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Research on the impact of climate change on food security in Africa

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Global warming and the rising frequency of extreme climate events pose significant threats to food security. We examine the influence of climate change on food security in Sub-Saharan Africa, with a specific emphasis on four key crops: maize, rice, wheat, and soybeans. We employ a random forest model to estimate spatial and temporal yield trends based on climate variables, land-use patterns, and irrigation ratios. We also studied the differential impacts of climate change on various crop types, taking into account their physiological characteristics and responses to changing environmental conditions. This prediction is performed under three Shared Socioeconomic Pathways (SSP2-4.5, SSP3-7.0, SSP5-8.5)—using five global climate models (GCMs): BCC-CSM2-MR, CanESM5, IPSL-CM6A-LR, GFDL-ESM4 and MPI-ESM1-2-LR. The findings suggest the following: (1) Maize, a C4 crop, is projected to experience a severe decrease in future harvests, especially under the SSP5-8.5 scenario. The worst declines are forecasted in eastern South Africa and Zambia. (2) Both rice and wheat are C3 crops that experience a "CO_2 fertilization effect," resulting in an increase in yields over time. The SSP5-8.5 scenario primarily focuses on the increase in rice production in West Africa, highlighting this phenomenon. Conversely, significant increases in wheat yield are observed in South Africa and Nigeria. (3) Soybean, a C3 nitrogen-fixing crop, is projected to retain consistent yields overall but with a modest decline in comparison with past norms. The general distribution pattern of soybean yields remains mostly consistent across the SSP scenarios, with the increase in high-yield regions occurring primarily in South Africa.

Keywords Climate change, Food security, Random forest, Spatial and temporal evolution, Sub-Saharan africa

The present state of global food security is confronted with significant obstacles. The Global Food Crisis Report 2024 (GRFC), which was published by various organizations, including the Food and Agriculture Organization (FAO) of the United Nations and the World Food Programme (WFP)[1], revealed that in 2023, approximately 282 million people in 59 countries and regions worldwide experienced severe food insecurity. This represents an increase of 24 million people compared with the previous year, indicating a significant deterioration in the food security situation. According to the Sixth Assessment Report of the IPCC, climate change has substantial and diverse effects on food security. The analysis suggests that due to global warming, heat waves and agricultural droughts are more common, resulting in a decrease in crop production worldwide. Temperature increases in several regions, including South and Central America, Asia, and Africa, are expected to cause a decline in maize yields of up to 35%[2]. Climate change not only results in decreased crop yields but also increases the occurrence and severity of extreme weather events, posing a greater risk to the stability of food production and supply networks. In Africa, the food security situation is quite severe due to the prevailing climate conditions. A significantly larger percentage of the population in Africa experiences hunger than other regions do, with approximately 20% of the population affected[3]. Maize is the predominant food in Sub-Saharan Africa[4], with rice production also increasing in the region[5]. Wheat and soybeans are also essential food crops in certain countries[6,7]. However, all of these crops face difficulties due to climate change and constraints on essential resources—such as water availability, arable land, soil nutrients, and agricultural inputs. Consequently, evaluating the effects of climate change on food security in Africa will provide a comprehensive understanding of the various impacts of climate change on agricultural production. This will facilitate the development of efficient and sustainable food security

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strategies and adaptation measures—recognizing that increased agricultural production is a key measure of food security.

Extensive research has been conducted on the consequences of climate change for agricultural productivity, with a primary emphasis on examining how alterations in temperature and precipitation patterns affect crop yield. Li et al.[8] performed a thorough examination of the correlation between climate change and agricultural pests. They reported that rising temperatures and changes in precipitation patterns not only directly affect crop yields but also indirectly impact crop production by altering the growth and reproduction cycles of pests. Dhaliwal et al.[9] found that growing-season temperatures exceeding 30 °C during anthesis reduce sweet corn yields by approximately 0.5% in irrigated fields and by 2% in rainfed fields. Hawkins et al.[10] reported that maize yield in France increased significantly from the 1960s to the 2030s as a result of thermal stress and that maize yield declined significantly during periods of high temperatures as temperatures rose. Piao et al.[11] explored the impacts of climate change on water resources and agriculture in China, where warmer temperatures and changes in precipitation patterns significantly affect rice and wheat yields. Berg et al.[12] found that, despite C4 crops' inherent heat tolerance, projected warming and altered precipitation patterns could markedly reduce tropical maize and sorghum yields, and that CO_2 fertilization only partially offsets these losses, especially in arid Köppen zones where rainfall uncertainty is greatest, thus threatening local food security. Challinor et al.[13] combined process-based crop modelling with province-level socioeconomic data, including fertilizer inputs, agricultural investment and rural household counts, to derive a vulnerability index that they applied to modelled drought events. They showed that elevated temperature extremes and precipitation variability significantly increase the risk of wheat crop failure in Northeast China. Proctor's[14] research further confirmed the significant reduction in rice yield caused by high temperatures and irregular precipitation patterns, particularly during critical growth stages. This finding reinforces the profound impact of temperature and precipitation changes on crop productivity. However, most of these studies focus on single crops or specific regions, failing to fully reveal the comprehensive impacts of climate change on multiple crops, especially in complex environments like Africa.

In addition, projects such as ISIMIP and AgMIP have made significant contributions to multi-model integrated assessments. ISIMIP evaluates climate impacts under standardized scenarios by integrating models from various fields, while AgMIP focuses on the agricultural sector, aiming to improve crop models and explore changes in socio-economic scenarios. Their latest CMIP6-forced ensembles reveal more pessimistic prospects for maize, soybean and rice, and earlier "emergence" of climate impacts than previously anticipated, while projecting larger CO_2-related gains for wheat at high latitudes[15] and estimating that once-in-a-century extremes could expose a further 11–36% of the world's population to hunger by mid-century[16]. Nevertheless, these projects concentrate mainly on global or continental scales, with limited attention to the pronounced regional heterogeneity within Sub-Saharan Africa (SSA). Their process-based crop models also idealise land-use dynamics and water-management constraints, factors that heavily condition real-world production in resource-limited environments.

Machine learning techniques are extensively employed in scientific studies to forecast forthcoming food production. Guilpart et al.[17] used machine learning techniques combined with climate data to study the self-sufficiency rate of soybeans in Europe and effectively predicted future yield changes. Ahvo et al.[18] used the random forest algorithm to simulate the impact of agricultural inputs, revealing its significant impact on crop yields in major production regions around the world. Van Klompenburg et al.[19] applied artificial neural networks to successfully predict wheat yields in Argentina, which further demonstrated the effectiveness of machine learning techniques. Srivastava et al.[20] investigated the yield prediction of winter wheat via convolutional neural networks (CNNs) in combination with weather, soil, and crop phenology data, effectively improving the prediction accuracy and demonstrating the potential of deep learning in agricultural prediction. Lobell et al.[21] developed a scalable crop yield mapper via satellite data and machine learning algorithms, demonstrating its application in large-scale crop monitoring. Crane-Droesch[22] used a yield modelling strategy that involved a semi-parametric deep neural network to anticipate the substantial negative effects of climate change on maize yields. Han et al.[23] utilized the Weather Research and Forecasting (WRF) model with Chemistry (WRF-Chem) and the extreme gradient boosting (XGBoost) machine learning algorithm to create a precise dataset of near-surface O_3 concentrations for the entire Beijing-Tianjin-Hebei region from 2014 to 2019. Paudel et al.[24] integrated crop modelling principles with machine learning to examine the efficacy of this approach in forecasting crop yields at the regional level for three nations and five specific crops. This study aims to investigate the benefits of using machine learning techniques in the prediction of crop yield on a wide scale. Prodhan et al.[25] introduced a nonlinear ensemble machine learning technique to forecast upcoming droughts and their influence on simulated agricultural yields in South Asia. Furthermore, many existing research has paid insufficient attention to variables such as land use and irrigation practices when applying machine learning models, even though these factors are crucial for accurately predicting crop yields in resource-constrained environments.

Despite advancements in various methods, research on the impact of climate change on food security still faces several challenges, primarily manifested in the following aspects: (1) Previous research has focused primarily on investigating the effects of climate change on a single crop, with few studies exploring the impact of climate change on the yields of various crops; (2) the majority of studies have examined only the influence of climate-related factors, such as temperature and precipitation on food production, neglecting important other factors, such as land use and irrigation practices; (3) existing studies have focused mostly on a broad-scale analysis, failing to utilize detailed grid-scale analysis, particularly in the African region, which is a key area of concern for food insecurity; and (4) existing research on future forecasting lacks a thorough assessment of prospective changes in future crop yield due to a lack of integrated application of numerous models and scenarios.

In light of the shortcomings above and the necessity of existing studies, our study uses machine learning techniques to forecast trends in yield changes for four primary crops—maize, rice, wheat, and soybeans—in Sub-Saharan Africa. The evaluation relies on historical and projected simulated data for climate, land use, and irrigation. It utilizes three future climate scenarios (SSP2-4.5, SSP3-7.0, SSP5-8.5) and five climate models (BCC-CSM2-MR, CanESM5, IPSL-CM6A-LR, GFDL-ESM4 and MPI-ESM1-2-LR) at a grid scale of 0.5°. In addition, it examines the spatial and temporal evolutionary patterns of past and future crop yields, offering scientific support for the development of efficient agricultural policies and strategies to ensure food security.

Data and methods

Our study focuses exclusively on sub-Saharan Africa as the research region, primarily because it has unique characteristics, such as a wide range of climates, vulnerability to environmental changes, and heavy reliance on agriculture. These variables exacerbate the food security difficulties arising from global climate change in this region. Figure 1 illustrates the past trends of climate change (a–c) and the average crop yield distribution (d–g) in the area under investigation.

Our research process included the following steps. First, climate data, land type data, irrigation ratio data, and crop yield data were collected and processed. Next, we extracted feature variables and constructed the model input dataset, followed by data preprocessing. A random forest model was employed for training, validation, and performance evaluation. We combined historical data with three shared socioeconomic pathway (SSP) scenarios, specifically SSP2-4.5, SSP3-7.0, and SSP5-8.5, from five global climate models (GCMs): BCC-CSM2-MR, CanESM5, IPSL-CM6A-LR, GFDL-ESM4 and MPI-ESM1-2-LR to predict future yield change trends and analyse the characteristics of both historical and projected yield changes. The detailed workflow is illustrated in Fig. 2.

Research data

The primary data utilized in this study are climate variables, land-use categories, irrigation ratios, and crop yields. Monthly climatic variables were derived to precisely capture the fluctuations in climate throughout the year. Additional variables were obtained on an annual basis to accurately represent long-term environmental patterns or agricultural methods over a prolonged duration. The historical data cover the time frame from 1981 to 2015, whereas the future data include the years 2030–2039, 2050–2059, and 2080–2089. All the datasets have a spatial resolution of 0.5°.

Crop yield data

Our study focused on investigating food security by analysing the yield of different crops as the target variable. The crop yield data were sourced from the global historical crop yield dataset of Scientific Data, which is freely accessible on the PANGAEA website (https://doi.org/10.1594/PANGAEA.909132). The dataset estimates annual yield statistics for maize, rice, wheat, and soybeans based on satellite-derived crop-specific vegetation indices and country yield statistics reported by the FAO, with a spatial resolution of 0.5°. Given the wide range of climates in Sub-Saharan Africa and its importance for food security, crop yield data not only demonstrate the direct influence of climate change on agriculture but also offer vital information for ensuring a stable food supply. This is crucial for assessing the effects of climate change and developing strategies for adaptation.

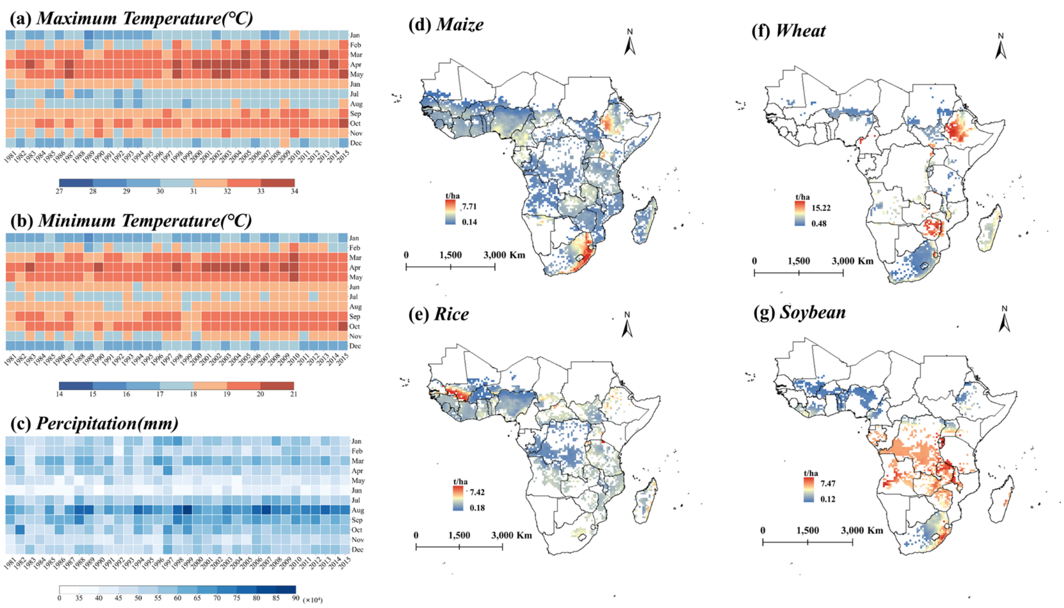

Fig. 1. Historical climate trends and mean crop yields in Sub-Saharan Africa (1981–2015). (**a**) Monthly average maximum temperature (°C); (**b**) monthly average minimum temperature (°C); (**c**) total monthly precipitation (mm); (**d**–**g**) spatial maps of mean yield (t ha^{-1}) for maize, rice, wheat, and soybean.

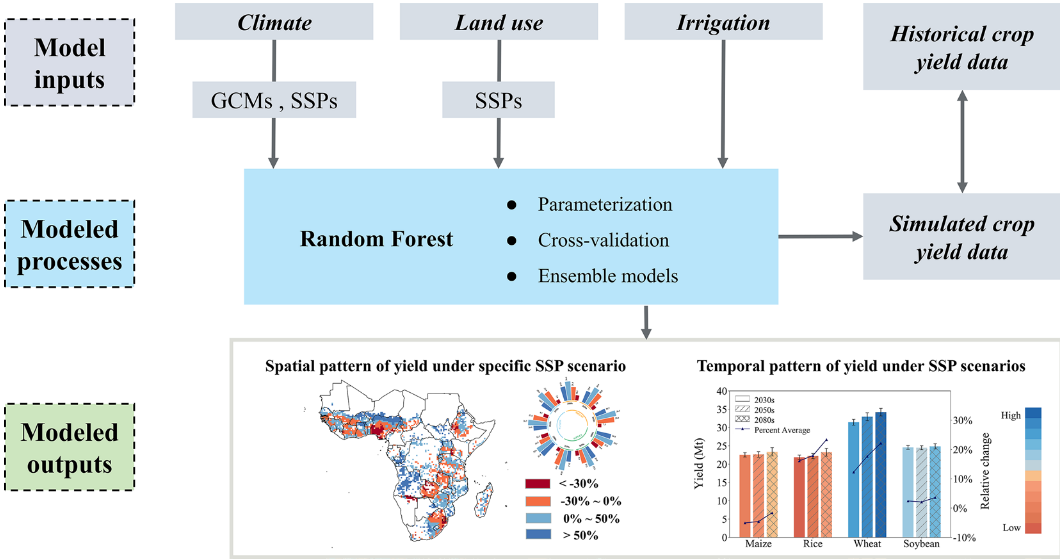

Fig. 2. Technical overview of the analysis process.

Climate data

The climate indicators we selected were total precipitation, monthly average maximum temperature, and monthly average minimum temperature. These climate variables have a direct effect on the growth cycle and production of crops[26]. The crop planting calendar in Sub-Saharan Africa is highly influenced by various environments, which range from arid to humid. As a result, there is substantial variation in the calendar across different locations, making it challenging to select specific months' data as being representative[27]. Hence, opting for data encompassing all 12 months of the year can offer a more thorough depiction of the total influence of climate on crops, thereby furnishing a more precise foundation for later investigations. To assess whether using all twelve months of climate data might dilute the signal, we assembled country-level planting calendars for maize, rice, wheat, and soybean across Sub-Saharan Africa using the USDA's global crop calendar. For each grid cell, we calculated both the growing-season mean (i.e., over locally defined planting–harvest months) and the 12-month annual mean of temperature and precipitation. We observed very high spatial agreement between seasonal and annual means, with Pearson's correlation coefficients exceeding 0.85 for both temperature and precipitation across all four crops (Supplementary Table S1). We then trained two sets of Random Forest models per crop—one using only growing-season climate averages and one using the full 12-month climate series. The models based on growing-season inputs yielded slightly lower cross-validated R^2 values compared to the full-year models (Supplementary Table S2). Given the strong concordance between seasonal and annual climate statistics and the modestly superior performance of full-year models, we conclude that including all twelve months does not introduce harmful noise but rather captures subtle inter-seasonal effects that improve predictive skill. Accordingly, we retained 12-month climate variables in our final analyses.

Historical climate data were obtained from the CRU website (https://crudata.uea.ac.uk), which includes monthly total precipitation, monthly average maximum temperature, and monthly average minimum temperature data, with a spatial resolution of 0.5°. Future climate model data were obtained from NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6), which are available through the AWS Open Data Registry (https://registry.opendata.aws/nex-gddp-cmip6/). We selected future temperature and precipitation data from five GCMs—BCC-CSM2-MR, IPSL-CM6A-LR, CanESM5, GFDL-ESM4 and MPI-ESM1-2-LR—under three SSPs—SSP2-4.5, SSP3-7.0, and SSP5-8.5—with a spatial resolution of 25 km. SSPs are a collection of standardized routes employed in climate change studies to forecast future greenhouse gas emissions and socioeconomic growth patterns[28]. SSP2-4.5 describes a moderately developed "middle of the road" scenario, indicating a mild global warming trend[29]; SSP3-7.0 represents a more challenging development trajectory with high economic growth and low environmental sustainability[30]; and SSP5-8.5 forecasts extreme global warming by the end of the century, which could lead to severe ecosystem damage and widespread socioeconomic impacts[31].

GCMs are sophisticated computer simulation systems utilized for the purpose of modelling and forecasting the complex dynamics of the Earth's climate system, encompassing the atmosphere, ocean, land, and cryosphere[32]. The BCC-CSM2-MR model is known for its accurate simulation of global mean temperature and precipitation patterns[33,34]. IPSL-CM6A-LR emphasizes the simulation of marine biogeochemical cycles and their impact on the climate system[35]. CanESM5 is suitable for simulating global climate warming trends[36].GFDL-ESM4 is recognized for its skill in capturing tropical precipitation variability and extreme weather events, offering robust projections of rainfall patterns that are critical for assessing climate impacts on African crop yields[37]. MPI-ESM1-2-LR features an advanced land surface component with dynamic vegetation schemes, improving the representation of land–atmosphere feedbacks and seasonal rainfall over Sub-Saharan Africa, which is essential for evaluating future changes in food production[38]. Aggregating forecasts from multiple GCMs can reduce the uncertainties associated with relying on a single model[16], allowing for a more precise evaluation of climatic hazards for future food security in Sub-Saharan Africa.

To unify the treatment, we aggregated the daily climate data monthly and resampled them via bilinear interpolation to standardize the resolution of all the variables to 0.5°.

Land use data

The historical and future cropland type data we selected were sourced from the Land-Use Harmonization V2 (LUH2) dataset published by Geoscientific Model Development, with a spatial resolution of 0.25°. The farmland types selected to align with the features of the chosen crops are C3 annual plants, C3 nitrogen-fixing plants, and C4 annual plants. We resampled the geographical resolution to 0.5°.

Proportion of irrigation data

The irrigation ratio data were obtained from the official website of the Spatial Production Allocation Model (https://mapspam.info). The irrigation ratio is the ratio of the irrigated area to the harvested area. We selected historical irrigation and harvest data from the SPAM 2010 V2.0 dataset to represent the irrigation ratio for the entire historical period (1981 ~ 2015). For the future periods (2030s, 2050s, 2080s), we used the SPAM 2017 V2.1 dataset. Although the base year of this dataset is 2017, it incorporates model-based projections of agricultural production patterns, which can be used to simulate future scenarios. The original spatial resolution of the SPAM data is 10 km, and it was resampled to 0.5° to ensure consistency with other datasets. In this study, harvested area and irrigation ratio from SPAM are treated as fixed baselines for all forecast years; any changes in cropping extent or irrigation practices over time are not reflected in our projections.

Research methodology

We employed a random forest model to investigate the influence of climate change on food yields in Sub-Saharan Africa. The random forest algorithm was selected for its ability to handle high-dimensional data effectively[39], including large datasets containing diverse climate, land, and irrigation factors. The model's ability to mitigate overfitting by creating numerous decision trees and averaging their predictions reduces the variance of the model and hence minimizes the danger of overfitting[40,41], which makes it an ideal predictive model for this research.

Each parameter is set during the model training process to enhance model performance, improve generalizability, and optimize computational efficiency. We began by splitting each crop dataset into an 80% training pool and a 20% hold-out set. Within the training pool, we performed an exhaustive grid search with five-fold cross-validation—over the number of trees (300, 400, 500, 600), the number of features considered at each split ("sqrt," "log2," or "None"), the maximum tree depth (None, 10, or 20), the minimum samples per leaf (1, 2, or 3), and the minimum samples required to split a node (2, 5, or 10). Out-of-bag scoring was enabled as an independent check on model performance. After selecting the best combination of hyper-parameters for each crop (via highest CV R^2), we retrained the final Random Forest models on the full training pool. The optimal hyper-parameter settings for each crop are provided in Supplementary Table S3**.** To ensure the robustness of the results, we trained the model 20 times via different random seeds, with values ranging from 1 to 20. We also adopted a ten-fold cross-validation method to further enhance the rigor of the model evaluation. Moreover, to eliminate performance inflation arising from year-to-year autocorrelation, we complemented the conventional 80/20 random split with two explicitly time-aware validation schemes. First, we applied a five-fold GroupKFold in which all observations from the same calendar year were forced into the same fold; the model was trained on four year-blocks and evaluated on the remaining block, cycling until every block had served once as the test set. This blocked arrangement ensures that weather anomalies, management shocks, and reporting biases specific to a given year never leak simultaneously into training and evaluation. Second, we executed a leave-one-year-out (LYO) protocol that sequentially removes one entire year of data, fits the model to the remaining years, and predicts the held-out year—thereby providing the strictest possible temporal hold-out. For every fold of both schemes, we recorded the coefficient of determination (R^2) and the root-mean-square error (*RMSE*); fold-wise scores were then averaged across folds (GroupKFold) or across years (LYO).

In the prediction phase, all 20 random forest models independently predict yields from multiband images, with the average of these predictions serving as the final yield prediction for that year. We finally obtained yield images of the four crops under the future scenarios, which facilitated the subsequent study of the spatial and temporal evolution characteristics of the future yields of each crop. Supplementary Fig. S1 displays the individual impact of each feature variable on the yields of the four crops.

Results

Model accuracy verification

In terms of performance evaluation, we used the coefficient of determination (R^2) and root mean square error (*RMSE*) as the leading indicators to assess the accuracy and fitting effect of the predictions comprehensively. R^2 represents the amount of variation in the predicted outcomes compared with the overall variation, demonstrating how well a model fits the data and its capacity to account for the variability of the dependent variable. The *RMSE* reflects the average magnitude of the error between the predicted and actual values and serves as an intuitive measure of prediction accuracy[42]. These two metrics evaluate the performance of a model from distinct angles. R^2 measures a model's ability to explain the data, whereas *RMSE* measures its accuracy in predicting crop yield variability and average error magnitude[43,44].

Figure 3 displays the random forest model accuracy in forecasting the yields of four different crops. The scatter density map depicts the associations between the 20 average predictions of the model and the observed values for corn, rice, wheat, and soybean. Supplementary Table S2 displays the evaluation metrics for the four crop models.

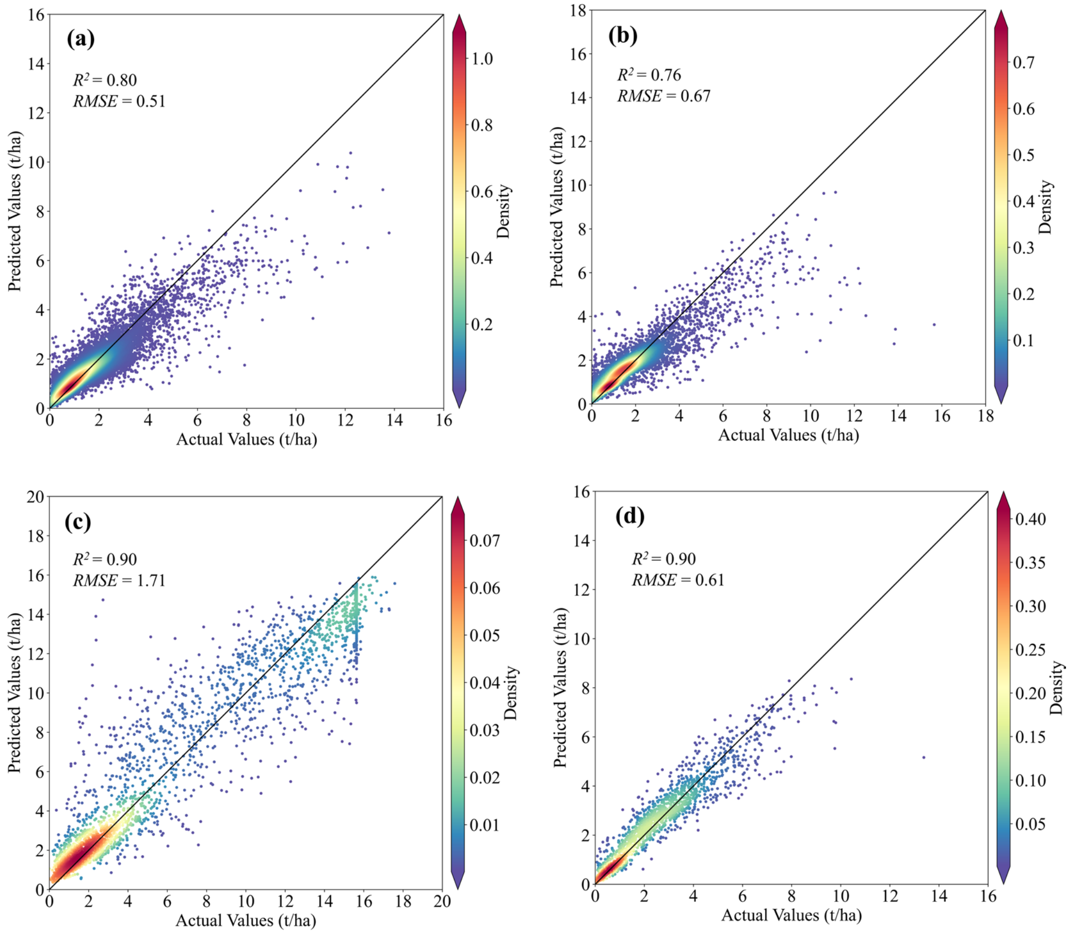

Fig. 3. Evaluation of random forest model accuracy for four crops: (**a**–**d**) correspond to maize, rice, wheat, and soybeans, respectively.

Crop	BlockCV R^2	BlockCV *RMSE*	LYO R^2	LYO *RMSE*
Maize	0.63	0.68	0.56	0.70
Rice	0.64	0.79	0.50	0.88
Wheat	0.80	2.43	0.66	2.67
Soybean	0.82	0.81	0.72	0.89

Table 1. Mean R^2 and RMSE under temporal cross-validation schemes.

The 80/20 random hold-out test shows that all four crops reach relatively high R^2 values, with at least 76% of the variance explained ($R^2 \geq 0.76$), accurately capturing the main trends in the data. Except for wheat, each crop also records an *RMSE* below 1 t ha⁻1, indicating that the random-forest framework has solid point-prediction accuracy. To determine whether these results are inflated by the randomness of the split, we applied two time-aware cross-validation schemes: a five-fold GroupKFold that groups entire calendar years and a stricter leave-one-year-out (LYO) procedure. The mean R^2 and *RMSE* for both schemes appear in Table 1. GroupKFold yields an overall R^2 of about 0.72; LYO lowers it to roughly 0.61, and *RMSE* rises only slightly, showing that the model still extrapolates reliably to truly unseen years.

Across the four crops, wheat and soybean post the highest R^2 values under both the random split and the two time-blocked validations. Wheat nevertheless shows a larger *RMSE*, because many observations cluster near 16 t ha⁻1, so errors in high-yield cells are magnified (frequency histograms and probability-density plots can be found in Supplementary Fig. S2). In comparison, maize and rice present slightly lower R^2 values. This behaviour likely stems from training-sample size[45]: maize and rice dominate cultivation in Sub-Saharan Africa, giving them sample sizes roughly ten times larger than those for wheat and soybean. Their data also contain more pronounced nonlinear relationships and interactions, for example the inverse-U relationship between yield and temperature, where yields peak at moderate temperatures but decline when temperatures are too low or too high. Such nonlinearities and interactions make it harder for the model to learn the underlying patterns[46].

Future yields of the four major crops

We simulated the total production of maize, rice, soybeans, and wheat in Sub-Saharan Africa from 1981 to 2015. The results reveal an average total production rate of 23.7 million tons (Mt) for maize, 18.8 Mt for rice, 28.0 Mt for wheat, and 24.0 Mt for soybean. Supplementary Fig. S2 and Fig. S3 show the frequency distributions of historical yields and the ratios of simulated to actual yields for the four crops. The average of each model's future yield predictions was calculated as the predicted yield for each scenario to assess the uncertainty of predictions and variability between models. Additionally, the standard deviation of the average yield predictions from the five climate models was calculated and represented with error bars in the yield prediction charts. Projected future yields and relative changes for each crop under the three SSP scenarios are summarised in Fig. 4. Ultimately, this study obtained the average predicted yields for different crops in Sub-Saharan Africa for the 2030s, 2050s, and 2080s under three different socioeconomic development pathways: SSP2-4.5, SSP3-7.0, and SSP5-8.5.

As a C4 crop, maize generally shows an overall declining yield trend over time, which becomes more pronounced with the progression of SSP scenarios. Under the SSP5-8.5 scenario, the predicted maize yield in the 2080s exhibits a sharp decline, with yield 5.2% below the historical baseline. In contrast, as C3 crops, rice and wheat, exhibit a different yield change trends under the future scenarios. The yields gradually increase over time in each scenario, transitioning from a decrease to an increase compared with the historical average yields. The yield increases more significantly with the progression of the SSP scenarios, with the rice yield under the SSP5-8.5 scenario in the 2080s increasing by 44.12%. Unlike the other three crops, soybeans, known as C3 nitrogen-fixing crops, exhibit slight fluctuations in future yield changes under each SSP scenario, but the overall yield remains stable at around 24 Mt, averaging a 2.7% increase over the historical baseline.

In the SSP2-4.5 scenario, the prediction shows a slight increase in maize yield over time, with an increase of nearly 1 Mt from the 2030s to the 2080s; however, overall, there is a decline relative to the historical baseline yield data. In all SSPs, the predicted rice yield in the 2080s is higher than the historical average yield. Under the SSP2-4.5 scenario, the predicted rice yield increases from 21.9 Mt to 23.3 Mt, showing a slight upward trend from a decline to an increase. Compared with that of rice, the yield of wheat tends to increase, albeit with a less pronounced increase. However, wheat consistently maintains a relatively high total yield, making it the crop with the highest yield among the four crops studied. In contrast, the projected soybean yield exhibited a modest increase over time, increasing from 24.5 Mt to 24.9 Mt, reflecting a change of approximately 1.6%.

In the SSP3-7.0 scenario, the predicted maize yield will experience a loss of less than 3% compared with the baseline yield data, which is slightly lower than the yield under the SSP2-4.5 scenario, with a total yield of approximately 23 Mt. The upward trend in rice yield is more significant, changing from a decrease to an increase compared with the baseline yield, with the average yield reaching 27.2 Mt by the 2080s. The wheat output exhibits a comparable pattern to that of rice, with a consistent increase over time. By the 2080s, the overall yield

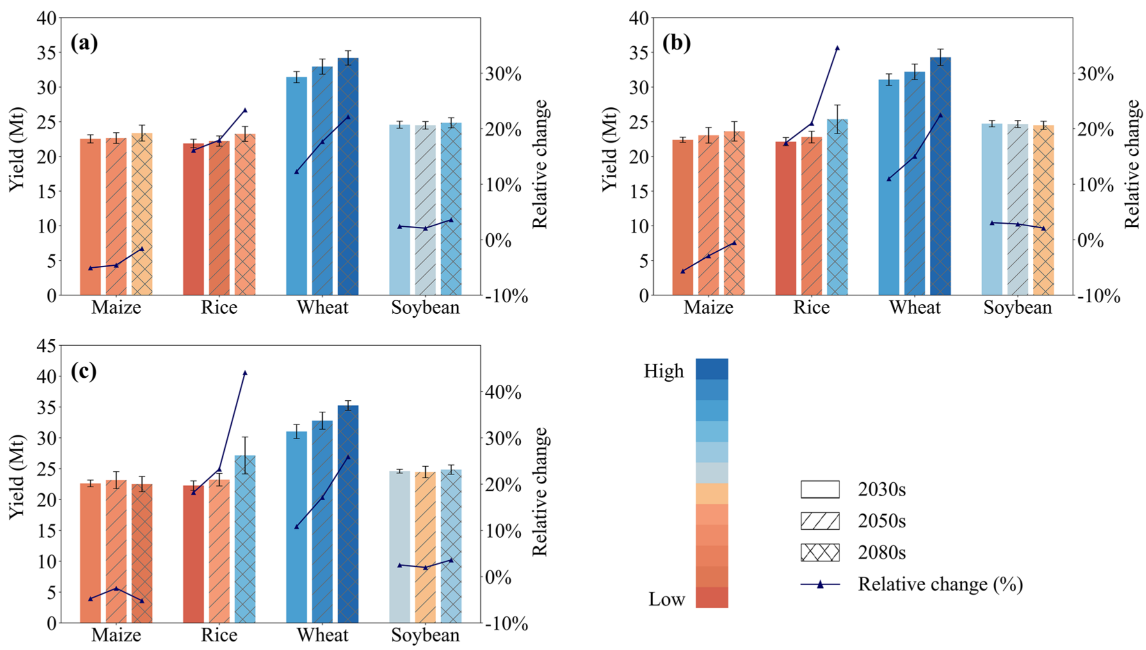

Fig. 4. Projected future yields and relative changes for each crop under three SSP scenarios. Bars show mean yield (left axis, Mt) and line markers show percent change from the 1981–2015 baseline (right axis, %). Error bars on each bar denote the standard deviation among the five GCM projections. RF model uncertainty is shown separately as spatial error maps in Supplementary Figs. S4 ~ S38. Panels: (**a**) SSP2-4.5; (**b**) SSP3-7.0; (**c**) SSP5-8.5. Decadal yield statistics for each crop and scenario, as well as national production estimates, are provided in Supplementary Tables S4 and S5, and annual yield predictions are shown in Supplementary Figs. S42 ~ S45.

surpasses 34 Mt, reaching its peak value. In this scenario, soybean productivity deviates from SSP2-4.5, resulting in a marginal decrease in output from 24.7 Mt to 24.5 Mt, representing a percentage shift of approximately 1%.

In the SSP5-8.5 scenario, the maize yield prediction exhibits a sharp drop in the 2080s, with the yield change dropping below −5.2% and the lowest total yield being 22.5 Mt. The rice yield increases most significantly, with the predicted yield reaching 27.2 Mt in the 2080s, an increase of 44.12% over the historical average yield, which is the most significant percentage increase among all the scenarios and crops. The growth trend for wheat is also more significant than that in the previous two scenarios, with a growth rate of 7% at each stage. In this scenario, the soybean yield slightly decreases, followed by an increase, with the predicted yield for the 2030s reaching 24.6 Mt, decreasing to 24.5 Mt by the 2050s, and then increasing to 24.9 Mt by the 2080s, with an overall change of approximately 1.1%.

Spatial distribution of future yield changes for four major crops

Owing to the complex geographic and temporal interactions involved in yield changes, single-dimensional time series data cannot fully describe yield changes. Therefore, to simulate the overall trends in crop yields in Sub-Saharan Africa, this study used ArcGIS software to comprehensively consider temporal and spatial dimensions, generating spatial distribution maps of future crop yields. To quantify total uncertainty, we combined Random-Forest variability and GCM spread into a single metric: for each crop–scenario–decade, we produced 100 ten-year mean yield rasters (5 GCMs × 20 RF seeds) and computed the per-pixel standard deviation across this stack. Figure 5 presents the 1981 ~ 2015 average total-uncertainty map for maize; corresponding maps for the other crops are provided in Supplementary Figs. S39 ~ S41, offering a spatial overview of predictive confidence. The

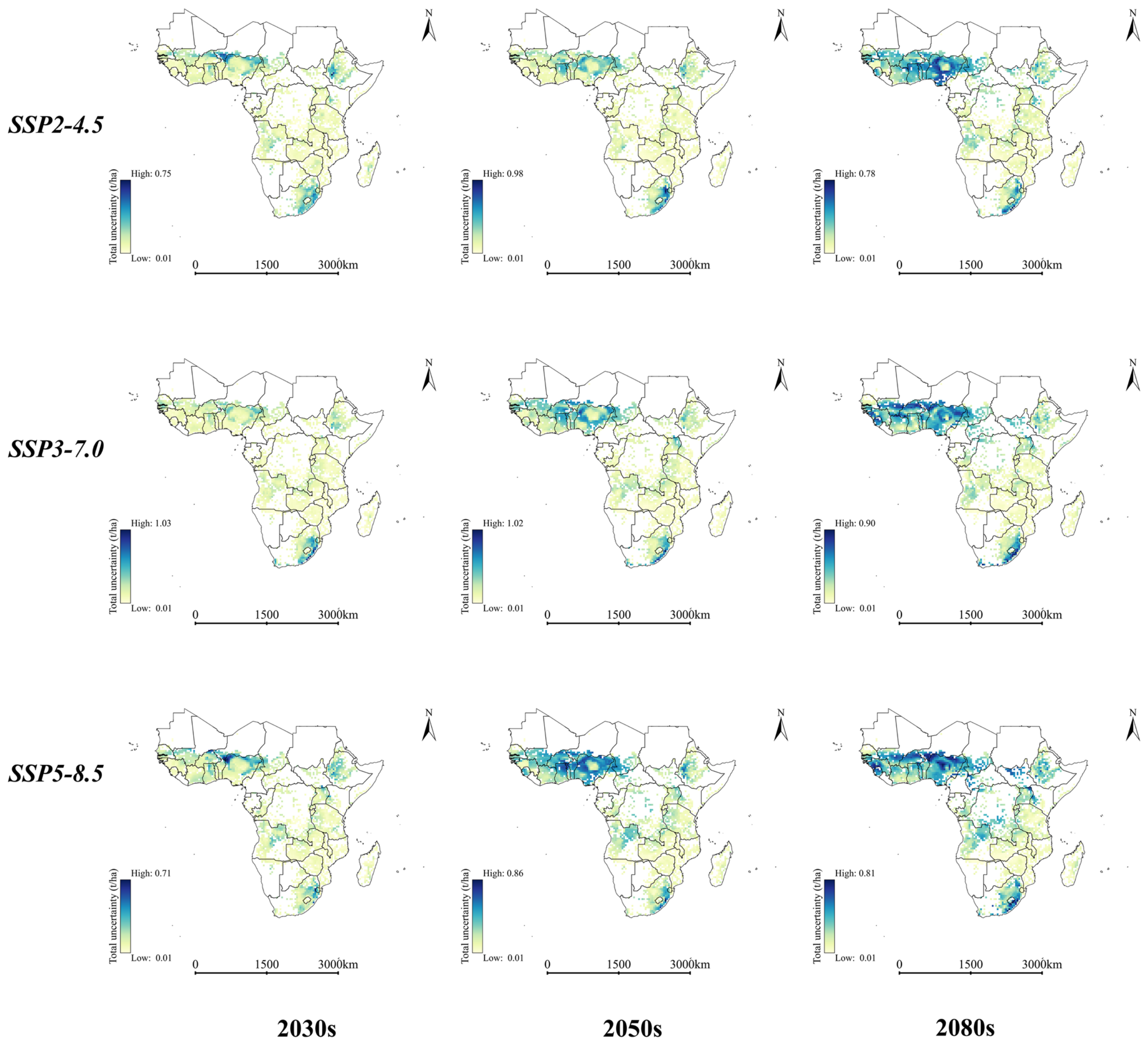

Fig. 5. Spatial distribution of average total uncertainty for maize yield.

results show that uncertainty is generally lower in the core production zones, indicating that our yield projections remain robust even when uncertainties from both statistical and climate models are considered jointly.

The distribution maps of yield changes predicted by each model for different time periods are shown in Supplementary Figs. S46 ~ S49. Through geographic information systems, we reveal the geographical characteristics of future crop yield distributions and the changing trends under different SSPs. These predictive results indicate that under different climate scenarios, Sub-Saharan Africa's crop yields face both the potential for yield increases and the risk of yield reductions over the coming decades.

The maize yield distribution map (Fig. 6) shows that the yield changes in specific regions exhibit significant spatial dependency. Most regions show a decreasing trend in yield, with areas of reduced yield stretching from eastern Africa through Ethiopia, Uganda, Tanzania, and Zambia to South Africa, with the most profound decreases occurring in Zambia and South Africa. Additionally, as the SSP scenarios progress, the area of reduced yield expands. For example, under the SSP5-8.5 scenario in the 2080s, almost all the eastern regions of Zambia and South Africa will exhibit a decreasing trend in maize yield. In contrast, the maize yields in Nigeria and Angola show an increasing trend, which, over time, also extends to Benin, Togo, and Ghana.

According to the rice yield distribution map (Fig. 7), most countries show an increasing trend in rice production; these regions are primarily concentrated in West African, such as Nigeria, Benin, and Burkina Faso. Rice production is also continuously increasing in the western region of the Democratic Republic of the Congo. As the SSP scenario progresses, the increasing trend in rice production becomes more significant, and the area of increased rice production expands over time. The expansion trend from Nigeria to the west, reaching Guinea, is the most evident. By the 2080s, under SSP5-8.5, in addition to a slight reduction in southern Mali, the rice yields in these countries will mostly exceed 150% of the historical average yield. However, in Mali, Angola, Zambia, and Tanzania, the rice distribution is relatively scattered, showing a decreasing trend in production.

In Mali specifically, projected declines in rain fed rice yield stem from a combination of climatic and agronomic factors[47]. Reduced and more erratic precipitation, which is characterized by delayed onset and early ending of the rainy season, leads to insufficient water during critical growth stages[48]. At the same time, rising daytime and nighttime temperatures increase spikelet sterility and accelerate crop maturation, which shortens the growing season and increases drought stress[49,50]. Rice is the staple crop for Malian smallholders; declines in rice yield may reduce food supply and thus affect total food availability[51]. Together, these conditions, including decreased rainfall, increased heat stress, and declining soil moisture retention, drive the downward rice yield trend observed in Mali.

The future yield distribution map of wheat shows that the planting area of wheat in Sub-Saharan Africa is minimal (Fig. 8). However, most of the planting areas show an increasing yield trend, which is mainly concentrated in South Africa and some regions in northern Nigeria. The yield trends of rice under various scenarios are also roughly the same over time, generally showing a significant increase. Notably, in the 2080s, the increased yield areas of rice in South Africa expanded further, with yields exceeding the historical average

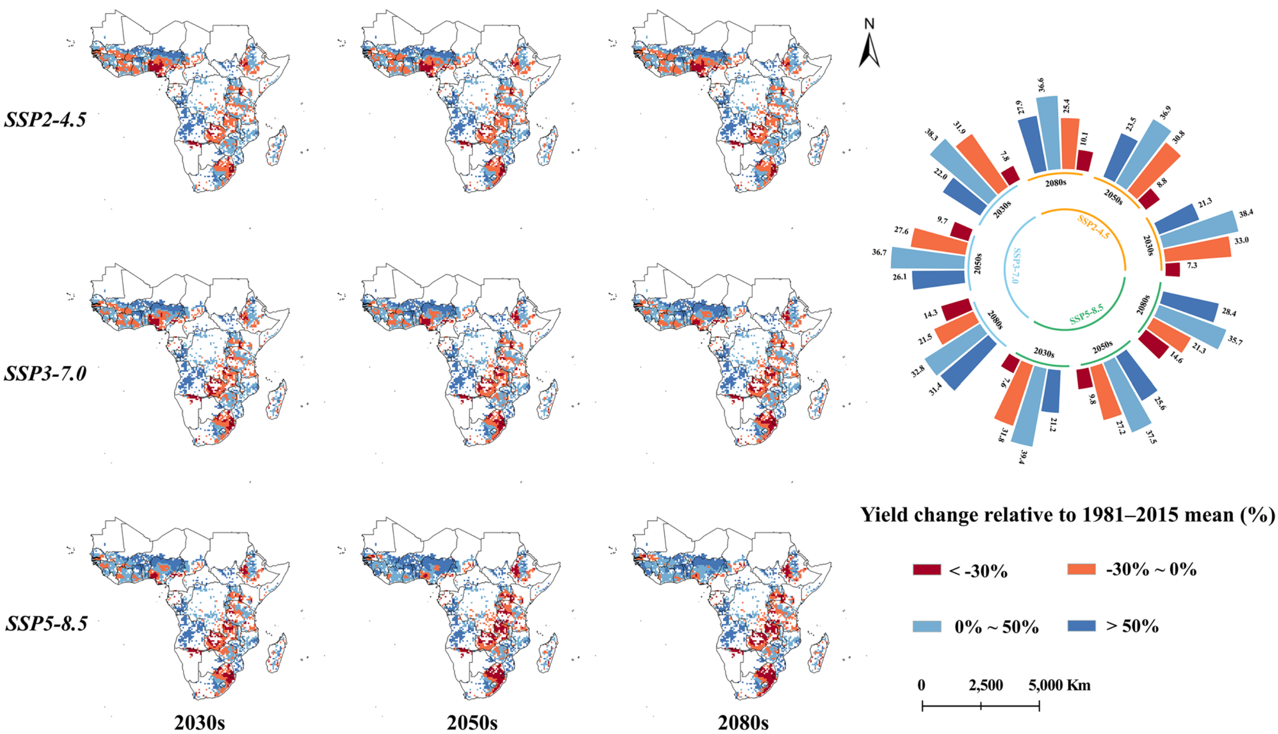

Fig. 6. Spatial distribution of future maize yield change (%) relative to the historical baseline under SSP2-4.5, SSP3-7.0, and SSP5-8.5 in the 2030s, 2050s, and 2080s (left); radial bar chart showing the corresponding sub-Saharan Africa-wide changes (right).

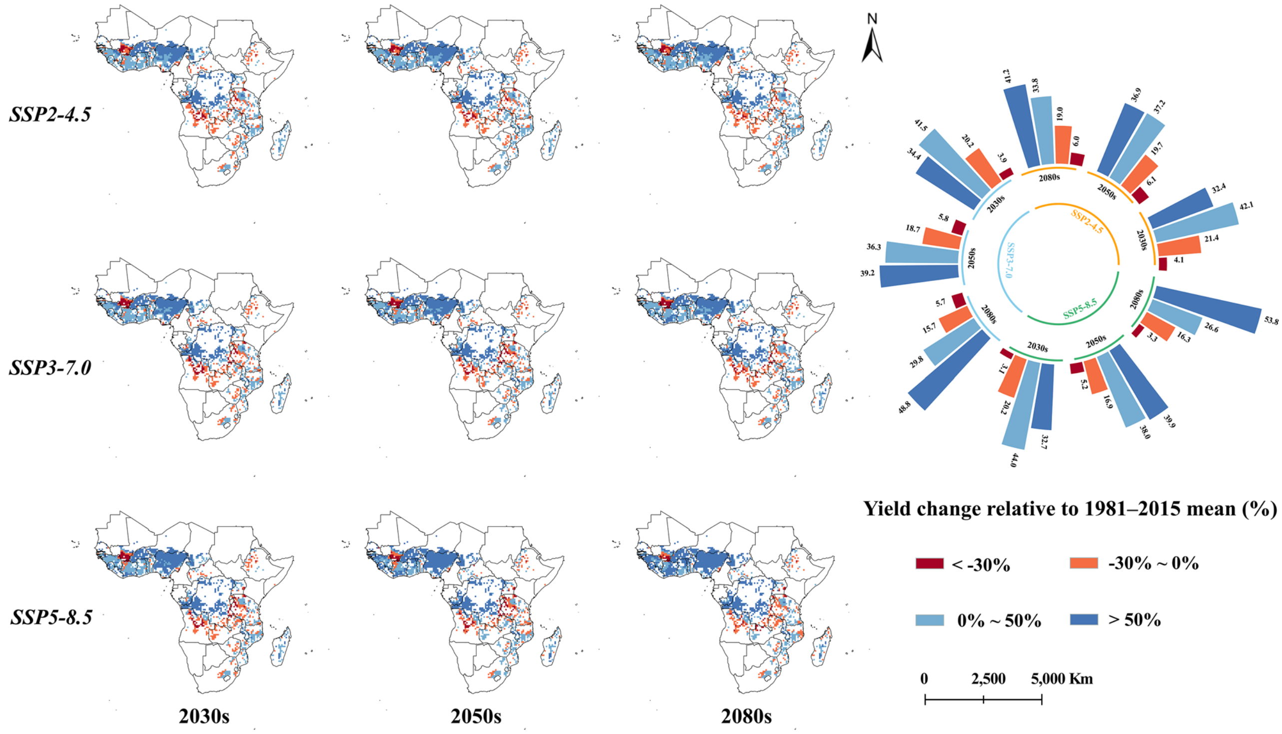

Fig. 7. Spatial distribution of future rice yield change (%) relative to the historical baseline under SSP2-4.5, SSP3-7.0, and SSP5-8.5 in the 2030s, 2050s, and 2080s (left); radial bar chart showing the corresponding sub-Saharan Africa-wide changes (right).

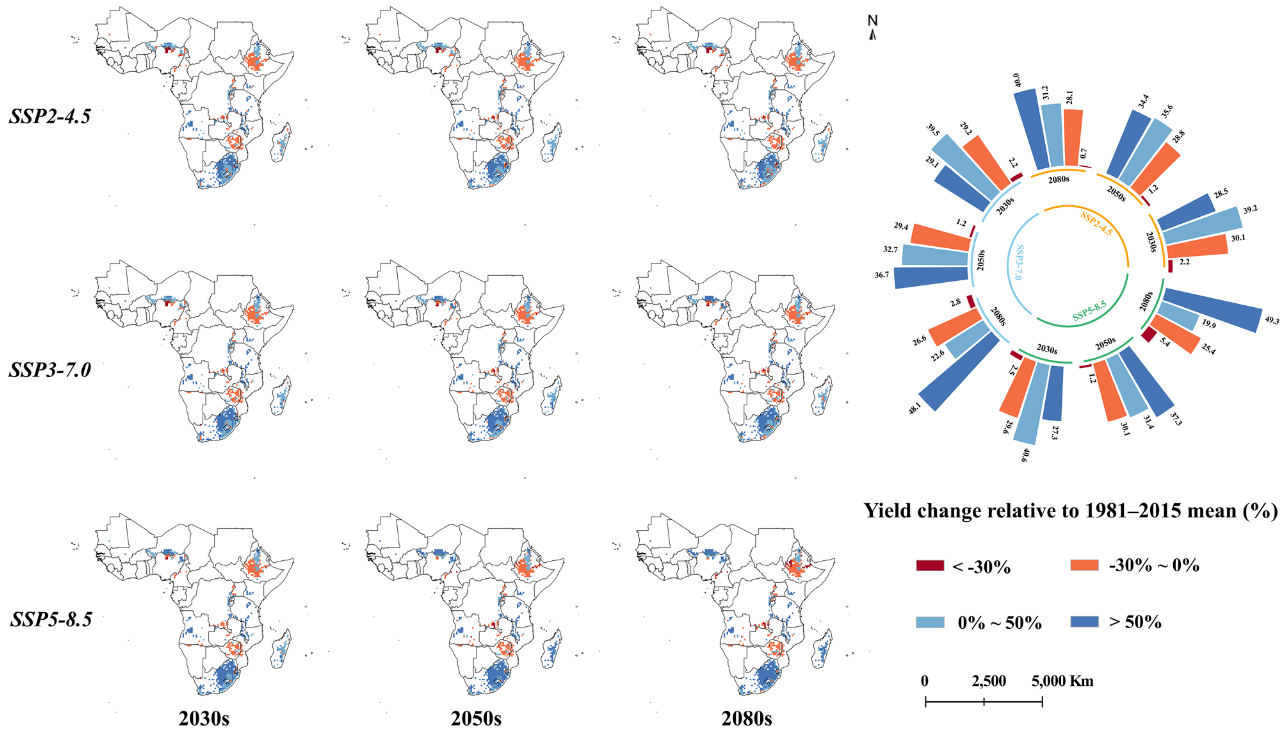

Fig. 8. Spatial distribution of future wheat yield change (%) relative to the historical baseline under SSP2-4.5, SSP3-7.0, and SSP5-8.5 in the 2030s, 2050s, and 2080s (left); radial bar chart showing the corresponding sub-Saharan Africa-wide changes (right).

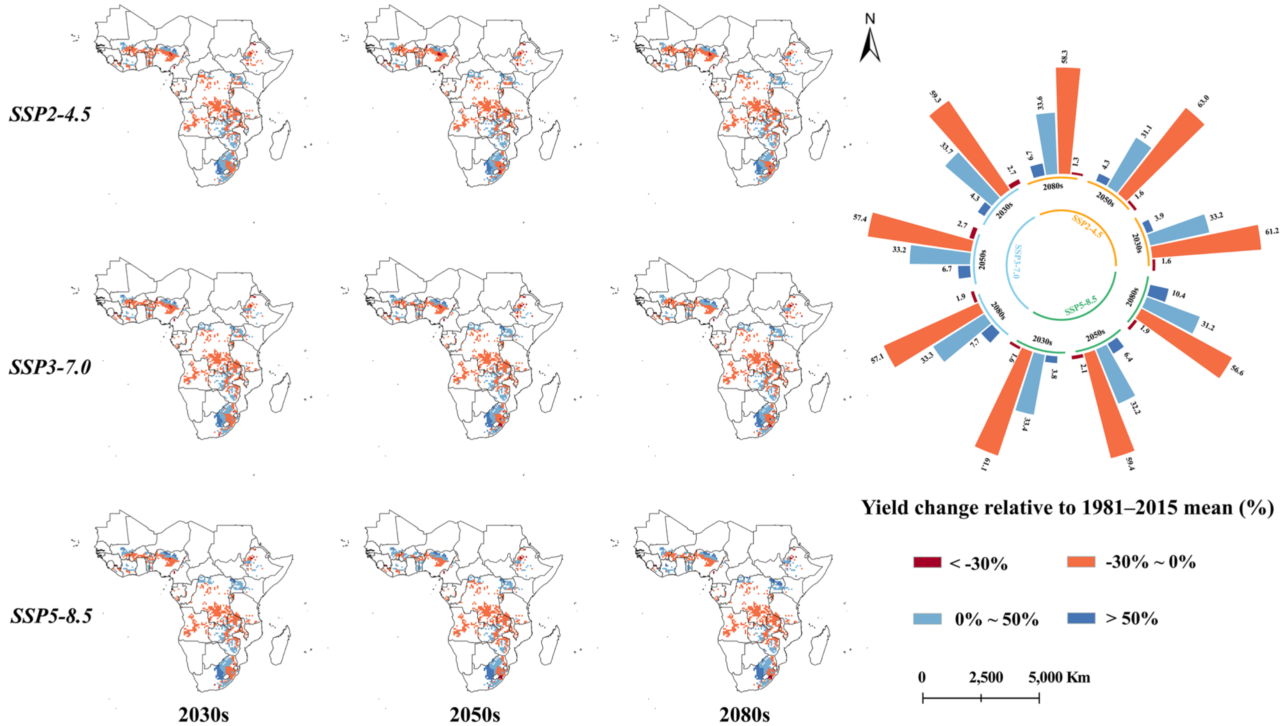

Fig. 9. Spatial distribution of future soybean yield change (%) relative to the historical baseline under SSP2-4.5, SSP3-7.0, and SSP5-8.5 in the 2030s, 2050s, and 2080s (left); radial bar chart showing the corresponding sub-Saharan Africa-wide changes (right).

by more than 50%. However, Ethiopia and Zimbabwe show a decline in yields under all the scenarios, and as the SSP scenario progresses, the areas with declining yields gradually expand.

Soybean high-yield zones are geographically patchy. Eastern South Africa, northern Nigeria, Uganda, and the Democratic Republic of the Congo are the main areas of increased production. In contrast, the areas of decreased production are concentrated in Zambia, Angola, central Nigeria, and the eastern coastal regions of South Africa. As the SSP scenario progresses, the soybean production distribution will remain essentially unchanged (Fig. 9). Over time, the areas of increased production in South Africa will slightly expand, while the areas of decreased production in Angola will also slightly increase. In Nigeria, areas of reduced production gradually decrease. Notably, under the SSP5-8.5 scenario, the areas with reduced soybean production in South Africa will slightly decrease over time.

Discussion

We examined future yield changes of maize, rice, wheat, and soybeans under multiple SSP–GCM combinations, using a Random Forest model trained on gridded climate, land use, and irrigation data. Projections reveal marked spatial heterogeneity in staple-crop yields across Sub-Saharan Africa: some areas may see increases exceeding 50% relative to the 1981 ~ 2015 baseline, while others could experience declines of over 10%. These divergent patterns highlight the urgency of place-specific adaptation, including climate-resilient cultivars for heat-prone regions and targeted investment in irrigation and water infrastructure in dry-season hotspots.

We predicts that maize yields will decline under future SSP scenarios, especially under the SSP5-8.5 scenario, with the most significant decline occurring by the 2080s. This conclusion is consistent with many existing studies[15,52–54]. Maize, as a C4 crop, can maintain relatively efficient photosynthesis under high temperatures; however, regions with limited water resources, such as Sub-Saharan Africa, will suffer growth restrictions due to extreme heat and drought, which negatively impact maize photosynthesis and growth cycles. For C4 crops, studies have shown that the CO_2 fertilization effect (enhanced photosynthetic efficiency due to higher atmospheric CO_2 concentrations) saturates at around 500 ppm, beyond this concentration further increases yield almost no additional productivity gains[55]. Although our yield projections under SSP2 4.5, SSP3 7.0, and SSP5 8.5 do not explicitly model CO_2 concentration or its saturation behaviour, IPCC RCP trajectories indicate that by the 2080s even RCP4.5 will approach 500 ppm, while RCP7.0 and RCP8.5 will exceed it by a large margin[56]. As a result, our model may overestimate maize yield gains under high-emission scenarios. Additionally, precipitation uncertainty increases as emissions increase under various scenarios[57,58]. Although maize is drought resistant, its photosynthetic rate decreases under extreme temperatures, leading to yield decreases[59].

Future changes in maize yield will exhibit significant spatial heterogeneity. We project a decrease in maize yield in Zambia and South Africa, a trend that intensifies with the progression of SSP scenarios and gradually expands the reduction areas over time. However, we anticipate an increase in maize yield in several regions, such as Nigeria and Angola. This finding is consistent with the findings of Siatwiinda et al.[60], who assessed the impact of climate change on maize yield in Zambia via five global circulation models and the WOFOST crop model and reported a significant decline in maize yield under the RCP4.5 and RCP8.5 scenarios. Another study investigated the spatiotemporal patterns of heatwaves, droughts, and extreme precipitation during the maize growing season in South Africa from 1986/87 to 2015/16 via a stress index and reported that extreme climate events negatively impacted South African maize yield[61]. Additionally, researchers have quantified the unprecedented extreme climate risks affecting South African maize production and studied the role of the El Niño-Southern Oscillation, finding that extreme climate anomalies (heatwaves, droughts, and extreme precipitation) pose a significant threat to maize production[62]. It is worth noting that extreme climate events also significantly affect C3 crops (such as rice and wheat), and this is elaborated in the subsequent sections on rice and wheat.

Projections indicate an increase in maize yield in Nigeria and Angola. However, our modelling framework holds maize cultivar distributions fixed and does not explicitly simulate the adoption or spread of early-maturing and drought-resistant varieties; instead, any gains from such improved cultivars are implicitly represented through our management scenario assumptions[63,64]. Likewise, optimized fertilizer management strategies are reflected only as part of these scenarios. Furthermore, research has shown that in some high-altitude areas, moderate temperature increases may extend the growing season, thereby positively impacting maize yield[65].

Rice, unlike maize, yields tend to increase over time under all SSP scenarios, particularly the SSP5-8.5 scenario. Multiple studies support and verify this conclusion[66–68]. The impacts of climate change under different SSP scenarios and the physiological characteristics of rice as a crop are related to the phenomenon whereby high emissions promote rice yield. Rice is a C3 crop and may exhibit enhanced photosynthetic efficiency at elevated CO_2 concentrations. Our projections for future rice yields are based on SSP2-4.5, SSP3-7.0, and SSP5-8.5 climate scenarios, which include temperature, precipitation, and implicitly the associated CO_2 concentration trajectories. Under these scenarios, the modelled increases in rice yield likely reflect an implicit CO_2 fertilization effect alongside other climatic drivers rather than CO_2 fertilization acting as a sole or isolated cause[67,69,70]. However, even though the overall yield shows an increasing trend, extreme weather events, such as droughts, floods, and heatwaves, may cause significant fluctuations in annual yields. While long-term projections under these combined climate factors indicate rising yields, extreme weather events may still damage crop growth, reducing yield in specific years[71].

We indicate that the main regions exhibiting increased rice yield are in West Africa, such as Nigeria and Benin, and that the yield-increasing areas will significantly expand. On the basis of a process-based crop simulation modelling approach, Yuan et al.[72] evaluated the potential for increasing rice yields on existing farmland in Africa by combining local weather, soil and high-input management datasets. The study revealed that, assuming stable international rice prices and domestic consumption patterns, increasing rice yield could reduce imports and land-use conversion—especially in West African countries such as Nigeria and Benin, where rice production is expected to increase significantly in the future. However, actual import volumes will also depend on global market prices and trade policies[73]. Another study analysed rain-fed rice in Senegal through experimental and simulation methods and reported that under high-emission scenarios (e.g., SSP5-8.5), increased temperatures and elevated carbon dioxide concentrations significantly increased rice yields[68].

African countries have attributed the trend of increased rice production to domestic policy strategies, such as the "Rice Offensive," which was launched in 2015 and aims to achieve self-sufficiency in rice in West Africa by reducing dependence on imports through increased local production[74]. Additionally, international partners, such as China, through the "South-South Cooperation Program," share their successful experiences in food technology innovation and agricultural extension with African countries[75], helping to improve local agricultural productivity.

Like rice, wheat is also a C3 annual plant and is projected to exhibit yield gains under future SSP scenarios, though these gains are expected to be smaller than those for rice[76–78]. This difference arises in part because wheat is more frequently grown in drier environments, which limits the extent of CO_2-induced enhancement. In regions with ample moisture or irrigation, rice typically benefits more from rising CO_2 concentrations[79]. Nonetheless, wheat's overall productivity often remains higher in many areas because it requires less water and is better adapted to drought conditions. Many high-yielding wheat varieties, however, depend on substantial fertilizer inputs and a stable water supply—resources that are often scarce in rain-fed systems[80,81]. Furthermore, wheat's greater genetic diversity may provide resilience against a wider array of climatic stresses[82]. While our projections for rice and wheat yield gains in the 2080s align with previous studies of CO_2 fertilization and growing-season extension[15,83], the impacts of future climate change on crop yields are highly complex. Factors such as temperature-driven shortening of the growing season, elevated respiration rates, and heat-induced physiological disorders may also play important roles in shaping future yield outcomes. Incorporating these physiological and phenological processes into future modelling efforts will help to provide a more comprehensive understanding of temperature effects on C3 crop production.

We found that the wheat planting area in Sub-Saharan Africa is minimal, but in South Africa, the yield has been increasing over time, whereas in Ethiopia and Zimbabwe, the yield has shown a downward trend. Research by Callaway et al.[84] also reached this conclusion. They reported that agricultural management and technological advancements in South Africa, particularly adaptation measures to cope with climate change, such as improved seeds and optimized irrigation systems, have helped increase wheat yields. Other studies have emphasized the trend of increasing wheat yields in South Africa, which is attributed mainly to farmers gradually adopting more efficient agricultural technologies and climate adaptation measures. These measures will help stabilize wheat yields in South Africa and improve overall food security[85]. However, future scenarios predict a decline in wheat yields in Ethiopia and Zimbabwe, primarily due to prolonged droughts, political conflicts, and the impact of pests and diseases[86–88]. We note that our model relies solely on climate, cropland-type, and irrigation variables and does not explicitly incorporate pest and disease dynamics, which may lead to an underestimation of yield losses in regions with high biotic stress risk.

Our research indicates that soybean yield may be relatively high under future scenarios, but it still tends to decline compared with historical yields. This aligns with the conclusions drawn by Khojely et al.[89]. The trend in soybean yield changes is closely related to its unique biological characteristics. As a C3 nitrogen-fixing crop, soybean plants can use symbiotic bacteria in their root nodules to turn nitrogen from the air into nitrogen fertilizer. This makes plants less reliant on chemical nitrogen fertilizers and better able to adapt to changes in the environment[90]. Unlike rice and wheat, soybeans require less nitrogen fertilizer, allowing them to maintain high productivity with lower nitrogen inputs. Additionally, soybean plants are relatively robust in terms of drought tolerance, making them relatively adaptable and stable in yield under changing climate conditions. As C3 nitrogen-fixing plants, soybean can exhibit greater photosynthetic rates under elevated CO_2 levels, yet its productivity remains highly contingent on temperature and moisture regimes. Our soybean yield estimates draw on the same SSP2-4.5, SSP3-7.0, and SSP5-8.5 projections, which encapsulate shifts in temperature, precipitation, and implicitly the trajectory of atmospheric CO_2. Because CO_2 concentrations are not included directly as model inputs, any beneficial effects are captured only via associated climatic covariates. Importantly, soybean is particularly vulnerable to heat stress during flowering and seed-filling stages, as well as to irregular rainfall; under sufficiently high temperatures or drought, yields can decline even when CO_2 levels rise. Future work should explore the explicit inclusion of CO_2 concentrations and finer-scale phenological data to better disentangle fertilization benefits from stress-driven losses[91,92].

The soybean distribution is relatively scattered and mainly concentrated in a few countries, such as South Africa, Nigeria, Zambia, and Zimbabwe. As the SSP scenario progresses, the overall distribution pattern of soybean production does not change much, primarily reflecting a slight increase in high-yield soybean areas in South Africa. This increase is due to South Africa's launch of an import substitution plan to promote the development of the domestic soybean industry and reduce external dependence, as the country is the largest importer of soybean meal in Sub-Saharan Africa[89]. Nigeria's soybeans have also benefited from this commercial expansion. Nigeria, the second-largest soybean producer in Africa, has significantly increased soybean yields by introducing new technologies, such as rhizobium inoculation and phosphate fertilizer application. The widespread application of these technologies is expected to increase Nigeria's future soybean production further, thereby reducing soybean imports[93]. Additionally, soybean production in Benin is also increasing. According to reports from the International Atomic Energy Agency (IAEA,2020), the Alibori region is the leading soybean production area, accounting for 47% of the country's total production. Biofertilizers and isotope technology have significantly improved soybean yields and soil fertility in Benin, making it a viable export commodity for the country[94].

Although we used random forest models and multiple climate scenarios to comprehensively evaluate future crop yields and conducted an in-depth analysis of the impacts of climate change on multiple crops at the grid scale, certain constraints need to be acknowledged. Projecting yield alone without an outlook on future harvested area cannot directly estimate total crop production, as our analysis uses the 2017 SPAM dataset's harvested area figures as a time invariant baseline for all forecast years, which may lead to overestimation or underestimation of production if cropping patterns shift in the future; Supplementary Tables S4 ~ S5 combine our yield projections with the 2017 harvested-area baseline to generate country-level production estimates, but these figures should be interpreted with caution: if cropland expands, contracts, or shifts geographically, production will deviate from the yield trends reported here. Future studies therefore need to account for changes in harvested area to provide a more realistic outlook on global food supply. We also did not incorporate trade flows (net imports) or changes in stock levels into our model, thus failing to fully capture the dynamics of food supply. Moreover, we failed to comprehensively account for non-climate factors, such as armed conflicts, pests and illnesses, and technical improvements, which are significant variables that impact food security. In particular, our simulations did not consider potential increases in research investment and technological innovation driven by economic growth (e.g., GDP), which may enhance future yields beyond what is projected here. Future research should integrate multiple influencing factors, such as extreme climate events, socioeconomic factors, biological diseases, regional conflicts, and research and development investment, to provide more effective solutions for global food security challenges.

Data availability

All datasets used in this study are publicly available. The crop yield data were obtained from the global historical crop yield dataset published in Scientific Data and can be freely accessed through the PANGAEA website (https://doi.pangaea.de/https://doi.org/10.1594/PANGAEA.909132). Historical climate data were retrieved from the Climatic Research Unit (CRU) (https://crudata.uea.ac.uk/cru/data/hrg/), while future climate projections were obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) dataset, which is available via the AWS Open Data Registry (https://registry.opendata.aws/nex-gddp-cmip6/). Land-use data were sourced from the Land-Use Harmonization V2 (LUH2) dataset (https://luh.umd.edu/) and are described in Geoscientific Model Development (https://gmd.copernicus.org/articles/13/5425/2020/). The irr igation ratio data were obtained from the Spatial Production Allocation Model (SPAM) (https://mapspam.info). A detailed description of these datasets, including their spatial resolution and processing methods, is provided in the Research Data section of the manuscript.

Code availability

All custom Python scripts used for model training, yield prediction, cross-validation, and uncertainty estimation in this study are openly available on Zenodo at the following DOI: https://doi.org/10.5281/zenodo.1643

9831. The repository includes complete source code and documentation required to reproduce the modeling workflow. There are no access restrictions.

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Author contributions
J.L. drafted the manuscript, performed data processing, conducted modeling analyses, and prepared the figures. J.W. collected and processed the data and contributed to developing the modeling approach. D.J. provided equipment, collected data, and reviewed the manuscript. S.C. critically reviewed the manuscript and verified the modeling methodology. M.H. proposed the methodology, analyzed the experimental results, and refined the manuscript. F.D. provided funding support, analyzed the modeling results, and supplied data. G.W. revised the initial draft and adjusted the manuscript format. H.L. conducted the results analysis, structured the manuscript, and enhanced the figures. All authors reviewed and approved the final version of the manuscript.

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Competing interests
The authors declare no competing interests.

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