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Research article

Guiding cultivar choice in smallholder agriculture: Identifying suitability hotspots for maturity groups of field crops

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ABSTRACT

The adoption of suitable crop cultivars is central to the sustainable intensification of smallholder cropping systems across Sub-Saharan Africa and plays a crucial role in improving smallholder incomes and food security. Breeding programmes have significantly increased the availability of early-, mid-, and late-maturing crop cultivars tailored to the Target Population of Environments in Sub-Saharan Africa. However, there is a substantial lack of data-driven maturity group recommendations at a detailed spatial scale. The absence of targeted guidance on the suitability of maturity groups limits the ability of smallholder farmers to make optimal cultivar adoption decisions. Here, we propose a framework using gridded crop modelling to identify locally relevant maturity group recommendations at a high spatial resolution for field crops. Implementing the framework for maize in Ghana, we employ the APSIM crop model across 3927 point locations and weather records for recent thirty years. We show that mid-maturing cultivars consistently provide the highest yields across all national production locations in the major growing season. In the minor growing season, we find that early- and mid-maturing cultivars provide the highest yields across distinct spatial suitability clusters. Specifically, in the minor growing season, mid-maturing cultivars provide the highest yields in high-yielding environments, while early-maturing varieties provide the highest yields in low-yielding environments. We identify specific environment-by-management combinations for which different maturity groups are optimal. The proposed framework enables the development of spatially and seasonally tailored maturity group recommendations that take advantage of prevailing genotype-by-environment-by-management interactions. The approach can readily be scaled to other crops and countries.

1. Introduction

With the slow pace of poverty reduction in Sub-Saharan Africa (SSA), global extreme poverty progressively concentrates in the continent's rural, agricultural-based livelihoods (World Bank, 2022). Increasing agricultural productivity is a necessary step to reduce poverty and food insecurity in rural Africa (Byerlee et al., 2009; Dhakal et al., 2022; Fischer et al., 2014). While it is controversial which policies provide feasible and efficient pathways to transition smallholder production systems towards a sustainable intensification (Grewer and Rodriguez, 2019; Kolapo et al., 2022), improved crop cultivars are a central technical component of more productive and profitable farming systems (Jaleta et al., 2018; Smale et al., 2013). The adoption of improved maize cultivars is of particular importance as maize is a central component of farming systems across SSA (Dixon et al., 2020) and constitutes the region's first and third most important crop in terms of cultivated area and production value (FAO (2024), Section 7 of the Supplementary Information (SI)). Historically, the lack of dedicated breeding programmes across SSA meant that suitable crop cultivars were only scarcely available (Pingali, 2012). This situation has drastically changed in recent decades (Krishna et al., 2023). Major investments in regional and national breeding efforts have resulted in the release of a large number of crop cultivars that are both highly adapted to local agro-ecological circumstances and provide diverse phenological traits (Bhargava and Srivastava, 2019; Masuka et al., 2017a,b). As one important trait, maize cultivars of diverse maturity groups are nowadays readily available for commercialisation by seed distribution systems (Tarekegne et al., 2023). However, only a small fraction of maize grown in SSA uses seeds from certified breeding

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sources that have been replanted less than three times (Abate et al., 2017). One reason for these low rates of adoption and replenishment is that current seed commercialisation systems fail to overcome prevailing market imperfections and consequentially do not effectively service smallholder producers (Chivasa et al., 2022). Another major limitation is the lack of maize cultivar recommendations. Specifically, the issue of optimising the choice of maize maturity groups has not yet been widely investigated at scale. Early-maturing cultivars can provide an important strategy to reduce the risk of crop failure in shorter growing seasons and escape late-season drought and heat stress (Badu-Apraku et al., 2013). Instead, mid- and late-maturing cultivars are better placed to achieve high crop yields when favourable growing conditions prevail. However, beyond such generic advice, specific, data-driven recommendations about site-specific maturity group suitability are lacking, aside from few exceptions (Grewer et al., 2024). Targeted recommendations and agricultural extension advice are central components of making cropping systems adapted to site-specific climatic conditions (Hasibuan et al., 2023; Tanimonure and Naziri, 2021). Here, we present an *in-silico* approach using cropping systems modelling to identify suitability hotspots of early-, mid-, and late-maturing crop cultivars to maximise grain yield at a high spatial resolution. As an example, we focus on maize in Ghana. Building on high-quality crop-physiological data from agronomic field trials, we calibrated crop model cultivar parameters for the widely grown, mid-maturing Obatanpa maize cultivar. Synthetic early- and late-maturing cultivars that only differ regarding their maturity requirements but have otherwise identical cultivar characteristics were derived as a form of *in-silico* experimentation. Using a range of typical crop management treatments, we simulate the rainfed, nitrogen-limited yield potential of maize cultivars across the main maize production locations in Ghana for recent thirty years. Based on local statistics of spatial association, it is subsequently evaluated if there is a high prevalence of spatial clusters where a specific maturity group is clearly more suitable than alternative options. We analyse the stability and sensitivity of yield for each cultivar maturity group under varying seasonal climate conditions and different crop management systems. The results quantify how much national maize production may vary due to changes in the maturity group of the maize cultivars grown. Overall, we identify main conclusions for maize maturity group recommendations at a high spatial resolution in Ghana and derive general lessons for identifying locally relevant cultivar maturity recommendations across smallholder agriculture. While existing gridded crop modelling analyses have predominantly focussed on evaluating the future impact of climate change on crop yield (Jägermeyr et al., 2021), the here provided novel approach showcases how to leverage gridded crop modelling for the analysis of farm-level crop management decisions. Our main contribution focuses on providing data-driven guidance on cultivar maturity group suitability at high spatial resolution that are tailored to different growing seasons.

2. Material and methods

This analysis employed cropping systems' modelling to simulate crop yield of one reference cultivar each for early-, mid-, and late-maturing maize in Ghana. Crop growth has been simulated across a regular spatial grid of 3927 point locations at a resolution of 0.05 decimal degrees (approximately 5.55 km at the equator) across the main national maize growing area (879,603 ha) during the major and minor growing seasons of recent thirty years (1986 to 2015).

2.1. Data sources

Meteorological data on daily precipitation as well as daily maximum and minimum temperature was obtained from the *Climate Hazards centre InfraRed Precipitation with Stations* (CHIRPS) dataset (Funk et al., 2015) and the *Climate Hazards centre InfraRed Temperature with Stations* (CHIRTS) dataset (Verdin et al., 2020). Both datasets have a spatial resolution of 0.05 decimal degrees and have been computed using infrared data from remote sensing, meteorological station data, and bias correction methods. CHIRPS ranked among the most accurate rainfall datasets when evaluated against weather station data in sub-Saharan Africa (Funk et al., 2015; Gebrechorkos et al., 2018). Daily data on solar radiation and wind speed were used from the *Daily Surface Meteorological Dataset for Agronomic Use* (AgERA5) at a spatial resolution of 0.1 decimal degrees (ECMWF, 2020; Hersbach et al., 2020). Daily reference evapotranspiration data employing the Penman–Monteith equation (Allen et al., 1998) at a spatial resolution of 0.1 decimal degrees was used from FAO (2021). We utilised soil data from the *Global High-Resolution Soil Profile Database for Crop Modelling Applications* (Han et al., 2015). The dataset has a resolution of 5-arc minutes and has been derived from the *SoilGrids-1 km* (Hengl et al., 2014) and the *Africa Soil Information Service* (AfSIS) datasets. Han et al. (2015) have complemented the soil data with soil hydraulic property variables using pedo-transfer functions. Soil pH values and the initial ammonium content of each soil layer were employed from the *Harvest Choice 27 Generic Soil Profile Database* (Koo and Dimes, 2013).

The spatial scope of the analysis covers the main maize-growing locations in Ghana. Starting from the entire geographic area of Ghana (OCHA, 2021), we disregarded areas occupied by major waterbodies (RCMRD, 2020), as well as all areas with a land cover of bare land, dense forests (>60%), open forest (30%–60%), or dense shrubland (>60%) according to the FAO *Land Cover Classification System* (LCCS1) within the *MODIS Land Cover Type Product* (Friedl and Sulla-Menashe, 2019). Further, locations that record less than 100 ha of maize cultivation per 5-arc minute pixel (appr. 10,000 ha at the equator) in the IFPRI *Spatial Production Allocation Model* (SPAM; Yu et al., 2020) were not considered in the analysis. The resulting considered *physical area* planted to maize in this analysis accounts for 879,603 ha which aligns with the government-recorded total annually *harvested area* across all seasons that varied between 880,250 ha and 1,266,000 ha for the most recently reported years between 2010 and 2021 (FAO, 2024).

Agronomic and crop-physiological data from agricultural field trials for crop model calibration and evaluation was utilised from the Accra plains in southern Ghana. A detailed description of the field trial data is provided by MacCarthy et al. (2015).

2.2. Crop model parameterisation and evaluation

We simulated maize growth using the *Agricultural Production Systems sIMulator* (APSIM-classic version 7.10; Holzworth et al., 2014). APSIM is a dynamic, process-based, biophysical simulation model of the climate-soil-crop interface. It has been widely evaluated by crop modelling studies against data from agronomic field trials in SSA (Beah et al., 2021; Chisanga et al., 2021; Falconnier et al., 2020; Feleke et al., 2021; Rodriguez et al., 2017; Seyoum et al., 2017, 2018; Traore et al., 2017), including various applications in Ghana (Adiku et al., 2015; Fosu-Mensah et al., 2012; MacCarthy et al., 2015, 2009).

We derived the initial nitrate content of soil profiles based on the total nitrogen content and bulk density of each soil layer, as reported in the *Global High-Resolution Soil Profile Database for Crop Modelling Applications* (Han et al., 2015). Following established approximations in gridded crop modelling (AgMIP, 2014), we assumed that initial N-NO_3 constituted 0.1% of total soil nitrogen. Initial soil water content at planting was determined by initiating simulations three months prior to the growing season start with a profile saturated at 10%. Soil water dynamics were then simulated over several months leading up to the planting date, taking into account daily meteorological data. We conducted APSIM parameterisation and model evaluation (detailed description in SI-Section 3) using agronomic field trial data from the major and minor cropping seasons of 2008 and 2009 across three sites at Kpong in the Coastal Savannah agroecological zone (MacCarthy et al., 2015). The experimental trial covers a range of fertilisation and residue management treatments. The field-measured data consists of

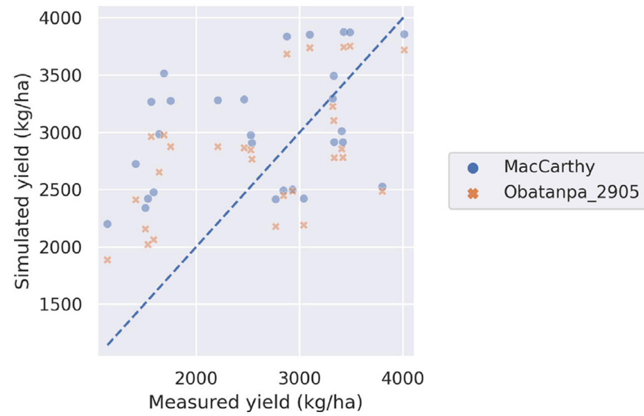


Fig. 1. Comparison of simulated and measured crop yield for two calibrated maize cultivars using the evaluation dataset.
Note: Comparison of simulated versus measured yield for the APSIM maize calibration used in this study ('Obatanpa 2905') and for the APSIM maize calibration from a previous study ('MacCarthy'; MacCarthy et al., 2015) using a different APSIM version across the same agronomic field trial dataset. Further details of the crop model calibration and evaluation process are provided in SI-Section 3.

phenology (number of days required to reach anthesis and maturity), maximum realised Leaf Area Index (LAI), plant nitrogen uptake, crop biomass and grain yield at maturity, as well as selected soil water measurements.

We parameterised an APSIM maize cultivar to represent the open-pollinating, mid-maturing Obatanpa maize cultivar, which is the most widely grown maize cultivar across all agro-ecological zones in Ghana (Abate et al., 2017; Ragasa et al., 2013). Obatanpa was released in 1992 by the Crops Research Institute of Ghana and is a white dent, flint endosperm *Quality Protein Maize* with elevated levels of lysine and tryptophan (Badu-Apraku et al., 2006). To obtain a cultivar parameterisation, we first defined stepwise increments of cultivar parameter values within a reasonable parameter range (SI-Tab. 5). We then generated 5184 potential cultivars based on all possible combinations across the discrete parameter space. The available measurement data were randomly split into equal-sized datasets for calibration and evaluation. The relative root mean square error (rRMSE) for all 5184 maize cultivars was calculated. During cultivar parameter calibration, we selected the maize cultivar ("*Obatanpa_2905*") with the lowest average rRMSE across the six field-measured outcome variables using the calibration dataset (thermal time requirements to anthesis and maturity, maximum LAI, plant nitrogen uptake, and crop biomass as well as grain yield at maturity). Considering this range of outcome variables for model calibration and evaluation avoids the prioritisation of cultivars that exclusively provide a good fit for grain yield while poorly reproducing crop physiological development. When ranking all cultivars using the evaluation data, the cultivar selected during calibration ranks 1/5184 in terms of average rRMSE (0.17) and 133/2078 regarding the RMSE of crop yield (722 kg/ha). Further details on the fit of simulated versus measured crop yield are provided in Fig. 1. Overall, the calibrated cultivar provides a reasonable fit to the available empirical dataset.

2.3. Crop simulation analysis

The crop simulation analysis considers a range of genotype-by-environment-by-management (G×E×M) combinations. We simulated all combinations of three nitrogen fertiliser rates (0, 45, 90 kg N/ha), three planting densities (4.4, 5.6, 6.7 plants/m^2), and three cultivar maturity types (early-, mid-, and late-maturing). The considered nitrogen fertiliser rates and planting densities encompass both the most prevalent current practices in Ghana and the recommendations of the Ghanaian Ministry of Food and Agriculture (Adu et al., 2014). Maize growth was simulated during the major and minor growing seasons over thirty years (1986–2015) and across 3927 point locations. Each year was simulated independently, without the consideration of any intertemporal carry-over of soil conditions. While the south of Ghana is characterised by a bimodal rainfall pattern, a unimodal rainfall pattern prevails in the north. We assumed that maize is cultivated during the minor growing season across southern Ghana up to a latitude of 8.5 decimal degrees. Across southern Ghana, not all farmers consistently cultivate the minor growing season, with the density of minor season cultivation across the farming population diminishing towards northern locations.

When comparing the performance of specific existing, commercially available early-, mid-, and late-maturing maize cultivars, it is not possible to disentangle the impacts of their maturity duration from other cultivar characteristics. To isolate the exclusive impact of a cultivar's maturity duration on crop performance, we used the APSIM-maize cultivar parameterisation of the mid-maturing Obatanpa cultivar as a reference point. We then defined hypothetical early- and late-maturing variants of the Obatanpa cultivar as a form of in-silico experimentation. These hypothetical cultivars only differ in terms of their maturity requirements and were defined by respectively subtracting or adding equal amounts of thermal time requirements for main growth stages (SI-Tab. 11).

For each year and location, we calculated a specific start of the growing season based on a combination of meteorological criteria. The growing season start was considered to likewise identify the start of the sowing window. Using such site- and year-specific, meteorological-driven start dates of the sowing window (Ferijal et al., 2022) instead of fixed dates from crop calendars or remote-sensing databases (Sacks et al., 2010; Whitcraft et al., 2015) more closely captures the inter-annual variability in seasonal climate conditions that farmers consider when deciding the timing of sowing. Specifically, we considered the growing season and sowing window to start when the subsequent criteria are fulfilled: (i) accumulation of at least 40 mm of precipitation during a five-day period; (ii) absence of any 10-day period with less than 5 mm cumulative precipitation during the 30 days consecutive to the start date (i.e., false season onset); and (iii) occurrence of the start date within a predefined reference period that corresponds to typically practised sowing times.[1] If the previous criteria were fulfilled, APSIM initiated a sowing event once cumulative rainfall exceeded 20 mm during any four-day period and extractable soil water exceeded 30 mm. If the previous criteria were never fulfilled, planting was enforced at the end of the predefined reference period. The resulting thirty-year average of the growing season start for the major and minor seasons are shown in SI-Section 5. The growing season was assumed to end at the first occurrence of a 15-day interval without any precipitation. A descriptive overview of the approximate duration of major and minor growing seasons across locations is provided in SI-Section 6.

2.4. Statistical indicators

To characterise the intensity of water availability at location l in year t during the growing season s, the water balance ratio (WBR) was calculated as:

$$Water\ Balance\ Ratio_{lts} = \frac{Total\ Precipitation_{lts}}{Total\ Reference\ Evapotranspiration_{lts}}$$

The input values of precipitation and reference evapotranspiration refer to total cumulative quantities during growing season s. To separate between various intensities of water surplus or deficit, we defined the three ranges: low water availability (WBR < 1), medium water

[1] 1 March to 15 May for the major season in southern Ghana (latitude <= 8.5 decimal degrees); 1 April to 31 July for the major season in northern Ghana (latitude > 8.5 decimal degrees); 15 August to 31 December for the minor season in southern Ghana.

availability (1< WBR < 1.5), and high water availability (WBR > 1.5).

The downside risk of crop yield at location l during the growing season s for cultivar c was defined as the average yield reduction below its long-term average yield:

$$Downside\ Risk_{lsc} = \frac{1}{N_{lsc}} \sum_{i=1}^{n} \left\{ abs\left(min\left[Y_{ilsc} - \overline{Y}_{lsc}, 0 \right] \right) \right\}$$

Whereby, N_{lsc} denotes the total number of yield observations, Y_{ilsc} indicates the i^{th} observation of crop yield, and $\overline{Y}_{lsc}$ denotes the average crop yield. This measure of downside risk indicates the extent to which maize yields fall below their long-term average in low-yielding seasons. It highlights which cultivars are prone to expose agricultural producers to severe reductions in crop production and associated income loss.

2.5. Analysis of spatial association

As the basis for calculating spatial relationships, we employed a binary spatial weights matrix that considers the closest 24 neighbours around each analysed location, which encompasses all first-level neighbours (8 direct neighbours) and second-level neighbours (16 neighbours' neighbours). As indicator of local spatial association, we computed Local Moran's I (Anselin, 1995) based on standardised spatial lag variables. Cluster maps of the direction and significance of spatial association were generated for a pseudo-p threshold value of 0.05 using the PySal library (Rey et al., 2022).

2.6. Software implementation

This analysis was conducted using Bash to organise and execute all software components and Python for all subscripts. Gridded APSIM crop simulation modelling was implemented using High Performance Computing (HPC) employing the Simple Linux Utility for Resource Management (SLURM) for job scheduling and workload management. To create and deploy a portable and reproducible computing environment, the Singularity container platform was used.

3. Results

3.1. Average performance of cultivar maturity groups across large spatial and temporal scales

During the major growing season of recent thirty years (1986–2015) in Ghana, the mid-maturing maize cultivar in general outperformed the late- and early-maturing cultivars (Fig. 2(a); SI-Tab. 1). The mid-maturing maize cultivar (mean: 4484 kg/ha) provided moderately higher yields than the late-maturing cultivar (mean: 4231 kg/ha) and much higher yields than the early-maturing cultivar (mean: 3821 kg/ha). All cultivars had similar levels of interannual yield variability and downside risk (SI-Fig. 3 & 4). With few exceptions, the identified yield ranking of the cultivar maturity groups (mid > late > early) in the major growing season was consistently found across all years (Fig. 2(b)), as well as across low-, medium- and high-yielding conditions (Fig. 2(c)).

During the minor growing season, the early-maturing cultivar generally outperformed the mid- and late-maturing cultivars (Fig. 2(d), SI-Tab. 1). The early-maturing cultivar (mean: 3942 kg/ha) provided moderately higher yields than the mid-maturing cultivar (mean: 3777 kg/ha), and drastically higher yields than the late-maturing cultivar (mean: 2690 kg/ha). During the minor season, the different cultivars observed strongly different levels of interannual yield variability and downside risk (SI-Fig. 3 & 4). The early-maturing cultivar provided the highest yield stability and the lowest level of downside risk. Both, the mid- and particularly the late-maturing cultivar were instead characterised by higher levels of yield variability and downside risk. The overall yield ranking of the cultivar maturity groups (early > mid > late) in the minor growing season was less spatially and temporally consistent than in the major growing season. While the early-maturing cultivar provided in general the highest yield, it was outperformed by the mid-maturing cultivar in several years (Fig. 2(e)) and for high-yielding conditions (Fig. 2(f)). While the early-maturing cultivar was most successful in reducing the risk of low yields and crop failure, it was also less successful than the mid-maturing cultivar to capitalise on favourable growing conditions. The late-maturing cultivar consistently provided strongly lower yields than the other cultivars across all years and seasonal conditions. Further, it led to a particularly high risk of crop failure.

Across all locations, years, and crop management options, the highest maize yield during the major growing season was achieved 1%, 85%, and 13% of the time by the early-, mid-, and late-maturing cultivar, respectively (SI-Tab. 1). Nationally, when considering the main maize growing areas during the major season, shifting from the lowest- to the highest-yielding cultivar would have increased the nitrogen-limited, rainfed maize production potential by 694,478 t or 19.9% per year.[2] Instead, shifting from exclusively growing the on average highest-yielding cultivar in the major growing season – i.e., the mid-maturing cultivar – to the site-, year-, and management-specific highest-yielding cultivar, would have increased total maize production by only 34,283 t or 0.8% per year.

The highest maize yield during the minor growing season was achieved 55%, 45%, and 0% of the time by the early-, mid-, and late-maturing cultivar, respectively (SI-Tab. 1). Nationally, when considering the main maize growing areas during the minor season, shifting from the lowest- to the highest-yielding cultivar would have increased the nitrogen-limited, rainfed maize production potential by 1,024,919 t or 58.6% per year. Instead, shifting from exclusively growing the on average highest-yielding cultivar in the minor growing season – i.e., the early-maturing cultivar – to the site-, year-, and management-specific highest-yielding cultivar, would have increased total maize production by 124,778 t or 4.7% per year.

3.2. Spatial hotspots of maturity group suitability

Beyond the aggregate national evaluation, a spatially disaggregated analysis can identify differences in cultivar performance across geographic locations. Overall, Ghana observes known spatial differences in rainfed maize yield potentials, with the southern Forest and Transition agro-ecological zones generally observing a higher maize yield potential than the northern Savannah agro-ecological zones (Boullouz et al., 2022; MOFA, 2022; WUR and UNL, 2024).[3] We found that maize growing locations in south-western Ghana constituted the largest spatially continuous area with a high yield potential across all cultivars (Fig. 3(a) & (d)). Further areas with a high yield potential were the northern *Volta*, southern *Oti*, eastern *Upper East*, and south-eastern *Upper West* regions. All other maize-growing areas north of the *Ashanti* region had a low maize yield potential.

In the following, we compare the long-term average maize yield by location for each of the cultivar maturity groups. This allows to examine how spatially consistent each maturity group performs. During the major growing season, the highest long-term average yield was achieved at 0%, 97.9%, and 2.1% of locations by the early-, mid-, and late-maturing cultivar, respectively (SI-Tab. 2). At locations where the mid-maturing cultivar performed best, the realised long-term average yield gain was 658 kg/ha and 260 kg/ha per year over the early- and late-maturing cultivar, respectively (SI-Tab. 3). At the few locations where the late-maturing cultivar performed best, the long-term average

[2] To calculate changes in production potentials at scale, we considered the average yield across all considered nitrogen application rates and planting densities.

[3] For reference, maps of the administrative divisions and agro-ecological zones of Ghana are provided in SI-Fig. 19 & 20.

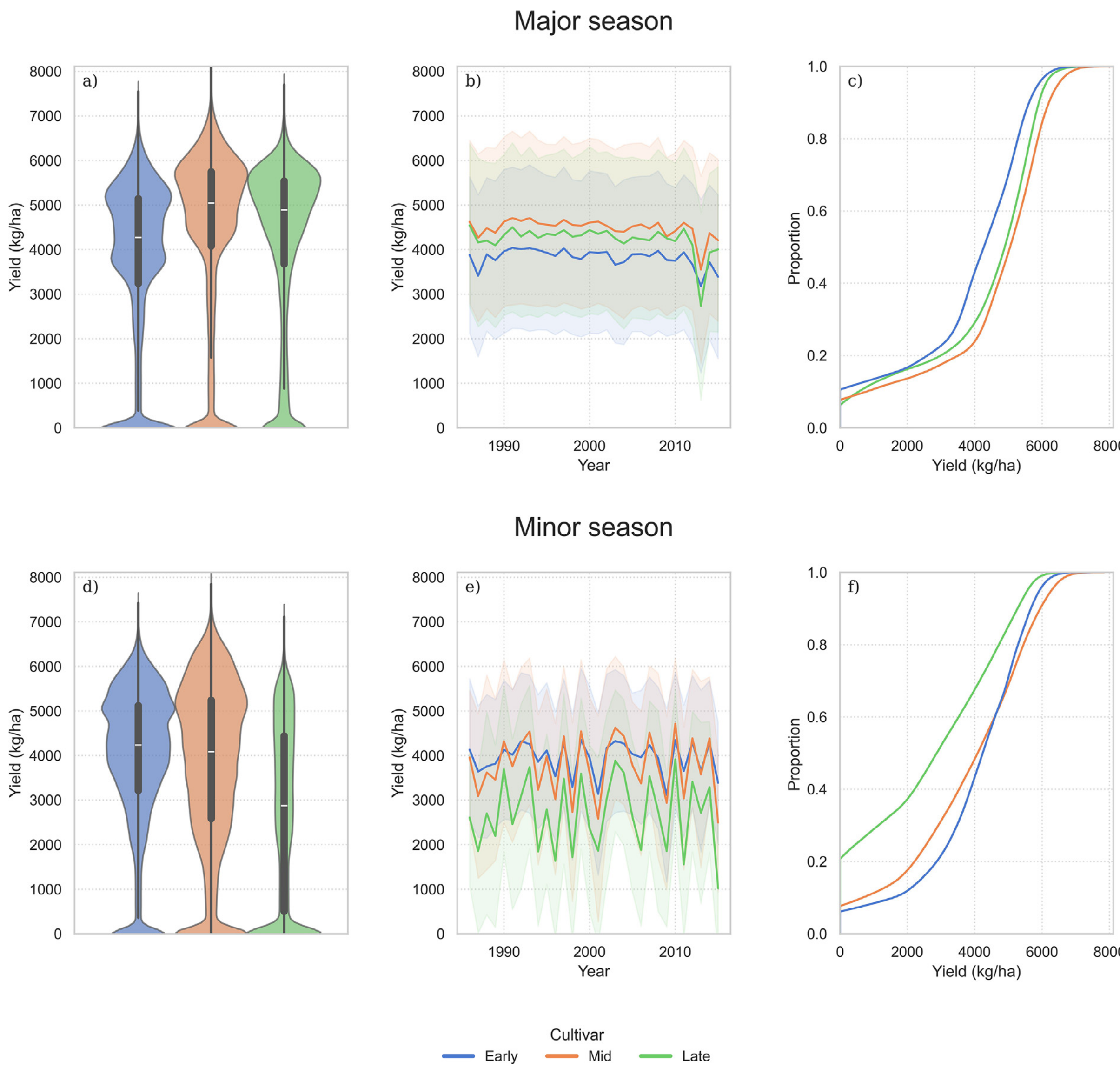


Fig. 2. Yield performance of early-, mid-, and late-maturing maize cultivars during the major and minor growing seasons in Ghana.
Note: Maize yield during 1986–2015 for the main maize cultivating locations in Ghana and across all considered treatments (nitrogen fertiliser rates; planting densities) for the major growing season (top row) and minor growing season (bottom row). (a) & (d): Combined violinplots and boxplots of maize yield across all years, locations, and treatments. (b) & (e): Annual maize yield averaged across treatments and locations. The shaded area indicates +/− 1 standard deviation around the average. (c) & (f): Cumulative distribution functions of maize yield for all years, locations, and treatments.

yield gain over the mid-maturing cultivar was only 56 kg/ha per year. Thereby, no high spatial variability in the yield differences between cultivars was found across the main maize production locations in Ghana (Fig. 3(b) & (c)). The yield advantage of the mid-maturing cultivar occurred largely in a uniform manner across space. Only a few locations constituted spatial hotspots where early- or late-maturing cultivars consistently either led to particularly low or slightly higher yields than the mid-maturing cultivar (Fig. 4). The northern *Ashanti,* northern *Volta*, and southern *Upper West* regions as well as the *Afram Plains* were spatially consistent clusters where the early-maturing cultivar led to particularly strong reductions in the long-term average yield compared to the mid-maturing cultivar (Fig. 4(a)). Across the entire *Northern* region, the early-maturing cultivar also provided lower yields than the mid-maturing cultivar, but the yield differences were consistently much smaller than in other locations. For the late-maturing cultivar, we identified spatial clusters of particularly strong yield reductions compared to the mid-maturing cultivar across all coastal production locations in the *Western*, *Central*, and *Greater Accra* regions (Fig. 4(b)). Instead, a small spatial cluster was detected in the north-western *Volta* region where the late-maturing cultivar consistently provided a marginally higher yield than the mid-maturing cultivar.

During the minor growing season instead, we found strong differences among maize growing locations in the long-term average yield of different cultivars. During the minor season, the highest long-term average yield was achieved at 59.0%, 41.0%, and 0.0% of locations by the early-, mid-, and late-maturing cultivar, respectively (SI-Tab. 2). At locations where the early-maturing cultivar performed best, the realised long-term average yield gain was 457 kg/ha and 1689 kg/ha per year over the mid- and late-maturing cultivar, respectively (SI-Tab. 3). At locations where the mid-maturing cultivar performed best, the realised long-term average yield gain was 254 kg/ha and 878 kg/ha per year over the early- and late-maturing cultivar, respectively. In strong contrast to the results for the major growing season, a high spatial variability in the yield differences between cultivars was found across

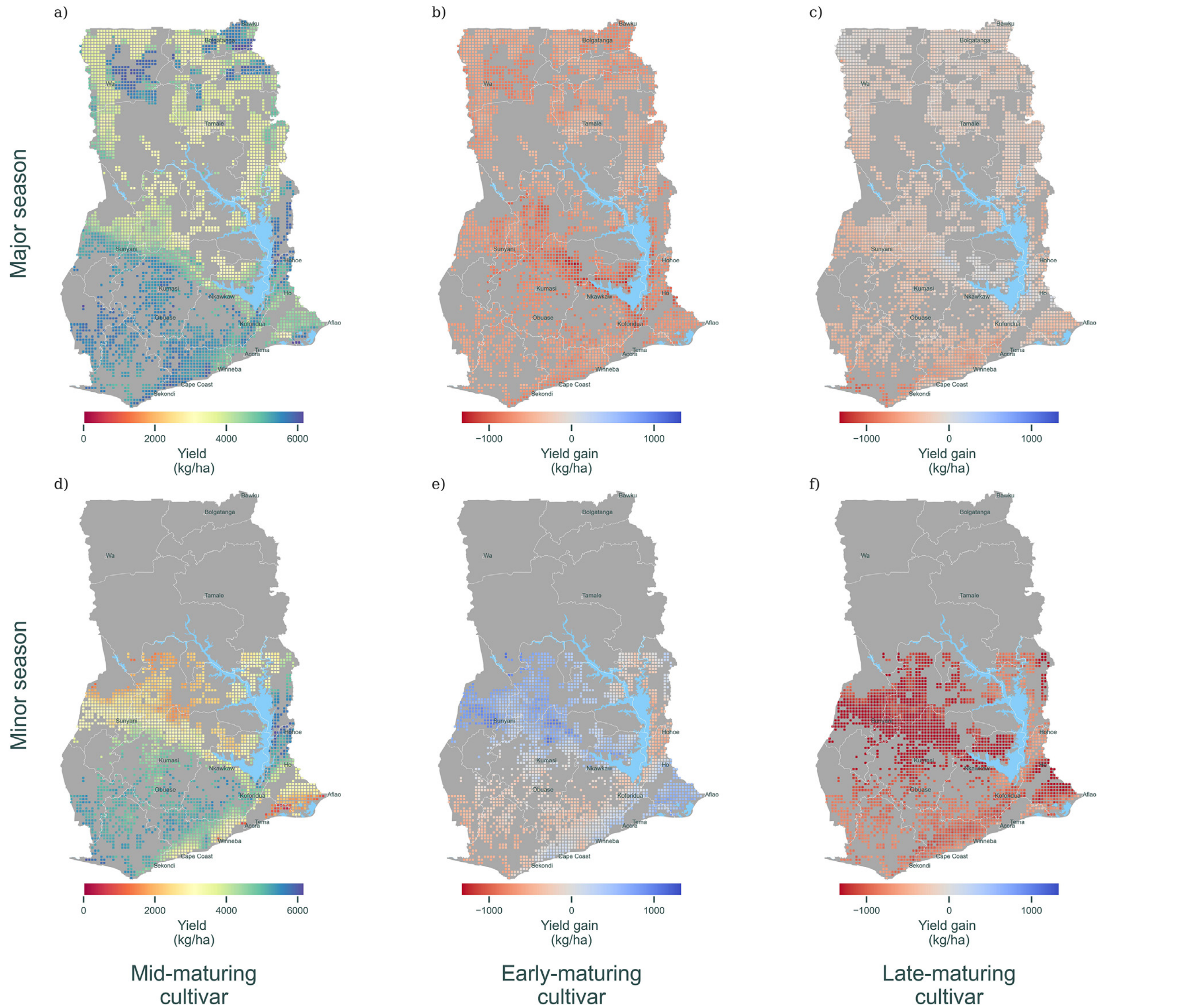


Fig. 3. Long-term average yield performance of early-, mid-, and late-maturing maize cultivars during the major and minor growing seasons.
Note: Maize yield performance averaged across treatments (nitrogen fertiliser rates; planting densities) and thirty years of cultivation (1986–2015). (a) & (d): Maize yield of the mid-maturing cultivar. (b) & (e): Maize yield gain of the early-maturing cultivar over the mid-maturing cultivar. (c) & (f): Maize yield gain of the late-maturing cultivar over the mid-maturing cultivar.

locations during the minor season (Fig. 3(e) & (f)). Locations with a generally low yield potential during the minor season constituted spatial hotspots where the early-maturing cultivar strongly outperformed alternative cultivars. These locations were the *Bono*, *Bono East*, northern *Ashanti*, southern *Volta*, and *Greater Accra* regions, as well as the *Afram Plains* (Fig. 4(c)). Instead, there was only one smaller spatial cluster in the northern *Volta* region where the mid-maturing cultivar consistently outperformed the early-maturing cultivar. Those locations in south-western Ghana (*Western North*, *Western*, *Central*, southern *Ashanti*, and southern *Eastern* regions) that are generally characterised by a high yield potential, recorded the highest long-term average yield from the mid-maturing cultivar (Fig. 3(d)–(f)). However, the yield advantage of the mid-maturing cultivar did not occur in a spatially consistent manner (Fig. 4(c)). Instead, across those regions, the yield difference between the early- and mid-maturing cultivar was predominantly small, without any clear continuous clusters of where a single cultivar would outperform the other. The late-maturing cultivar consistently led to strong yield reductions compared to the other cultivars, across all locations in the minor season. Spatial hotspots where yield losses from growing the late-maturing cultivar were particularly pronounced were the *Bono*, *Bono East*, *Ahafo*, and northern *Ashanti* regions (Fig. 4(d)).

3.3. Interactions of maturity group suitability with environmental conditions and crop management choices

When specific genotypes (G) are cultivated in particular environments (E) using a certain system of crop management (M), the interaction of these three factors (G × E × M interactions) may cause the various cultivar maturity groups to perform differently from the previously identified aggregate outcomes. The importance of G × E × M interactions is widely documented across diverse maize genotypes, environments, and production systems (Cooper et al., 2021; Teixeira et al., 2017). Here, we investigate specifically the interaction between maize cultivar maturity groups, water-deficit environments, and nitrogen fertiliser management strategies.

During the major growing season, we did not find strong G × E × M interactions at the aggregate level. For low nitrogen and water stress conditions in the major growing season (Fig. 5.1(e), (f), (h), (i)), we

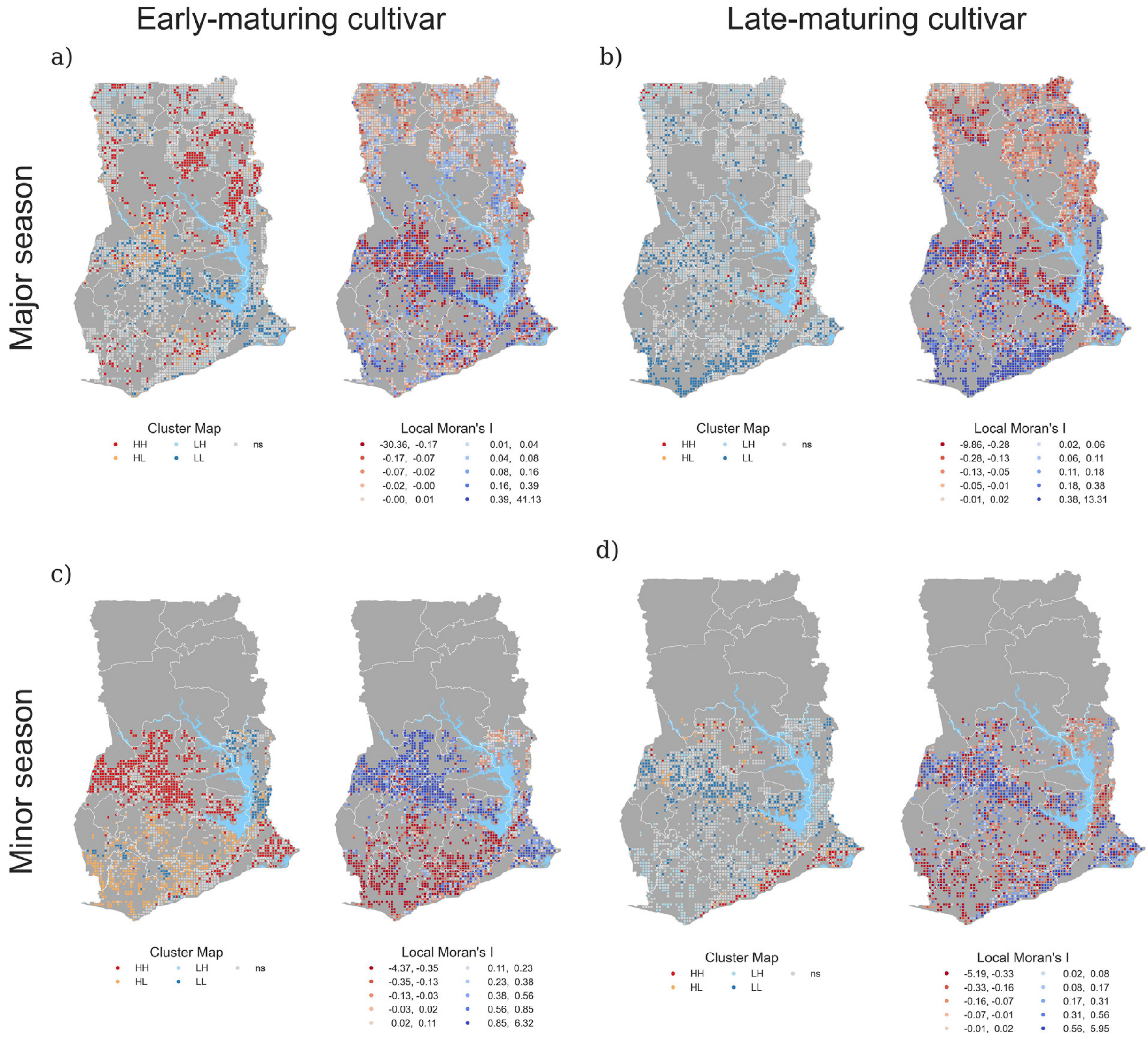


Fig. 4. Cluster maps and local Moran's I maps of yield gains of the early- and late-maturing cultivars over the mid-maturing cultivar during the major and minor growing seasons. *Note: The cluster maps identify locations with statistically significant levels of spatial association between a point-location and its neighbours (pseudo-p threshold: 0.05; "ns": not statistically significant). In addition, the cluster maps classify the type of positive ("HH": high-high, "LL": low-low) or negative ("LH": low-high, "HL", high-low) spatial association. Maps of Local Moran's I indicate the estimated strength of spatial association between a point-location and its neighbours.*

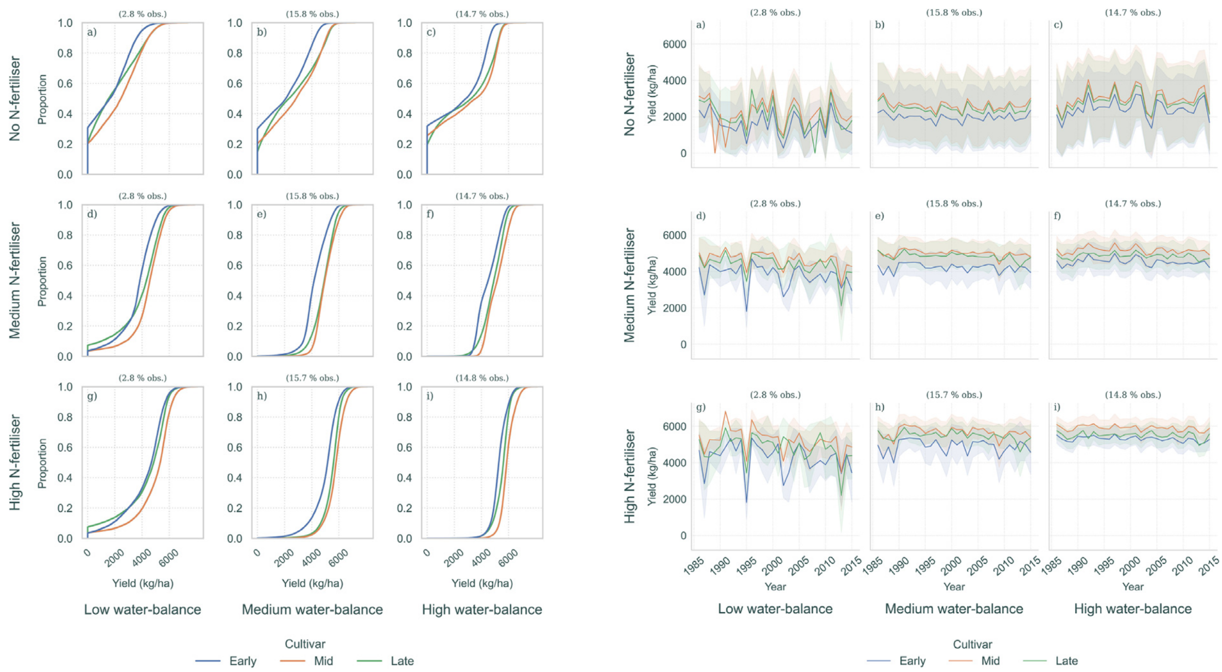
confirm the previously identified consistent yield ranking of the cultivar maturity groups (mid > late > early), whereby the mid-maturing cultivar was still found to have provided moderate and large yield benefits over the late- and early-maturing cultivar, respectively. With minor deviations, the same result was found for conditions of nitrogen stress (Fig. 5.1(a), (b), (c)). Instead, when considering conditions that experienced water-stress while receiving nitrogen fertiliser (Fig. 5.1(d), (g)), the early-maturing cultivar provided a lower likelihood of both low-yield and high-yield outcomes than the late-maturing cultivar, thus reducing both downside and upside production risks. When analysing the average yield of specific years, the presence of either nitrogen- or water-stress caused a strong increase in yield variability of all cultivars (Fig. 5.2(a), (b), (c), (d), (g)), with the early-maturing cultivar frequently observing large yield shocks.

During the minor growing season, we found strong G × E × M interactions at the aggregate level. Under conditions of water stress while receiving nitrogen fertiliser, the early-maturing cultivar consistently provided the highest yield by a large margin (Fig. 6.1(d), (g)). Instead, under conditions of sufficient water supply and low nitrogen fertilisation, the mid-maturing cultivar consistently provided the highest yield (Fig. 6.1(b), (c), (f)). Under all other conditions, the early-maturing cultivar provided a lower likelihood of both low-yield and high-yield outcomes than the mid-maturing cultivar, effectively reducing production risks.

4. Discussion

4.1. Big-picture results of maturity group suitability in Ghana

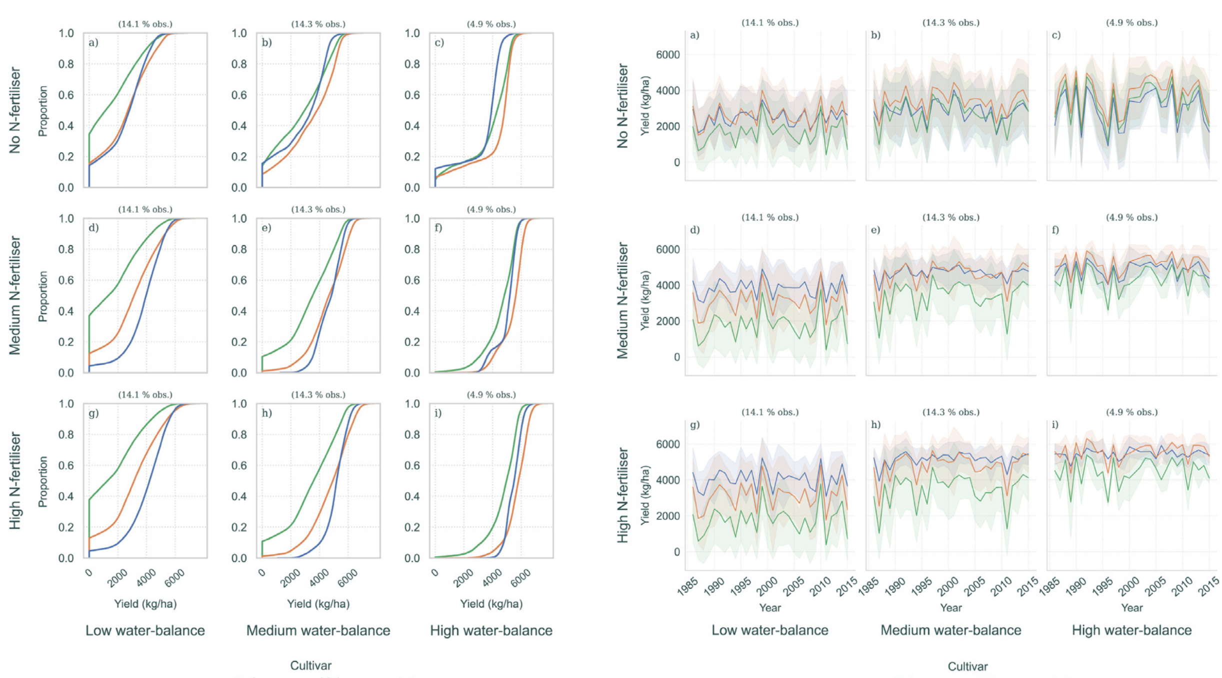
Across the main maize-producing locations in Ghana, mid-maturing cultivars provide by far the highest yield during the major growing season and a similar level of downside risk as other maturity groups. The yield reductions from growing early-maturing cultivars during the major growing season are substantial. In the minor growing season, early- and mid-maturing cultivars provide the highest maize yield and early-maturing cultivars provide the lowest downside risk. Cultivating late-maturing cultivars in the minor growing season causes drastic yield reductions and frequent crop failure. These findings differ partially from Adu et al. (2014), who recommended late-maturing varieties for the Transition and Forest agro-ecological zones and early-maturing varieties for the Sudan Savannah. Their recommendations were based on promoting early-maturing cultivars in low-rainfall environments and



5.1 Cumulative Distribution Functions of maize yield

5.2 Annual average maize yield

Fig. 5. Maize yield by water-balance conditions and nitrogen fertiliser intensities for various cultivar maturity groups during the major growing season.
Note: Nitrogen fertiliser application intensities: no (0 N kg/ha), medium (45 N kg/ha), high (90 N kg/ha). Water-balance ratio (WBR) categories: low (WBR < 1), medium (1 < WBR < 1.5), high (WBR > 1.5). Percentage of observations (obs.) within each category indicated on top of subplots. Shaded area in Fig. 5.2 indicates +/− 1 standard deviation around the average.



6.1 Cumulative Distribution Functions of maize yield

6.2 Annual average maize yield

Fig. 6. Maize yield by water-balance conditions and nitrogen fertiliser intensities for various cultivar maturity groups during the minor growing season.
Note: Nitrogen fertiliser application intensities: no (0 N kg/ha), medium (45 N kg/ha), high (90 N kg/ha). Water-balance ratio (WBR) categories: low (WBR < 1), medium (1 < WBR < 1.5), high (WBR > 1.5). Percentage of observations (obs.) within each category indicated on top of subplots. Shaded area in Fig. 6.2 indicates +/− 1 standard deviation around the average.

late-maturing varieties in high-rainfall areas, while not being based on empirical data of maize yields for different cultivars.

4.2. Benefits of sub-national maturity group recommendations

At various locations, higher maize yields can be achieved, when diverting from the above identified general suitability pattern. However, the achievable yield gains from further optimising cultivar maturity group selection are usually small. This finding supports that, at an aggregate level in Ghana, it is adequate to promote the adoption of mid-maturing cultivars in the major season and early-maturing cultivars in the minor season – when no further site- and farm-specific characteristics are known. At a more granular level, some clear spatial clusters of cultivar maturity group suitability and unsuitability have been identified. Spatial clusters of cultivar suitability are stronger in the minor growing season than in the major growing season. In the minor season, all maize production locations with generally lower yield potential, situated across the agro-ecologies of the Coastal Savannah and the Transition Zone, were found to strongly benefit from the adoption of early-maturing cultivars, while experiencing strong yield reductions from late-maturing cultivars. Instead, the higher yield potential locations in the northern *Volta* and southern *Oti* regions were found to constitute a spatial cluster where mid-maturing cultivars perform best during the minor season. During the major growing season, the mid-maturing cultivar consistently provided the highest yield across all locations, without any diverting spatial clusters. Across the eastern Transition Zone, we identified a spatial cluster where early-maturing cultivars led to particularly strong yield reductions during the major growing season. These sub-national maturity group recommendations derived from gridded crop modelling are a novel contribution to the literature and importantly complement other forms of site-specific cultivar evaluations such as on-farm trials and farmers' participatory assessments (Worku et al., 2020).

4.3. Benefits of management-specific maturity group recommendations

Knowledge about the average suitability of cultivar maturity groups is important to guide national agricultural policy and programme development. For regional and local stakeholders, such as the district offices of the Ministry of Food and Agriculture, it is instead feasible and necessary to further refine such generic maize maturity group recommendations based on locally prevailing crop management systems. This analysis has shown that the performance of cultivar maturity groups depends on their interaction with environmental and management conditions. Specifically, we identified strong prevailing $G \times E \times M$ interactions during the minor growing season. For fertilised maize crops that developed a higher amount of biomass during vegetative growth, exposure to water stress caused the early-maturing cultivar to strongly outperform all other maturity groups. Under this combination of $E \times M$ conditions, the early-maturing cultivar transfers limited resources from the vegetative to the reproductive crop growth stages, which effectively limits the negative impact of water stress. This finding aligns with Badu-Apraku et al. (2013, p. 1307), who observed higher maize yields under drought stress in West Africa for varieties with shorter maturity requirements to reach anthesis. In addition, Rezende et al. (2020), p. 116) suggest that under drought stress the yield advantage of early-maturing varieties over other maturity groups may partially stem from differences in secondary traits, such as a shorter anthesis-silking interval. Instead, when no fertiliser was applied and crops accordingly developed a smaller amount of biomass during the vegetative growth stages, exposure to sufficient water supply caused the mid-maturing cultivar to strongly outperform all other maturity groups. Under this combination of $E \times M$ conditions, the mid-maturing cultivar increased the time-period during which the maize crop could uptake and benefit from sufficient water supply. Across several agro-ecological zones in Ghana, the findings by Owusu et al. (2018) have found a similarly large importance of $G \times E \times M$ interactions. For regional and local providers of agricultural extension, it is thus essential to move beyond generic recommendations about the suitability of cultivar maturity groups and account for the locally prevailing crop management practices.

4.4. Suitability of the available cultivar palette and implications for breeding targets

The number and diversity of maize cultivars released and registered in Ghana have steadily increased over recent decades (CORAF and CSIR-CRI, 2019; Ragasa et al., 2013). When following the variety suitability zones identified by CORAF and CSIR-CRI (2019), a range of mid- and early-maturing cultivars is available for all five agro-ecological zones, with no significant gaps (Fig. 7). However, the underlying qualitative classification of maize cultivar suitability across agro-ecological zones should only be given an indicative interpretation, while a systematic evaluation of all major maize cultivars across the Target Population of Environments in Ghana via experimental trials and crop-physiological modelling remains a research gap.

4.5. Optimality of prevailing cultivar adoption patterns

Data on maize cultivar adoption across large spatial and temporal scales in Ghana is scarce, as the major national household panel survey does not track crop cultivar use (Ghana Statistical Service, 2018). Existing data is either outdated (Abate et al., 2017; Ragasa et al., 2013) or considers only few locations (Adu et al., 2021; Asante et al., 2024; Danso-Abbeam et al., 2017; Quarshie et al., 2021). The available estimates suggest that with 13% (in 2015; AGRA and USAID, 2016) or 15% (in 2012; Ragasa et al., 2013) only a small share of the national maize area is cultivated with certified seed that has not been replanted more than twice. Among the certified maize seeds grown, the two largest surveys indicated that Obatanpa, the cultivar analysed in our study, remained by far the most widely used (Abate et al., 2017; Ragasa et al., 2013), while more recent smaller surveys found Obatanpa to be cultivated at a roughly similar proportion as several other cultivars (Aburohema, Aburotia, Ekomasa, Suntem; Quarshie et al., 2021). Specifically, this includes the wider diffusion of some early-maturing cultivars, such as Aburohema and Abontem. The data scarcity on maize cultivar use and performance across Ghana prevents breeding and extension programmes from functioning optimally. Collecting data on cultivar use for major crops in future rounds of the nationally representative Ghana Living Standard Survey is a clear recommendation of this analysis.

The predominance of recycling seeds locally over prolonged periods implies that farmers are currently locked into growing a single cultivar across all seasons and management systems. Thereby, local seed recycling often involves mixing seeds from various sources (Audet-Bélanger et al., 2016), resulting in the cultivation of a heterogeneous mix of cultivars with non-uniform phenological traits. While this practice provides a certain level of risk diversification, it prevents farmers from selecting those maize cultivars that are most suitable for specific seasonal, location, and management characteristics. Releasing farmers from the lock-in of cultivating an ambiguous, heterogeneous cultivar mix and adopting targeted cultivar maturity groups would provide substantial increases in maize yield across smallholder agriculture. Farmer Based Organisations (FBOs), a widely institutionalised form of farmer organisation and collective action in Ghana, could play an important role in implementing such changes to seed provisioning patterns (Grewer, 2013).

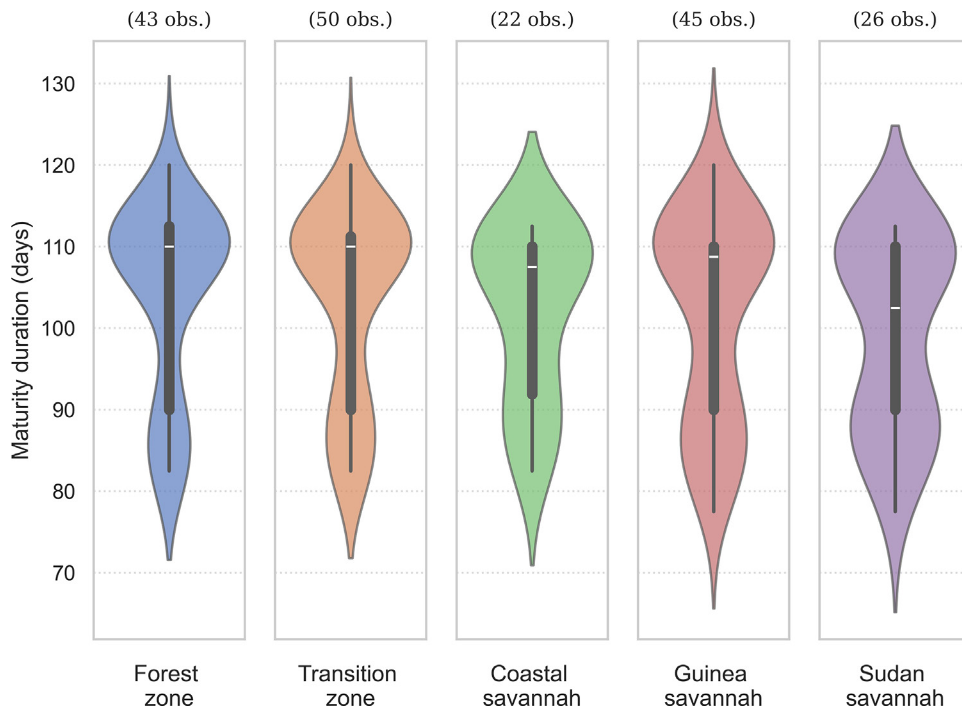


Fig. 7. Maturity duration of maize cultivars released and registered in Ghana by most suitable agro-ecological zone.
Note: Observations (obs.) indicate the number of maize cultivars declared as suitable for each agro-ecological zone as reported in CORAF and CSIR-CRI (2019). For details on maize cultivars, see SI-Tab. 4. For delineation of agro-ecological zones, see SI-Fig. 20.

4.6. Scalability, limitations and implications for future research

The here provided research framework allows identifying clear season-, location-, and management-specific cultivar maturity group recommendations at a high spatial resolution. The framework can be readily scaled to other countries and target crops.

To complement this simulation-based study, it would be valuable for future research to analyse the empirical evidence on the performance of different maize maturity groups based on farmer-reported survey data. For example, in an econometric analysis of farmer-reported maize yield in Malawi, Grewer et al. (2024) found that the timing of water-stress was another central factor in determining which maturity group performed best.

Implementing the here proposed research framework requires the availability of sufficient agronomic trial data as well as crop modelling expertise. While the availability of agricultural trial data has increased across low-income countries in recent decades (Kyveryga, 2019), it still remains a major bottleneck. Particularly, comparable agronomic trial data for all major agro-ecological environments across a country is often not available. This also constitutes a main limitation of the current study that exclusively relied on agronomic field trial data from sites in southern Ghana. We recommend that future gridded crop modelling applications prioritise the use of data from multiple environments and investigate the sensitivity of study results to using calibration datasets from contrasting environments. Another valuable focus of future studies would be to extend the current research to focus on further outcome indicators beyond crop yield, such as resource use efficiency, soil quality, and greenhouse gas emission intensity (Grewer et al., 2018).

4.7. Implications for productivity and rural poverty

This analysis found that the maturity groups prioritised in the national breeding programme in Ghana are well aligned with the most suitable maturity groups identified by this study. However, agricultural extension campaigns lack communication about the significant differences in the suitability of cultivar maturity groups. Further, the market failure of the seed commercialisation and distribution system leads to very low rates of maize seed replenishment from certified sources. Addressing these two major bottlenecks of the Ghanaian maize seed sector has the potential to substantially increase maize yields and total production. Across rural, agricultural-based livelihoods, this would provide direct benefits to increase agricultural incomes and reduce rural poverty.

5. Conclusion

The choice of cultivar maturity groups plays a central role in determining the crop yields smallholder farmers can achieve and the yield variability they face. While many practice changes and technological innovations remain out of reach for smallholder farmers due to substantial investment requirements and other adoption barriers, changing cultivars is feasible, accessible, and practical when rural seed commercialisation channels function efficiently. An alternative cultivar can be tested on a small portion of the farm, and its impact is directly observable by farmers as part of standard production procedures, which facilitates a faster pace of adoption and diffusion (Rogers, 2003).

However, the large number of available maize varieties and the lack of clear agricultural extension advice on their suitability represent a major gap in agricultural innovation systems. Advice on the suitability of cultivar maturity groups should be specific to (i) the growing season, (ii) the agro-ecological zone, and (iii) key crop management practices, such as the intensity of nitrogen fertiliser application.

In the specific context of maize in Ghana, we found that selecting the most appropriate cultivar maturity group for the respective growing season had substantial yield impacts. Instead, the yield benefits from spatially fine-tuning which maturity group to grow, were less sizeable.

The research framework provided by this study allows for quantifying the suitability of cultivar groups across the multiple identified dimensions. It can readily be scaled to other crops and countries and can be complemented with supplementary research using agricultural field trials and household survey data analysis.

CRediT authorship contribution statement

Uwe Grewer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Peter de Voil:** Writing – review & editing, Software, Conceptualization. **Dilys S. MacCarthy:** Writing – review & editing, Data curation, Conceptualization. **Daniel Rodriguez:** Writing – review & editing, Conceptualization.

Code availability

The computer code scripts used to generate this study are available upon request from the corresponding author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary information

Supplementary information (SI) related to this article can be found online at https://doi.org/10.1016/j.resenv.2025.100204.

Data availability

The database of gridded crop model simulation results produced by this study can be downloaded from the repository: https://zenodo.org/doi/10.5281/zenodo.12593584. The various raw datasets used as input to this study are available from the cited sources.

References

Abate, T., Fisher, M., Abdoulaye, T., Kassie, G.T., Lunduka, R., Marenya, P., Asnake, W., 2017. Characteristics of maize cultivars in Africa: How modern are they and how many do smallholder farmers grow? Agric. Food Secur. 6 (1), 30. http://dx.doi.org/10.1186/s40066-017-0108-6.

Adiku, S.G.K., MacCarthy, D.S., Hathie, I., Diancoumba, M., Freduah, B.S., Amikuzuno, J., Traore, P.C.S., Traore, S., Koomson, E., Agali, A., Lizaso, J.I., Fatondji, D., Adams, M., Tigana, L., Diarra, D.Z., N'diaye, O., Valdivia, R.O., 2015. Climate change impacts on West African agriculture: An integrated regional assessment (CIWARA). In: Handbook of Climate Change and Agroecosystems. pp. 25–73. http://dx.doi.org/10.1142/9781783265640_0014.

Adu, G.B., Abdulai, M.S., Alidu, H., Nustugah, S.K., Buah, S.S., Kombiok, J.M., Obeng-Antwi, K., Abudulai, M., Etwire, P.M., 2014. Recommended Production Practices for Maize in Ghana. Council for Scientific and Industrial Research (CSIR), http://dx.doi.org/10.13140/2.1.4376.3527.

Adu, G.B., Badu-Apraku, B., Akromah, R., Amegbor, I.K., Adogoba, D.S., Haruna, A., Manigben, K.A., Aboyadana, P.A., Wiredu, A.N., 2021. Trait profile of maize varieties preferred by farmers and value chain actors in northern Ghana. Agron Sustain. Dev. 41 (4), 50. http://dx.doi.org/10.1007/s13593-021-00708-w.

AgMIP, 2014. Report on the Workshop to Improve the Use of Soil Data in Large-Scale Multi-Model Tools for Climate Impact Assessments in Africa. AgMIP, https://agmip.org/wp-content/uploads/2018/08/Advancing-Global-Agricultural-Assessments.pdf.

AGRA, USAID, 2016. Ghana early generation seed stuty. Alliance for a Green Revolution in Africa (AGRA) & United States Agency for International Development (USAID). https://agrilinks.org/sites/default/files/resource/files/ghana_early_generation_seed_report.pdf.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, Vol. 56. FAO.

Anselin, L., 1995. Local indicators of spatial association - LISA. Geogr. Anal. 27 (2), 93–115. http://dx.doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Asante, B.O., Ma, W., Prah, S., Temoso, O., 2024. Farmers' adoption of multiple climate-smart agricultural technologies in Ghana: determinants and impacts on maize yields and net farm income. Mitig. Adapt. Strat. Glob. Chang. 29 (2), 16. http://dx.doi.org/10.1007/s11027-024-10114-8.

Audet-Bélanger, G., Gildemacher, P., Hoogendoorn, C., 2016. Seed Sector Functioning and the Adoption of Improved Maize Varieties. Zambia Study Report. K. R. T. Institute.

Badu-Apraku, B., Oyekunle, M., Menkir, A., Obeng-Antwi, K., Yallou, C.G., Usman, I.S., Alidu, H., 2013. Comparative performance of early-maturing maize cultivars developed in three eras under drought stress and well-watered environments in West Africa. Crop. Sci. 53 (4), 1298–1311. http://dx.doi.org/10.2135/cropsci2012.11.0640.

Badu-Apraku, B., Twumasi-Afriyie, S., Sallah, P.Y.K., Haag, W., Asiedu, E., Marfo, K.A., Dapaah, S., Dzah, B.D., 2006. Registration of 'Obatanpa GH' maize. Crop. Sci. 46 (3), 1393–1395. http://dx.doi.org/10.2135/cropsci2005.11-0398.

Beah, A., Kamara, A.Y., Jibrin, J.M., Akinseye, F.M., Tofa, A.I., Ademulegun, T.D., 2021. Simulation of the optimum planting windows for early and intermediate-maturing maize varieties in the Nigerian savannas using the APSIM model. Front. Sustain. Food Syst. 5, http://dx.doi.org/10.3389/fsufs.2021.624886.

Bhargava, A., Srivastava, S., 2019. Advantages and cost of participatory plant breeding. In: Bhargava, A., Srivastava, S. (Eds.), Participatory Plant Breeding: Concept and Applications. Springer Singapore, pp. 87–107. http://dx.doi.org/10.1007/978-981-13-7119-6_4.

Boullouz, M., Bindraban, P.S., Kissiedu, I.N., Kouame, A.K.K., Devkota, K.P., Atakora, W.K., 2022. An integrative approach based on crop modeling and geospatial and statistical analysis to quantify and explain the maize (Zea mays) yield gap in Ghana. Front. Soil Sci. 2, http://dx.doi.org/10.3389/fsoil.2022.1037222.

Byerlee, D., de Janvry, A., Sadoulet, E., 2009. Agriculture for development: Toward a new paradigm. Annu. Rev. Resour. Econ. 1 (1), 15–31. http://dx.doi.org/10.1146/annurev.resource.050708.144239.

Chisanga, C.B., Phiri, E., Chinene, V.R.N., 2021. Evaluating APSIM-and-DSSAT-CERES-Maize models under rainfed conditions using zambian rainfed maize cultivars. Nitrogen 2 (4), 392–414. http://dx.doi.org/10.3390/nitrogen2040027.

Chivasa, W., Worku, M., Teklewold, A., Setimela, P., Gethi, J., Magorokosho, C., Davis, N.J., Prasanna, B.M., 2022. Maize varietal replacement in Eastern and Southern Africa: Bottlenecks, drivers and strategies for improvement. Glob. Food Secur. 32, http://dx.doi.org/10.1016/j.gfs.2021.100589.

Cooper, M., Voss-Fels, K.P., Messina, C.D., Tang, T., Hammer, G.L., 2021. Tackling G × E × M interactions to close on-farm yield-gaps: creating novel pathways for crop improvement by predicting contributions of genetics and management to crop productivity. Theor. Appl. Genet. 134 (6), 1625–1644. http://dx.doi.org/10.1007/s00122-021-03812-3.

CORAF, CSIR-CRI, 2019. Catalogue of Crop Varieties Released and Registered in Ghana. The West and Central African Council for Agricultural Research and Development (CORAF) and The Crops Research Institute of the Council for Scientific and Industrial Research of Ghana (CSIR-CRI).

Danso-Abbeam, G., Bosiako, J.A., Ehiakpor, D.S., Mabe, F.N., 2017. Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Econ. Financ. 5 (1), 1416896. http://dx.doi.org/10.1080/23322039.2017.1416896.

Dhakal, C., Khadka, S., Park, C., Escalante, C.L., 2022. Climate change adaptation and its impacts on farm income and downside risk exposure. Resour. Environ. Sustain. 10, 100082. http://dx.doi.org/10.1016/j.resenv.2022.100082.

Dixon, J., Garrity, D.P., Boffa, J.-M., Williams, T.O., Amede, T., Auricht, C., Lott, R., Mburathi, G., 2020. Farming Systems and Food Security in Africa, first ed. Routledge, http://dx.doi.org/10.4324/9781315658841.

ECMWF, 2020. Daily Surface Meteorological Dataset for Agronomic Use, Based on ERA5 (AgERA5). ECMWF, http://dx.doi.org/10.24381/cds.6c68c9bb.

Falconnier, G.N., Corbeels, M., Boote, K.J., Affholder, F., Adam, M., MacCarthy, D.S., Ruane, A.C., Nendel, C., Whitbread, A.M., Justes, É., Ahuja, L.R., Akinseye, F.M., Alou, I.N., Amouzou, K.A., Anapalli, S.S., Baron, C., Basso, B., Baudron, F., Bertuzzi, P., et al., 2020. Modelling climate change impacts on maize yields under low nitrogen input conditions in sub-saharan africa. Global Change Biol. 26 (10), 5942–5964. http://dx.doi.org/10.1111/gcb.15261.

FAO, 2021. Daily reference evapotranspiration derived from AgERA5. https://data.apps.fao.org/catalog/iso/f22813e9-679e-4864-bd92-d48f5dfc436c.

FAO, 2024. FAOSTAT. Production: Crops and Livestock Products. FAO, https://www.fao.org/faostat/en/#data/QCL.

Feleke, H.G., Savage, M.J., Tesfaye, K., 2021. Calibration and validation of APSIM–Maize, DSSAT CERES–Maize and AquaCrop models for Ethiopian tropical environments. S. Afr. J. Plant & Soil 38 (1), 36–51. http://dx.doi.org/10.1080/02571862.2020.1837271.

Ferijal, T., Batelaan, O., Shanafield, M., Alfahmi, F., 2022. Determination of rainy season onset and cessation based on a flexible driest period. Theor. Appl. Climatol. 148 (1), 91–104. http://dx.doi.org/10.1007/s00704-021-03917-1.

Fischer, T., Byerlee, D., Edmeades, G., 2014. Crop Yields and Global Food Security: Will Yield Increase Continue To Feed the World? Vol. 158. ACIAR, https://www.aciar.gov.au/sites/default/files/legacy/mn158_web_5_0.pdf.

Fosu-Mensah, B.Y., MacCarthy, D.S., Vlek, P.L.G., Safo, E.Y., 2012. Simulating impact of seasonal climatic variation on the response of maize (Zea mays L.) to inorganic fertilizer in sub-humid Ghana. Nutr. Cycl. Agroecosystems 94 (2), 255–271. http://dx.doi.org/10.1007/s10705-012-9539-4.

Friedl, M., Sulla-Menashe, D., 2019. MCD12Q1 MODIS/Terra+Aqua land cover type yearly L3 global 500 m SIN grid V006. http://dx.doi.org/10.5067/MODIS/MCD12Q1.006.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2 (1), 150066. http://dx.doi.org/10.1038/sdata.2015.66.

Gebrechorkos, S.H., Hülsmann, S., Bernhofer, C., 2018. Evaluation of multiple climate data sources for managing environmental resources in East Africa. Hydrol. Earth Syst. Sci. 22 (8), 4547–4564. http://dx.doi.org/10.5194/hess-22-4547-2018.

Ghana Statistical Service, 2018. Ghana Living Standard Survey 2017 (GLSS 7). Ghana Statistical Service.

Grewer, U., 2013. Which methodology to support farmer based organizations for stable collective action and increased farm incomes. An evaluation study from Ghana. In: Brazda, J., Dellinger, M., Rözl, D. (Eds.), Genossenschaften Im Fokus Einer Neuen Wirtschaftspolitik. LIT Verlag.

Grewer, U., Kim, D.-H., Waha, K., 2024. Too much, too soon? Early-maturing maize varieties as drought escape strategy in Malawi. Food Policy 129, 102766. http://dx.doi.org/10.1016/j.foodpol.2024.102766.

Grewer, U., Nash, J., Gurwick, N., Bockel, L., Galford, G., Richards, M., Junior, C.C., White, J., Pirolli, G., Wollenberg, E., 2018. Analyzing the greenhouse gas impact potential of smallholder development actions across a global food security program. Environ. Res. Lett. 13 (4), 044003. http://dx.doi.org/10.1088/1748-9326/aab0b0.

Grewer, U., Rodriguez, D., 2019. The sustainable intensification of farming systems. A review of cross-disciplinary research methods. CAB Rev. 14 (060), 1–18. http://dx.doi.org/10.1079/PAVSNNR201914060.

Han, E., Ines, A., Koo, J., 2015. Global High-Resolution Soil Profile Database for Crop Modeling Applications. Harvard Dataverse, http://dx.doi.org/10.7910/DVN/1PEEY0.

Hasibuan, A.M., Wulandari, S., Ardana, I.K., Saefudin, Wahyudi, A., 2023. Understanding climate adaptation practices among small-scale sugarcane farmers in Indonesia: The role of climate risk behaviors, farmers' support systems, and crop-cattle integration. Resour. Environ. Sustain. 13, 100129. http://dx.doi.org/10.1016/j.resenv.2023.100129.

Hengl, T., Mendes de Jesus, J.S., Macmillan, R.A., Batjes, N.H., Heuvelink, G.B.M., Carvalho Ribeiro, E.D., Samuel Rosa, A., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Ruiperez Gonzalez, M., 2014. SoilGrids1km— global soil information based on automated mapping. PLOS ONE 9 (8), e105992. http://dx.doi.org/10.1371/journal.pone.0105992.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., et al., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 146 (730), 1999–2049. http://dx.doi.org/10.1002/qj.3803.

Holzworth, D.P., Huth, N.I., de Voil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., Brown, H., Whish, J.P.M., Verrall, S., Fainges, J., Bell, L.W., Peake, A.S., Poulton, P.L., Hochman, Z., et al., 2014. APSIM – Evolution towards a new generation of agricultural systems simulation. Environ. Model. Softw. 62, 327–350. http://dx.doi.org/10.1016/j.envsoft.2014.07.009.

Jägermeyr, J., Müller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J.A., Fuchs, K., Guarin, J.R., Heinke, J., Hoogenboom, G., Iizumi, T., Jain, A.K., Kelly, D., Khabarov, N., Lange, S., et al., 2021. Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat. Food 2 (11), 873–885. http://dx.doi.org/10.1038/s43016-021-00400-y.

Jaleta, M., Kassie, M., Marenya, P., Yirga, C., Erenstein, O., 2018. Impact of improved maize adoption on household food security of maize producing smallholder farmers in ethiopia. Food Secur. 10 (1), 81–93. http://dx.doi.org/10.1007/s12571-017-0759-y.

Kolapo, A., Didunyemi, A.J., Aniyi, O.J., Obembe, O.E., 2022. Adoption of multiple sustainable land management practices and its effects on productivity of smallholder maize farmers in Nigeria. Resour. Environ. Sustain. 10, 100084. http://dx.doi.org/10.1016/j.resenv.2022.100084.

Koo, J., Dimes, J., 2013. HC27 Generic Soil Profile Database. Harvard Dataverse, http://dx.doi.org/10.7910/DVN/90WJ9W.

Krishna, V.V., Lantican, M.A., Prasanna, B.M., Pixley, K., Abdoulaye, T., Menkir, A., Bänziger, M., Erenstein, O., 2023. Impact of CGIAR maize germplasm in Sub-Saharan Africa. Field Crop. Res. 290, http://dx.doi.org/10.1016/j.fcr.2022.108756.

Kyveryga, P.M., 2019. On-farm research: Experimental approaches, analytical frameworks, case studies, and impact. Agron. J. 111 (6), 2633–2635. http://dx.doi.org/10.2134/agronj2019.11.0001.

MacCarthy, D.S., Akponikpe, P.B.I., Narh, S., Tegbe, R., 2015. Modeling the effect of seasonal climate variability on the efficiency of mineral fertilization on maize in the coastal savannah of Ghana. Nutr. Cycl. Agroecosystems 102 (1), 45–64. http://dx.doi.org/10.1007/s10705-015-9701-x.

MacCarthy, D.S., Sommer, R., Vlek, P.L.G., 2009. Modeling the impacts of contrasting nutrient and residue management practices on grain yield of sorghum (Sorghum bicolor (L.) Moench) in a semi-arid region of Ghana using APSIM. Field Crop. Res. 113 (2), 105–115. http://dx.doi.org/10.1016/j.fcr.2009.04.006.

Masuka, B., Atlin, G.N., Olsen, M., Magorokosho, C., Labuschagne, M., Crossa, J., Bänziger, M., Pixley, K.V., Vivek, B.S., von Biljon, A., Macrobert, J., Alvarado, G., Prasanna, B.M., Makumbi, D., Tarekegne, A., Das, B., Zaman-Allah, M., Cairns, J.E., 2017a. Gains in Maize genetic improvement in Eastern and Southern Africa: I. CIMMYT hybrid breeding pipeline. Crop. Sci. 57 (1), 168–179. http://dx.doi.org/10.2135/cropsci2016.05.0343.

Masuka, B., Magorokosho, C., Olsen, M., Atlin, G.N., Bänziger, M., Pixley, K.V., Vivek, B.S., Labuschagne, M., Matemba-Mutasa, R., Burgueño, J., Macrobert, J., Prasanna, B.M., Das, B., Makumbi, D., Tarekegne, A., Crossa, J., Zaman-Allah, M., van Biljon, A., Cairns, J.E., 2017b. Gains in Maize genetic improvement in Eastern and Southern Africa: II. CIMMYT open-pollinated variety breeding pipeline. Crop. Sci. 57 (1), 180–191. http://dx.doi.org/10.2135/cropsci2016.05.0408.

MOFA, 2022. Facts and Figures: Agriculture in Ghana 2021. Ministry of Food and Agriculture (MOFA).

OCHA, 2021. Ghana - Subnational Administrative Boundaries. United Nations Office for the Coordination of Humanitarian Affairs (OCHA), https://data.humdata.org/dataset/cod-ab-gha.

Owusu, G.A., Nyadanu, D., Owusu-Mensah, P., Adu Amoah, R., Amissah, S., Danso, F.C., 2018. Determining the effect of genotype × environment interactions on grain yield and stability of hybrid maize cultivars under multiple environments in Ghana. Ecol. Genet. Genom. 9, 7–15. http://dx.doi.org/10.1016/j.egg.2018.07.002.

Pingali, P.L., 2012. Green revolution: Impacts, limits, and the path ahead. Proc. Natl. Acad. Sci. 109 (31), 12302–12308. http://dx.doi.org/10.1073/pnas.0912953109.

Quarshie, P.T., Abdulai, A.R., Fraser, E.D.G., 2021. Africa's seed revolution and value chain constraints to early generation seeds commercialization and adoption in Ghana. Front. Sustain. Food Syst. 5, http://dx.doi.org/10.3389/fsufs.2021.665297.

Ragasa, C., Dankyi, A., Acheampong, P., Wiredu, A.N., Chapoto, A., Asamoah, M., Tripp, R., 2013. Patterns of Adoption of Improved Maize Technologies in Ghana. IFPRI.

RCMRD, 2020. Africa Water Bodies. The Regional Centre for Mapping of Resources for Development (RCMRD), https://rcmrd.africageoportal.com/datasets/africageoportal::africa-water-bodies.

Rey, S.J., Anselin, L., Amaral, P., Arribas-Bel, D., Cortes, R.X., Gaboardi, J.D., Kang, W., Knaap, E., Li, Z., Lumnitz, S., Oshan, T.M., Shao, H., Wolf, L.J., 2022. The PySAL ecosystem: Philosophy and implementation. Geogr. Anal. 54 (3), 467–487. http://dx.doi.org/10.1111/gean.12276.

Rezende, W.S., Beyene, Y., Mugo, S., Ndou, E., Gowda, M., Sserumaga, J.P., Asea, G., Ngolinda, I., Jumbo, M., Oikeh, S.O., Olsen, M., Borém, A., Cruz, C.D., Prasanna, B.M., 2020. Performance and yield stability of maize hybrids in stress-prone environments in eastern africa. Crop. J. 8 (1), 107–118. http://dx.doi.org/10.1016/j.cj.2019.08.001.

Rodriguez, D., de Voil, P., Rufino, M.C., Odendo, M., van Wijk, M.T., 2017. To mulch or to munch? Big modelling of big data. Agricult. Sys. 153, 32–42. http://dx.doi.org/10.1016/j.agsy.2017.01.010.

Rogers, E.M., 2003. Diffusion of Innovations, fifth ed. Free Press.

Sacks, W.J., Deryng, D., Foley, J.A., Ramankutty, N., 2010. Crop planting dates: an analysis of global patterns. Glob. Ecol. Biogeogr. 19 (5), 607–620. http://dx.doi.org/10.1111/j.1466-8238.2010.00551.x.

Seyoum, S., Chauhan, Y., Rachaputi, R., Fekybelu, S., Prasanna, B., 2017. Characterising production environments for maize in Eastern and Southern Africa using the APSIM model. Agricult. Forest. Meterol. 247, 445–453. http://dx.doi.org/10.1016/j.agrformet.2017.08.023.

Seyoum, S., Rachaputi, R., Chauhan, Y., Prasanna, B., Fekybelu, S., 2018. Application of the APSIM model to exploit G × E × M interactions for maize improvement in ethiopia. Field Crop. Res. 217, 113–124. http://dx.doi.org/10.1016/j.fcr.2017.12.012.

Smale, M., Byerlee, D., Jayne, T., 2013. Maize revolutions in sub-saharan africa. In: Otsuka, K., Larson, D.F. (Eds.), An African Green Revolution: Finding Ways to Boost Productivity on Small Farms. Springer Netherlands., pp. 165–195. http://dx.doi.org/10.1007/978-94-007-5760-8_8.

Tanimonure, V.A., Naziri, D., 2021. Impact of climate adaptation strategies on the net farm revenue of underutilised indigenous vegetables' (UIVs) production in Southwest Nigeria. Resour. Environ. Sustain. 5, 100029. http://dx.doi.org/10.1016/j.resenv.2021.100029.

Tarekegne, A., Wegary, D., Cairns, J.E., Zaman-Allah, M., Beyene, Y., Negera, D., Teklewold, A., Tesfaye, K., Jumbo, M.B., Das, B., Nhamucho, E.J., Simpasa, K., Kaonga, K.K.E., Mashingaidze, K., Thokozile, N., Mhike, X., Prasanna, B.M., 2023. Genetic gains in early maturing maize hybrids developed by the International Maize and Wheat Improvement Center in Southern Africa during 2000–2018. Front. Plant Sci. 14, http://dx.doi.org/10.3389/fpls.2023.1321308.

Teixeira, E.I., Zhao, G., Ruiter, J.d., Brown, H., Ausseil, A.-G., Meenken, E., Ewert, F., 2017. The interactions between genotype, management and environment in regional crop modelling. Eur. J. Agron. 88, 106–115. http://dx.doi.org/10.1016/j.eja.2016.05.005.

Traore, B., Descheemaeker, K., van Wijk, M.T., Corbeels, M., Supit, I., Giller, K.E., 2017. Modelling cereal crops to assess future climate risk for family food self-sufficiency in southern Mali. Field Crop. Res. 201, 133–145. http://dx.doi.org/10.1016/j.fcr.2016.11.002.

Verdin, A., Funk, C., Peterson, P., Landsfeld, M., Tuholske, C., Grace, K., 2020. Development and validation of the CHIRTS-daily quasi-global high-resolution daily temperature data set. Sci. Data 7 (1), 303. http://dx.doi.org/10.1038/s41597-020-00643-7.

Whitcraft, A.K., Becker-Reshef, I., Justice, C.O., 2015. Agricultural growing season calendars derived from MODIS surface reflectance. Int. J. Digit. Earth 8 (3), 173–197. http://dx.doi.org/10.1080/17538947.2014.894147.

Worku, M., De Groote, H., Munyua, B., Makumbi, D., Owino, F., Crossa, J., Beyene, Y., Mugo, S., Jumbo, M., Asea, G., Mutinda, C., Kwemoi, D.B., Woyengo, V., Olsen, M., Prasanna, B.M., 2020. On-farm performance and farmers' participatory assessment of new stress-tolerant maize hybrids in eastern africa. Field Crop. Res. 246, 107693. http://dx.doi.org/10.1016/j.fcr.2019.107693.

World Bank, 2022. Poverty and Shared Prosperity 2022: Correcting Course. World Bank.

WUR, UNL, 2024. Global Yield Gap and Water Productivity Atlas. Wageningen University and Research (WUR) & University of Nebraska Lincoln (UNL), Retrieved 10.06.2024 from www.yieldgap.org.

Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A.K.B., Fritz, S., Xiong, W., Lu, M., Wu, W., Yang, P., 2020. A cultivated planet in 2010 – part 2: The global gridded agricultural-production maps. Earth Syst. Sci. Data 12 (4), 3545–3572. http://dx.doi.org/10.5194/essd-12-3545-2020.