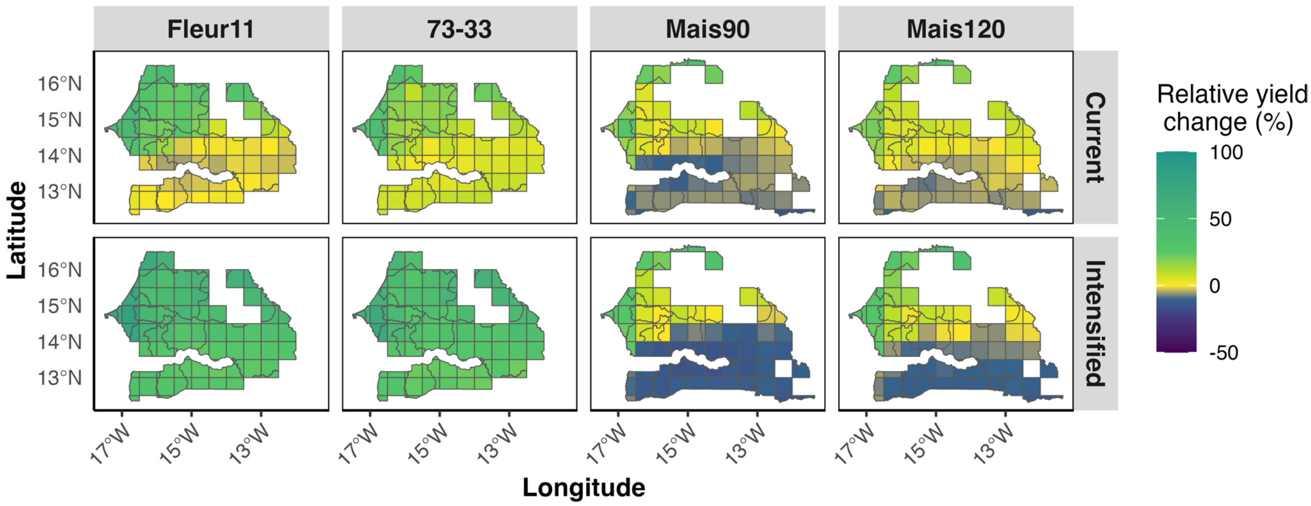

Fig. 4 Spatial patterns of projected relative yield change for two peanut cultivars (Fleur 11 and 73–33) and two maize cultivars (Mais90 and Mais120) in the columns for the period 2045–2074 under the scenario SSP2-4.5. Results are shown here for the current fertilization (top row) and the intensification fertilization case (bottom row)

losses reached up to −50%. For current fertilizer use, peanut yield gains were slightly higher for the 73–33 (medium cycle variety) than the Fleur11 (short-cycle variety). An opposite result was detected for the intensification fertilization case.

However, yield gains for peanut are high under the SSP5-8.5 scenario and for the long-term period (Fig. S6). For maize cultivars, yield losses are higher for the SSP5-8.5, in the long-term and for the intensification fertilization case. On the other hand, we see yield gains for maize in large parts of western and northern countries, mostly at the current fertilization case for the SSP5-8.5 scenario and in the long-term. When looking at the mid-term simulations and focusing on maize yield losses across GCMs, similar spatial variability was present but with higher losses for SSP5-8.5 in both intensification cases. The results emphasize the importance of region and crop-specific adaptation strategies under climate change.

Figure 5 presents the relative changes in yield for peanut and maize, aggregated across cultivars and GCMs, under the intensification fertilization case for both scenarios (SSP2-4.5 and SSP5-8.5) during the mid-term period. There was a significant change in yield of peanut and maize under climate change. Yield differences for peanut ranged between 20 and 100% across the country, with the highest gains observed under the SSP5-8.5 scenario, particularly in the western regions. For maize, yield changes ranged from losses of up to 50% to gains of a similar magnitude, depending on the region and scenario. Notably, yield increases for maize were also observed in the western part of the country under both SSP2-4.5 and SSP5-8.5 scenarios. However, yield losses for maize were generally more pronounced under the SSP5-8.5 scenario compared to SSP2-4.5, with substantial negative impacts concentrated in the southern and eastern regions.

Under the current fertilization case the yield losses for maize decrease by 20%, while yield gains for peanut decrease from 100 to 60% compared to the intensification fertilization case (Fig. S7).

Discussion

Model evaluation

The model performance during calibration had lower RMSE compared to the subsequent evaluation. This difference can be attributed to the higher variability in yield observed in Bambey, ranging from 0.5 to 2.2 t ha^{-1} (data used for evaluation), compared to Nioro, where yield varied from 1.5 to 2.5 t ha^{-1} (data used for calibration). Additionally, the experiments performed better in Nioro due to lower soil variability with higher nutrient content and higher water quality, whereas in Bambey, the lower soil nutrient content and slightly salty water negatively impacted crop performance. Similar results were shown in (Faye et al 2018a), where the model performed better under calibration than for the independent evaluation.

Yield variability in Bambey is primarily due to the low yield observed under the rainfed treatment, which was associated with the unfavorable growing conditions during the 2015 season under severe water stress. In contrast, the irrigated treatment produced higher yields, benefiting from well-watered conditions. This highlights the importance of differentiating management strategies in evaluation datasets, as models evaluated under mixed conditions may be sensitive to these underlying differences.

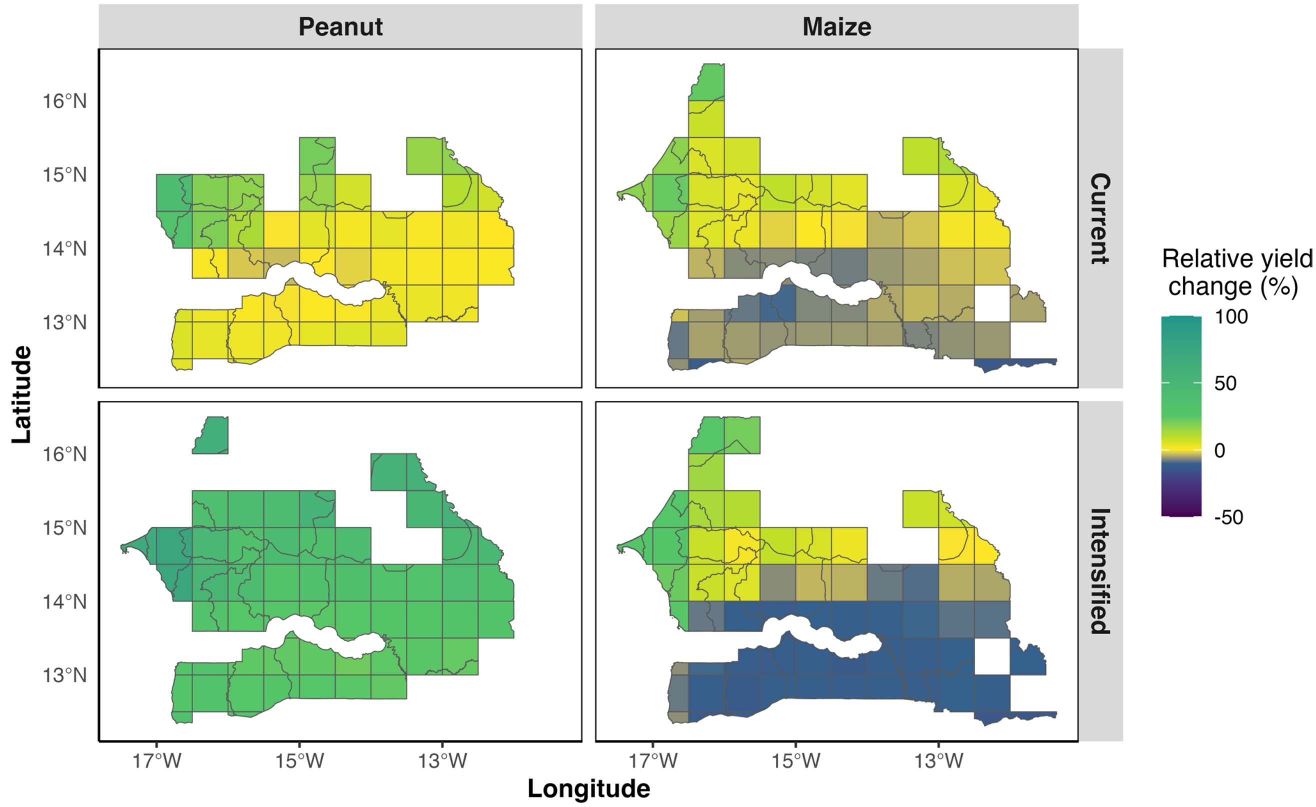

Fig. 5 Spatial patterns of projected relative yield change of peanut and maize aggregated across cultivars in the columns for the period 2045–2074 under the current fertilization (top row) and intensification fertilization case (bottom row). Results are shown here for the scenarios SSP2-4.5

Although the RMSE increased during evaluation, this does not critically undermine the reliability of future yield projections, especially since the model successfully captured interannual variability and average yields within the observed ranges during both calibration and evaluation. This suggests that while some overfitting may have occurred during calibration, the model maintains reasonable predictive skill and generalizability under historical climate variability. Nonetheless, this highlights the need for improved calibration datasets and model evaluation techniques to further strengthen future projection confidence.

Model evaluation for peanut had better performance than for maize, which compared simulated yield with FAO yield datasets. The relatively low agreement observed for maize ($R^2 = 0.29$) reflects the challenges associated with using national-level datasets for crop model evaluation, especially in regions with heterogeneous agroecological conditions. These findings are consistent with previous studies that have reported similar discrepancies between simulated and reported maize yields (Bondeau et al. 2007; Sultan et al. 2013, 2019). The limitations of FAO data stem not only from potential inaccuracies in data collection and reporting in developing countries, but also from the aggregation of yields across both rainfed and irrigated systems, and the absence of controls for biotic stresses such as pests and diseases.

In West Africa, several studies have compared crop model outputs against FAO or field-based yield observations of maize. Gaiser et al. (2010) evaluated the EPIC model at 22 sites across the sub-humid and semi-arid zones and reported a moderate correlation of 0.4 between simulated and observed data. In Burkina Faso, Waongo et al. (2024) achieved R^2 values ranging from 0.2 to 0.7 with the Aquacrop crop model. Similarly, Leroux et al. (2019) modeled rainfed maize across West Africa using SARRA-O with remote sensing data and reported R^2 values above 0.4. At a national scale, Asfaw et al. (2018) used GLAM to simulate Ghanaian maize yields with a Pearson correlation from 0.3 to 0.67 when compared simulated yields to FAO data, despite some overestimation during years with drought. These studies collectively suggest that, despite inherent uncertainties, well-calibrated crop models in combination with multi-source data can reliably reproduce interannual yield variability in West Africa.

Climate change impacts on crop yield

This study is the first to assess the impacts of climate change on crop yields under intensification scenarios in Senegal, expected to predominate in the country in the coming decades using a new generation of CMIP6 climate projections. A previous study assessed the impact of climate change on millet and sorghum for different cultivars (Faye et al. 2022) but did not consider intensification cases which are essential for West Africa to reduce the import of cereals.

Maize yield increased strongly between the current fertilizer use and the intensification fertilization case due primarily to the currently very low fertilizer rates now applied to maize both under baseline and future periods. This largely explains the actual maize yields which are very low at only approximately 30% of potential levels of maize (Silva et al. 2023; Van Ittersum et al. 2016). For peanut, a similar trend was observed, with actual yields significantly constrained under current fertilization practices, particularly when both nitrogen and phosphorus limitations are considered. Interestingly, the small difference in peanut yield simulated in the two intensification fertilization cases (with nitrogen limitation only as the current fertilizer) was the result of nitrogen fixation on one hand, and on the other hand, the cultivars used were calibrated and validated at an experimental research station with the recommended dose of fertilization. For these reasons, the use of nitrogen fertilizer on peanut will not be beneficial unless at fields where soil fertility is very low. These results align with previous research (Araya et al 2022; Campbell et al. 1980; Faye et al 2016) that showed no significant difference in peanut grain yields for different levels of nitrogen fertilizer. The higher variability in simulated yields in the future scenarios is a result of the uncertainty about the nine GCMs. However, when phosphorus limitation is considered on peanut, it clearly shows a lower yield of up to half of the yield under the intensification fertilization case. These results are in line with the results of Sun et al. (2023) which showed a reduction in peanut productivity under phosphorus limitation conditions.

Crop yield response to intensification differed between maize and peanut. Maize intensification is primarily constrained by nitrogen limitation due to its high nitrogen demand and inability to fix atmospheric nitrogen, making it highly responsive to nitrogen fertilization (Balemi et al. 2019; Rawal et al. 2024). In contrast, peanut intensification must address both nitrogen and phosphorus limitations. Although peanut is a C3 legume capable of biological nitrogen fixation, its response to nitrogen fertilizer is generally low under normal conditions. However, under well-watered environments and nutrient-depleted soils, the application of small amounts of nitrogen can enhance early root development and increase root volume, which supports more effective nodule formation and biological nitrogen fixation (Ding et al. 2022). Moreover, phosphorus plays a critical role in nodule initiation and function, energy transfer, and root development, making it a key nutrient for optimizing peanut productivity, particularly in P-deficient soils commonly found in West Africa (Kamara et al. 2011; Naabe Yaro et al. 2021). Therefore, dual-nutrient management involving both N and P is essential for realizing the full yield potential of peanut under intensification strategies (Argaw 2018).

The projected yield losses for maize grain yield can be attributed to the increase in temperature in both scenarios that shortened the length of the growing cycle duration. This thermal stress accelerates phenological development, leading to reduced biomass accumulation and lower yields. These findings were consistent with the previous work of Sultan et al. (2023) and MacCarthy et al. (2021b) who reported similar yield losses for grain maize in Senegal. At a regional scale across West Africa, reductions in maize yields have also been primarily driven by the shortened crop duration, as observed by Faye et al. (2018b). At the global scale Jägermeyr et al. (2021) identified widespread declines in maize productivity associated with warming trends. Supporting this, Hu et al. (2024) provided robust evidence of a global maize yield decrease of up to 7.5% in response to a 1 °C increase in temperature. These results are corroborated for other cereals such as millet and sorghum where most studies predicted losses in yield in West Africa (Faye et al. 2022; Sultan et al. 2013; Tofa et al. 2024). The simulated millet yield is projected to decrease by up to 11% (Singh et al. 2017) by 2050 where Sultan et al. (2013) further estimated that mean millet and sorghum yields could decline by as much as 41% over the course of the twenty-first century in West Africa.

The positive effect of climate change on peanut yields is driven by atmospheric CO_2 fertilization which provides much higher benefits for C3 crops. The positive response of C3 crops is attributed to the fact that the higher temperature effect on growth and phenology is compensated for by the effect of CO_2 fertilization, which reduces stomatal conductance and transpiration and improves water use efficiency. These results were largely consistent with other climate impact studies that have used process-based crop models for peanut in Senegal (Faye et al 2018a; MacCarthy et al. 2021b) and demonstrated the positive effect of elevated CO_2 concentration. Similarly, the reduction in stomatal conductance (Ainsworth and Rogers, 2007; Kimball 1983; Purcell, et al 2018) and transpiration under elevated CO_2 concentration has been extensively studied (Kimball 2016; Manderscheid et al 2016, 2018) in both C3 and C4 crops.

Toreti et al. (2020) showed that although CO_2 fertilization offset the negative effects of climate change on crop yield, it has been observed to negatively impact food quality by reducing protein concentrations in crops such as barley, potato, rice, wheat, and soybean.

Additionally, aside from the differences between C3 (peanut) and C4 (maize) crops due to their photosynthesis mechanism, a larger difference was observed between climate scenarios (SSP2-4.5 and SSP5-8.5) and less variation between intensification fertilization cases. The difference in climate scenarios can be attributed to the CO_2 concentration levels used for these two scenarios. Furthermore, the smaller differences between intensification fertilization cases were explained by the fact that intensification had a lesser effect on CO_2 concentration. However, the greatest source of uncertainty for peanuts was across GCMs, while for maize, the climate signal varied most with the SSP scenarios.

The simulations suggested that climate change impacts would be less severe in the western part of the country for both crops. This is largely attributable to the cooler temperatures (Fig. S10) but also to the increase in rainfall projected in the CMIP6 data (Fig. S11). Such results increase uncertainties in predicting yield changes over the region as compared to the findings from Sultan et al. (2023). Similar results were found in different agroecological zones in Niger where rainfall is projected to increase in the future under CMIP5 data leading to an increase in yield for pearl millet (Tofa et al. 2024). Both crops exhibited yield losses in the southern part of the country that can be attributed to an increase in temperature and a decrease in rainfall. However, yield increases were projected over the country for peanut; in some locations, the decrease in rainfall and the increase in temperature were not compensated by the CO_2 fertilization mainly in the south and southeast. Such results were shown by Sarr and Camara (2018) who predicted yield losses in peanut in both the near and far future in the southern part of the country. Rainfall was the main driver of yield variation, accounting for more than 65% of the variation in maize and 45% in peanut by mid-century (Fig. S12). The sensitivity of maize to rainfall was demonstrated in South Africa, where it accounted for up to 40% of yield variation (Mangani et al. 2025). However, this effect is site-specific, with a greater impact in low-rainfall areas. The uncertainty in yield response to precipitation was shown by Hu et al. (2024) while an increase in temperature had a negative impact on yield.

Uncertainties and limitations of the study

The sources of uncertainty related to the climate models stem from both their structural differences and parameterization approaches. These uncertainties translate into variability in yield projections across different scenarios. In our study, yield variability across GCMs was more pronounced for peanut, which can be attributed to the physiological crop response to elevated CO_2 concentrations, a factor that differs among climate models and significantly influences peanut growth. In contrast, for maize, the variability was more closely associated with the choice of SSPs, reflecting the higher sensitivity of maize to temperature changes. This contrasts with the findings of Zhang et al. (2019), who reported greater uncertainties across GCMs than across RCP scenarios for maize yield projections.

Another source of uncertainty is related to the use of spatially aggregated yield data. Aggregating yield at broader national scales can mask important local heterogeneity in crop responses. Maharjan et al. (2019) have shown that the aggregation error of climate and soil data can increase uncertainties in simulated crop yield responses, as it may obscure local-scale variability and lead to less accurate representation of site-specific conditions. However, the resolution and source of input data may not significantly affect the aggregation itself, but they can influence the accuracy and representativeness of the aggregated outputs, especially when assessing spatial variability in crop responses (Rezaei et al. 2024). Interestingly, our results showed potential positive impacts of climate change in regions currently characterized by cooler temperatures. In such areas, moderate warming, combined with elevated CO_2 concentration, could enhance growth conditions, leading to improved yields.

In addition to the sources of uncertainty discussed above, our study has several important limitations that should be acknowledged. Firstly, we did not consider adaptation strategies of sowing dates and growing season length, where Alimagham et al. (2024) demonstrated a compensation of the negative effect of climate change on cereal yields in East and Southern Africa by planting new cultivars with a longer growing season duration. Omitting such adaptive responses may lead to an overestimation of climate-induced yield losses. Secondly, our analysis relied on a single crop model, which could be a source of structural or parameterization uncertainties. It is well established that using a multi-model ensemble generally provides more robust and accurate projections compared to relying on a single model (Falconnier et al. 2020). Therefore, future studies could benefit from incorporating multiple crop models to better capture the range of possible outcomes and reduce model-specific biases. However, our study aimed not at projections but rather an exploration of the potential of different varieties and fertilization strategies as climate change adaptation for which insights from a single model still have value. Thirdly, there are limited or no datasets on peanut that account for the response to elevated CO_2 concentration for model calibration, which may increase uncertainty. This is particularly relevant for simulating climate change impacts, as elevated CO_2 concentration can significantly alter crop physiology and yield responses.

A study from Kothari et al. (2022) demonstrated the need to use experimental data under elevated CO_2 concentration and temperature for model development, to reduce the uncertainties in individual soybean models when assessing climate change impacts on crop yield. A similar approach would be beneficial for improving peanut model performance under future climate scenarios.

Finally, our simulations assumed rainfed conditions throughout, which may not reflect localized use of irrigation in certain areas, such as the North region. Although irrigation is relatively limited in the study region, its omission may slightly underestimate yield potential or buffer effects under extreme dry conditions. Future studies could incorporate spatially explicit irrigation data to better assess its potential role in climate adaptation strategies.

Conclusion

This study assessed the impacts of climate change on maize and peanut in Senegal considering both adapted varieties and intensified fertilization application. The process-based crop model used in the study was calibrated with local varieties and was previously demonstrated as suitable for capturing complex interactions of temperature, water status, CO_2 concentration, and fertilization levels. The results revealed contrasting impacts of climate change between the two crops. Maize yields were projected to decline, particularly for short-cycle varieties, with losses exacerbated under the SSP5-8.5. With the intensified fertilization case, yield reductions persisted up to a 10 percentage point drop compared to current fertilization levels. Conversely, peanut yields were projected to benefit from future climate conditions, largely due to their positive physiological response to elevated CO_2 concentration. However, the analysis showed that phosphorus limitations can reduce peanut yields by over 50% compared to water-limited conditions, underscoring the need for nutrient-specific management and urgently needed experimental evidence on grain legume response to elevated CO_2 under phosphorus-limited conditions.

These findings emphasize the importance of developing climate-resilient varieties and adjusting fertilization strategies, particularly for maize. While improved management is suggested to not be sufficient to reverse the overall negative signal of climate change on cereals, it could help close yield gaps and reduce losses.

Despite these contributions, the study has several limitations. Uncertainty remains high due to reliance on a single crop model and the lack of empirical data on crop responses to elevated CO_2, especially for C3 crops like peanut. Additionally, spatial aggregation of inputs and yield data may obscure local variability. A multi-model ensemble approach and inclusion of experimental data under elevated CO_2 and temperature conditions would strengthen future analyses. In spite of these limitations, the study adds to existing research by contrasting varietal responses of a main C3 legume and C4 cereal with different fertilization levels under climate change in SSA. The study supports the promotion of intensification especially for cereals, which may reduce yield gaps and enhance food security though it highlights the concurrent need to consider climate change adaptations Such knowledge can support policy and practices development to reduce dependence on food imports and improve national self-sufficiency.

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