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Rice yield stability compared to major food crops in West Africa

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Abstract

West Africa is one of the regions the most concerned with structural food and nutrition security. Consequently, agricultural development pathways and scenarios are under high scientific and political scrutiny in this region. Rice, as a rapidly growing staple plays a key role in the West African diet representing close to 40% of the total volume of cereal consumed in the region. In the context of the 2008 food price crisis several West African countries have since proclaimed rice self-sufficiency as a target. Here, we show that rice yields tend to be, on average over the entire region, less stable (by a range of 15%–30%) than that of alternative crops, possibly substitutable in diets. The regions where yields of alternative crops are more stable than those of rice correspond to the main climatic regions where these crops are grown: sorghum, millet in the Sahelian and Sudanian regions and tubers in the Guinean region. Rice yields are significantly less stable for 33% of the comparisons considered and are significantly more stable than any alternative crop for 15% of the comparisons in few areas without clear longitudinal patterns. Models accounting for climate variability explain up to 17% of the variance of the data and reveal that yield variability differences between rice and alternative crops tends to widen in the areas where the monsoon precipitation is more variable between-years. The highest levels of variability of rice yields compared to alternative crops are recorded in regions where the monsoon varies strongly between years. Our analysis advocates for an explicit account of yield stability in West African rice expansion scenarios and supply strategies.

1. Introduction

With a large fraction of structurally food insecure people (from about 11% in 2009 to 14% in 2019), West Africa is one of regions of the world most concerned about food availability and access. A combination of contextual factors underlies this situation [1]. Strong population growth [2] and rapid urbanization [3], international food prices volatility [4], biotic and abiotic adverse conditions [5], climate variability and change [6, 7], and political instability or wars [7], affect both food availability and access under continuous demand growth. This region is characterized by a relatively small diversity of plant-based foods [8, 9], and staples (i.e. cereals and roots and tubers) form the basis of food security and represent about 68% of the daily West African caloric supply [10]. The relative share of rice in West African diets has been progressively growing in the last decades, and its consumption has reached about 22 million tons or about 36% of the total cereal consumed in the region in 2018 [10, 11]. The average annual rate of demand growth is about 4.6% since the early 1990s and is expected to continue growing in the near future [12]. This rapid growth, associated with the 'rice diet transition' [12, 13], now

generates a structural imbalance between production and imports with imported rice volumes contributing to about 50% of the total rice supply in West Africa [11]. In the context of the 2008 food price crisis—in which international rice prices tripled in a few months [14], this situation has been regularly questioned and several countries have since proclaimed rice self-sufficiency as a target (e.g. in Senegal and in Mali) [12]. More recently, the Economic Community of West African States (ECOWAS) proclaimed to target rice self-sufficiency in the region by 2025 [15].

West African rice production has been steadily increasing from about 3.2 million tons in 1980 to 18.5 million tons in 2018 [16]. This increase has primarily relied on an extension of agricultural land dedicated to rice production with an annual increase of harvested areas of about 7.5% (especially in Nigeria, Senegal, Mali, Ghana and Cote d'Ivoire) [17, 18]. Over roughly the same time period, yields increased from about 1–2.1 t ha^{-1}, i.e. reaching about half of worldwide average rice yields [18]. Unless the rice yield gaps are reduced within the coming decade, regional expansion of rice harvested areas seems unavoidable to meet self-sufficiency targets [19]. If allocating more agricultural land to rice would help increase average rice production in the region, one important unknown concerns the stability of the rice production especially compared to alternative crop species.

Climate variability has been shown to explain about one third of global maize, rice, wheat and soybean yield variability [20]. In West Africa, the characteristics of the West African monsoon is a key determinant of precipitation levels, generating high variability from intra-seasonal to multi-decadal time scales [21, 22], with impacts on rainfed crops, including rice [23]. Due to its important water needs, rice yields are known to be sensitive to water stress [24]. The recurrently limited availability in surface water may disproportionately affect rice production compared to more resilient crop species, better adapted to sporadic water unavailability (e.g. millet and sorghum) [25]. It has already been shown, for example, that rice yields are more sensitive to extreme climatic conditions (e.g. very high temperatures or droughts) than alternative crops yields (i.e. finger millet, sorghum, pearl millet and maize) in India [24]. The comparative yield stability of rice to alternative crops (defined here as crop species that are as important as rice in annual volume of production and possibly substitutable in diets) is hence a salient element in this context. Are those crops more or less stable than rice? If so, what are the geographical and climatic determinants of this stability?

Contrary to the dynamics of average crop yields and farm profitability, which are widely studied [26–32], much smaller attention has been given to yield interannual variability. Several recent studies analyzed yield stability of one or several crop species in various parts of the world [20, 24, 33–38], with only a few including rice [20, 34, 38, 39] and only a few covering West African countries [20, 39–42]. Hence, only two studies analyzed rice yield stability in West Africa [20, 39]. These are based on (a) a downscaling of national data and (b) simulations of yield potential. Hence, a data-based analysis of the comparative stability of rice over West Africa, at subnational scales is still lacking in the literature. Here, to make progress, we compare the levels of yield variability of rice to five alternative major staple crops in West African regions and evaluate the impact of climate local features on these between-crops differences. We rely on yield time-series at the scale of small regions (administrative level 1) over the totality of the West African region. Our comparisons are based on normalized yield residuals standard deviation (henceforth referred to as standard deviation ratio (SDR) in the following, see section 2). In the last section, we thrive to explain SDR variability based on the interannual variability of cumulated precipitation and indices of monsoon continuity.

2. Materials and methods

2.1. Yield data

We rely on publicly available data at subnational level 1 over the 15 countries defining West Africa as defined by the Food and Agriculture Organization of the United Nation (FAO) classification (excluding islands). These are Benin, Burkina Faso, Côte d'Ivoire, the Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo. Two distinct datasets, based on public statistical offices, are available for time periods up to 23 consecutive years between 1984 and 2015 (a) FAOCountrySTAT [43] and (b) AgroMAPS [44]. FAOCountrySTAT and AgroMAPS cover administrative levels 1 and 2 and inform annual production (in tons) and annual harvested areas (in ha). We compute yields from these two variables. In total, there are 201 geographical units at administrative level 1 over West Africa. The maximum number of available yield time-series is 1206 (i.e. number of units × number of alternative crops). The five most produced alternative crops to rice in the region (in fresh weight), according to FAOSTAT annual data are cassava, maize, millet, sorghum and yams (with 81, 19, 10, 12, 57 million tons per year respectively, on average in the last decade, see figure S1 (available online at stacks.iop.org/ERL/16/124005/mmedia)).

We apply several selection criteria to the raw time-series collected based on (a) the precision of yield values (i.e. we select yield values informing at least two decimals); (b) the coherency of yield values: we remove outliers above crop-dependent maximum potential yields estimated from the literature (see table S1), we remove the geographical areas where

yield, production and area harvested are equal to 0 or any duplicate; (c) the length of the time-series (i.e. we select those with at least nine years with gaps of length inferior to three consecutive years). These three criteria are completed in 316 time-series from FAO-CountrySTAT and 267 time-series from AgroMAPS. In a final step, we merge both datasets and remove redundant values, obtaining a total of 399 yield times series at administrative level 1 for time periods of length 9–23 years between 1984 and 2015 (see figure S2). Note that in the merging process we have prioritized FAOCountrySTAT data because it is a more recent dataset. In the supplement we present the length, time-span and origin of each of the 399 selected time-series (see table S2).

We detrend each yield time-series to remove any signal due to low frequency variability, for example expected from long-term technological changes or low-frequency climate variability. To this end, a polynomial regression of degrees 1, 2 or 3 is fitted to each of the 399 time-series independently. The best model is selected according to the Akaike Information Criteria (AIC). To assess the sensitivity of our results to the detrending method, we also compute yield trends based on local regressions (spline and loess, see figure S3) and compare with solutions obtained without any detrending (see figure S4). We rely on normalized yield values by dividing yields or yield residuals by average or expected yields, respectively. Normalized yield residuals are computed following:

$$\bar{Y}_{t,i,j} = \frac{Y_{t,i,j} - \hat{Y}_{t,i,j}}{\hat{Y}_{t,i,j}} \quad (1)$$

where i indicates crop species (i.e. rice, cassava, maize, millet, sorghum, yams) and j indicates the area (at administrative level 1). $Y_{t,i,j}$ is the observed yield at year t, for species i, in the area j. $\hat{Y}_{t,i,j}$ is the expected yield at year t (estimated from the fitted yield trends), for species i, in the area j. $\bar{Y}_{t,i,j}$ is thus the normalized yield residual at year t, for species i, in the area j. Note that in the main document we present the results obtained from polynomial detrending only, the results obtained with the other two methods or for non-detrended yields being presented in the supplements.

2.2. Climate data

We compute four annual precipitation variables based on the CHIRPS precipitation dataset. CHIRPS merges satellite information on cloud temperatures and rain gauge data to estimate daily precipitation from 1981 to 2020 at a $0.05° \times 0.05°$ resolution. We only use grid cells where at least 1% of the areas are cultivated (see supplements section A for more detail on the method used) to compute the aggregated climate variables of interest at the administrative level 1. We consider (a) the yearly sum of precipitation based on the calendar year (mm^{-1}); (b) monsoon length, defined as the number of days between onset and retreat days. The onset monsoon day is defined as the day following a sequence of rainy events as in [45]. If the onset day is estimated to have occurred after the 1 of October, it is filled out as missing value by default. The retreat day is computed as the last day of a sequence of rainy days, as defined by Diaconescu *et al* [45]. When occurring after the end of the calendar year, it is replaced by the 31 of December. (c) Monsoon precipitation, defined as the sum of precipitation from onset to retreat; (d) the number of dry spells is calculated as the number of dry episodes of strictly more than seven consecutive calendar days between onset and retreat. A day is defined as dry when it receives less than 1 mm precipitation. These four precipitation variables are then spatially-averaged, over cultivated areas (with a threshold of 1%, see above), on each administrative area (level 1) for the time period corresponding to that of each SDR. We compute the average, interannual standard deviation and coefficient of variation for each climate time-series to obtain 12 climate indices in each considered area over the totality of West Africa. Note that these four precipitation variables tend to be strongly correlated (see figure S8). For example, the average occurrence of dry spells is positively correlated to precipitation variability and to the variability of monsoon length.

2.3. Statistical analysis of ratios of yield standard deviation

We estimate a ratio of standard deviation of yield for each alternative crop i and region j as:

$$\mathrm{SDR}_{i,j} = \frac{\mathrm{SD}_{\mathrm{rice},j}}{\mathrm{SD}_{i,j}} \quad (2)$$

where $\mathrm{SDR}_{i,j}$ is the ratio of rice normalized yield residual standard deviation ($\mathrm{SD}_{\mathrm{rice},j}$) to that of alternative crop i ($\mathrm{SD}_{i,j}$) in area j. We only compute ratios for yield times series composed of the exact same years for rice and the alternative crop considered (i.e. cassava or maize or millet or sorghum or yams). We obtain 261 SDR in total over West Africa. We then estimate the SDR confidence intervals based on (a) a bootstrapping method with 500 resamples per couple of crop species and areas (b) analytical estimations based on the Nakagawa *et al* (2015) formulas for estimating the variance of standard deviations ratios [46]. Note that both of the above-mentioned methods chosen to estimate SDR confidence intervals do not rely on Gaussian assumptions.

Next, we estimate SDR for each of the five alternative crops considered in our study over the totality of West Africa based on the following random-effect model:

$$\log\left(\mathrm{SDR}_{i,j}\right) = \mu_i + b_j + e_{ij} \quad (3)$$

where μ_i is the mean log of SDR for crop i (i.e. cassava, maize, millet, sorghum or yams) and b_j is a random regional effect and e_{ij} is the residual error. Model (3) is fitted to the data using the method REML implemented with the function lmer of the package lme4 of R [47]. During the fitting process, the values of SDRs are weighted by their variances relying on [46]. The fitted model is used to estimate the mean log variability ratio of rice to each alternative crop species. The estimated log ratios are then back transformed to estimate the variability ratios. The uncertainty is described by computing the 95% confidence interval. Rice to alternative crops yield variability are considered significantly different when the confidence intervals do not include one. To assess the role played by irrigation in offsetting the effects of monsoon variability, we identify areas where irrigated rice is predominant (i.e. superior to 80% of the total rice area) according to the SPAM2000 dataset [48] (see supplement section B for details). We then assess the impact of 12 climate indices on relative rice yield variability (i.e. the SDR) in the areas where rainfed systems (i.e. lowland and upland) are predominant. We also identified the areas where irrigation is predominant according to two other datasets, namely MIRCA 2000 and GAEZv3, and compared the results obtained with these two alternative datasets. This sensitivity analysis does not reveal any substantial difference (see supplements section B). When yield data for several alternative crops is available in one given area, several SDR can be computed (i.e. one per crop species). A random regional effect is included to relax the assumption that SDR common to one area are independent. We test possible effects of the climate indices on the 261 SDR altogether based on a model with all the alternative crops together and location fixed effects:

$$\log\left(\mathrm{SDR}_{i,j}\right) = \alpha + \beta x_j + b_j + e_{ij} \qquad (4)$$

where α and β are fixed parameters (common to all species), x_j is one of the 12 climate indices measured in area j, b_j is a random regional effect and e_{ij} is the residual error. Model (4) is fitted to the data using the method REML implemented with the function lmer of the package lme4 of R [47]. During the fitting process, the values of SDRs are weighted by their variances relying on [46].

We also build a model for each alternative crop i separately:

$$\log\left(\mathrm{SDR}_{i,j}\right) = \alpha_i + \beta_i\, x_j + e_{ij} \qquad (5)$$

where α_i and β_i are species-specific fixed parameters, x_j is one of the 12 climate indices measured in area j and e_{ij} is the residual error. The analysis is expanded by combining several factors (crop species and climate indices) with or without interaction. Note that, in all models, the data are weighted by their variances. Model's summaries are presented in tables S7, S8, S12 and S15.

3. Results

3.1. Inconsistent relative levels of rice yield variability

We estimate a yield variability difference between rice and each of the five alternative crops based on 261 SDR in 80 administrative level 1 areas over West Africa. We show that yields tend to be, on average over the entire region, more variable for rice than for the alternative crops (figure 1). In other words, rice yields tend to be less stable than that of the alternative crops. The mean effect sizes are 1.15 (p-value = 0.25), 1.14 (p-value = 0.16), 1.25 (p-value < 0.05), 1.23 (p-value < 0.05) and 1.23 (p-value < 0.1) for cassava, maize, millet, sorghum and yams respectively, when irrigated areas are included. When excluded, the ratios are only marginally changed (figure 1). While millet, sorghum and yams exhibit a significant stability advantage over rice, there are no significant differences between alternative crops. Hence, we cannot rank the five alternative crops in terms of their relative stability. This explains the pattern shown in figure 2 in which there is no evident systematic stability advantage for one given crop species over West Africa. Figure 2 also shows that 33% (when confidence intervals are estimated based on [46] or 28% via bootstrapping, see section 2) of the computed SDR are significantly higher than one (13 SDR for cassava, 19 for maize, 20 for millet, 17 for sorghum and 11 for yams). In these 45 regions (a few regions sometimes cumulate several SDR), rice yields are significantly more variable than the alternative crops. Fewer areas are characterized by rice yields significantly more stable than alternative crops with about 15% (or 9% via bootstrapping) of the SDR significantly lower than one. A significant higher yield stability for rice is estimated from [45] for Sud-Ouest (Burkina Faso), North Bank, West Coast (Gambia), Gao, Kayes, Mopti, Tombouctou (Mali), Abia, Benue, Ebonyi, Enugu, Gombe, Kaduna, Kwara, Sokoto (Nigeria), Tambacounda (Senegal), Centrale, Kara (Togo) (figure 3). There are also at least half of SDR regional confidence intervals which include one (about 52%, or 63% via bootstrapping). In these regions, rice yield interannual variability is not significantly different from that of the alternative crops. This reflects a large uncertainty in the estimated regional stability ratios due to the relatively small number of yield data available within each region.

For clarity, we divide the area into three broad climatic zones defined by average cumulated precipitation since 1980. The Guinean, Sudanian and Sahelian regions correspond to average total precipitation above 1200 mm, between 700 and 1200 mm

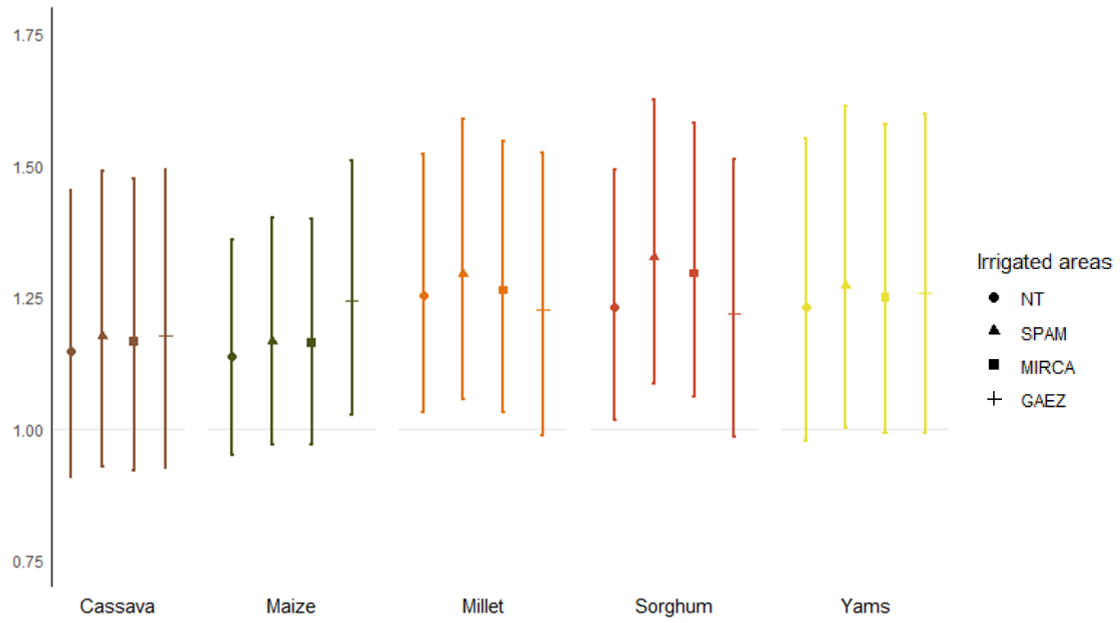

Figure 1. Mean effect sizes of rice yield variability compared to that of alternative crops over West Africa, measured without removing predominantly irrigated areas (i.e. 'NT') and measured after removing predominantly irrigated areas identified from SPAM2000 (i.e. 'SPAM'), MIRCA2000 (i.e. 'MIRCA') and GAEZ v3.0 (i.e. 'GAEZ'). Mean effect sizes are estimated from equation (3) for all regions of West Africa. Average yield variability of rice compared to alternative crops are represented in brown for cassava, in dark green for maize, in orange for millet, in red for sorghum and yellow for yams. 95% confidence intervals are estimated based on the standard error of each estimate. The grey horizontal bar delineates SDR equal to one (rice yield variability is equal to that of the other crop species). A ratio superior to one indicates that rice yield variability is higher than that of the other crop (i.e. rice is less stable than the alternative crop).

and below 700 mm, inspired by FAO definitions [49] (see figure S13). Note that there is no systematic pattern in any of these broad climatic areas (figure 2). Areas with SDR significantly superior (alt inferior) to one are distributed on a large range of latitudes across the West African region, i.e. they are not spatially aggregated. For example, the areas where rice yields are significantly more stable than the alternative crops are dispersed among these three broad regions. The most intensive rice production basins, characterized by large-scale irrigation schemes, high meccanization level and intensive use of inputs (e.g. Senegal River Valley and Office du Niger in Segou, Mali [12]) are not associated with SDR significantly lower than one. In other words, intensive rice yields are not more stable than alternative crops in these regions. In Segou, millet and sorghum SDR are 2.04 and 1.85, respectively. This means that the yields of alternative crops are nearly twice as stable than rice yields, on average in this region. In St Louis region, SDR are non-significant.

Noticeably, the areas where alternative crops have more stable yields than rice (i.e. SDR $>$ 1) tend to be located in the climatic regions where these crops are mostly cultivated. In the Sahelian and Sudanian regions, where cereals constitute the larger share of the production, sorghum, millet and maize yields tend to be more stable while in the Guinean region, which produces large quantities of tubers cassava and yams tend to exhibit more stable yields (figures 3 and S14).

3.2. Monsoon patterns explains a significant but small fraction of yield variability differences

We look for climatic determinants of SDR variability across crops and areas. We analyze the relationship between a series of 12 monsoon indices and SDR variability. These indices measure monsoon interannual variability both in terms of cumulated precipitation and dry spells events. We show that the coefficient of variation of monsoon precipitation (measuring the interannual variability of monsoon cumulated precipitation, see table S8) explains a small fraction of SDR variability across West Africa with the model including all alternative crops (model (4)). Monsoon precipitation coefficient of variation has a significant positive impact on SDR (p-value $= 8 \times 10^{-4}$, see table S8). This means that yield variability differences between rice and alternative crops tends to widen in the areas where the monsoon precipitation is more variable between-years: rice yields are the most variable relative to alternative crops in regions where the monsoon varies strongly between years. When considering all alternative crops together, other precipitation indices (such as dry spell events) do not significantly impact SDR. We also test model (5) independently for each alternative crop to rice ratio. Note that, because the areas considered in this study extend over a wide geographical area, the distribution of values for climate indices differ between alternative crop species (see figure 4). More complex models do not explain a higher fraction of total variability (see table S16).

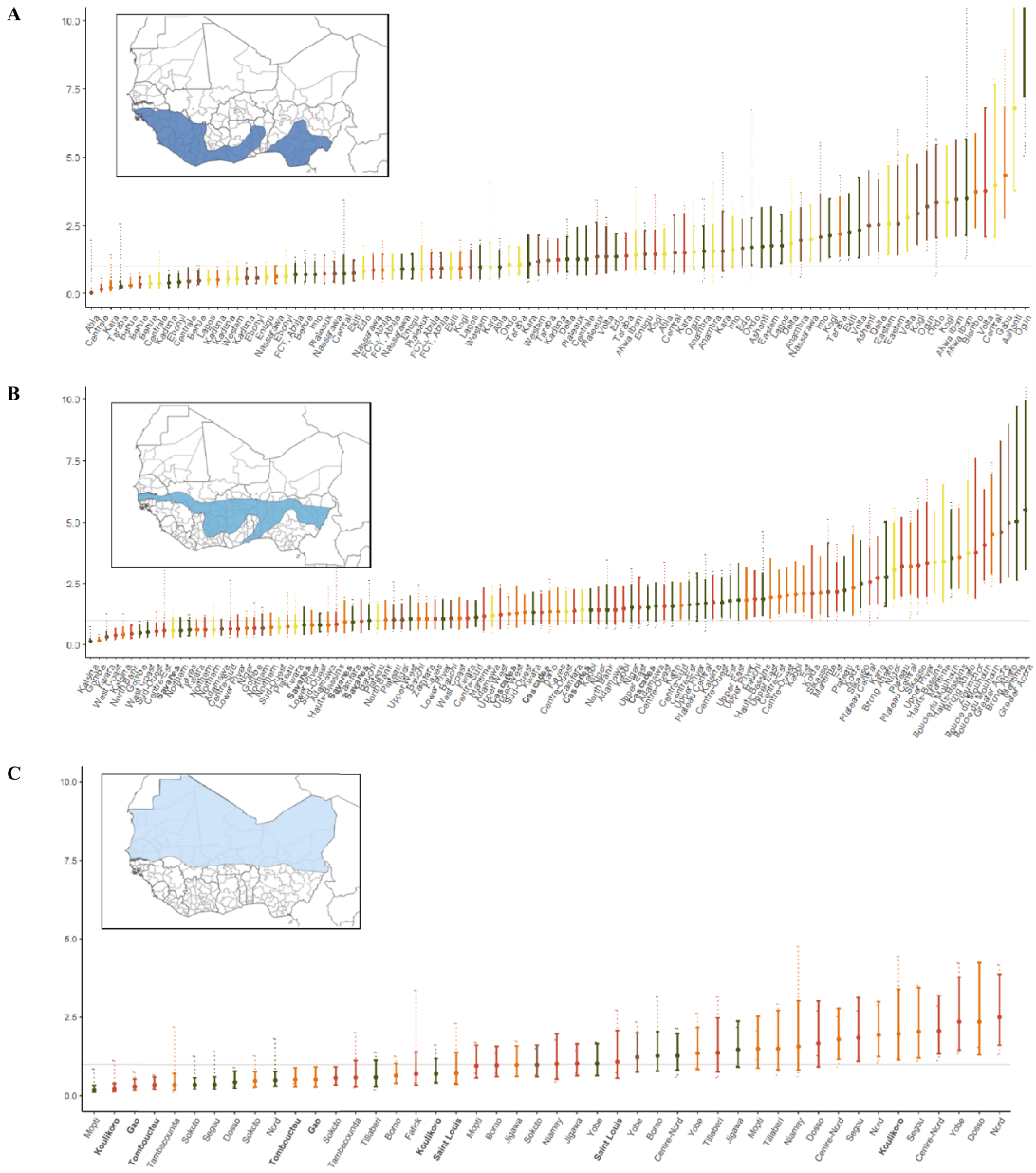

Figure 2. SDRs in the Guinean (A), Sudanian (B) and Sahelian (C) regions of West Africa. SDR are measured via equation (2). Results are presented per crop region combination for cassava (brown), maize (dark green), millet (orange), sorghum (orange) and yams (yellow). Note that one area where several crops of interest are cultivated is represented several times. Confidence intervals estimated via bootstrapping (dotted lines) and based on Nakagawa *et al* [46] analytical approximations (bold lines). The areas written in bold refer to the predominantly irrigated areas (i.e. >80% of the total area is irrigated), identified from SPAM2000. The points are organized by ascending order for each of the three broad climatic regions with the Guinean region delineated by cumulative annual rainfall superior to 1200 mm, the Sudanian region with cumulative rainfall between 700 and 1200 mm and the Sahelian below 700 mm (see figure S13). Areas are split into the three climatic regions, according to the geographical position of their barycentre. Grey horizontal bar delineates SD ratio equal to one (rice yield variability is equal to that of the other crop species). A ratio superior to one indicates that rice yield variability is higher than that of the other crop (i.e. rice is less stable than its alternative). A confidence interval including one indicates non-significant results.

For each rice-alternative crop comparison we select models with covariates that present smallest AIC and highest slope significance: monsoon precipitation coefficient of variation for cassava and yams, average and standard deviation of the number of dry spells occurring during the monsoon season for maize and sorghum respectively and monsoon length coefficient of variation for millet (figure 4). Note that these models have very similar performances (see table S15). Per-food crop selected models explain a relatively small share of the total variance, about 17% of the total variance for maize and millet, about 15% for cassava, about 10% for yams and less than 10% for sorghum. For yams, the slope is barely significant ($p = 0.0546$). The stability of cassava, maize and millet yields are significantly improved, relative to rice, in the areas where the monsoon is the most variable, either in terms of interannual variation of cumulated

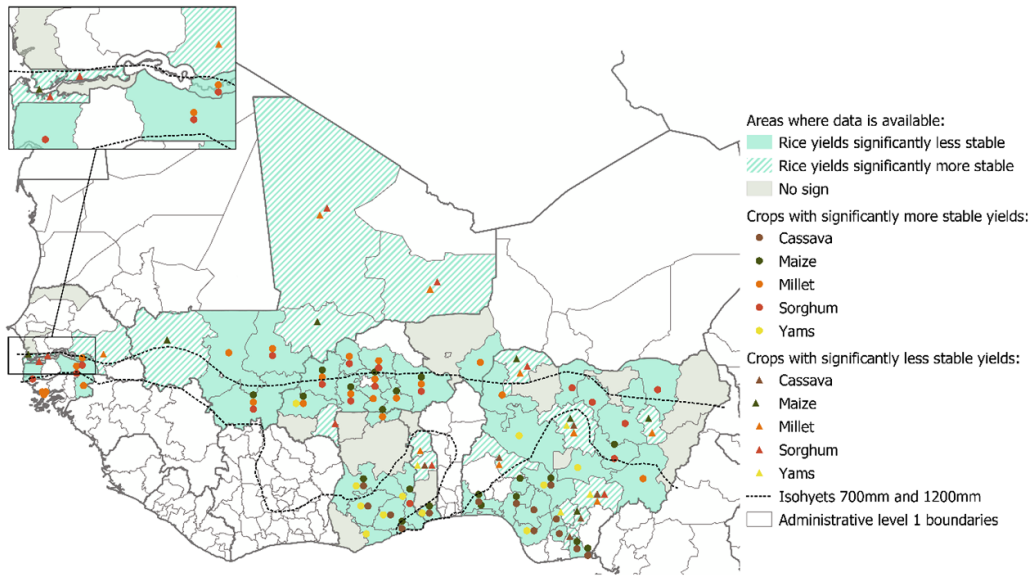

Figure 3. Spatial pattern of yield variability differences across west Africa. We present the spatial distribution of average ratios presented in figure 1. Full green areas delineate the regions where the yields of at least one alternative crop is significantly more stable than rice (i.e. SDR superior to one with a probability of 95%). Filled circles indicate the alternative crop species which are more stable than rice (brown for cassava, dark green for maize, orange for millet, red for sorghum and yellow for yams). Dashed green areas delineate the regions where rice yields are significantly more stable than any alternative crop species. Open triangles indicate which alternative crop species were compared to rice yields in these regions. When the SDR are not significantly different from one (either superior or inferior to one) the areas are colored in grey. A delimitation between three west African climatic regions are indicated with dashed black line (the isohyet 700 mm is the frontier between the Sahelian region at the North and the Sudanian region at the South and the isohyet 1200 mm is the frontier between the Sudanian region at the North and the Guinean region at the South). Spatial patterns of yield variability differences detailed per crops are presented in figure S14.

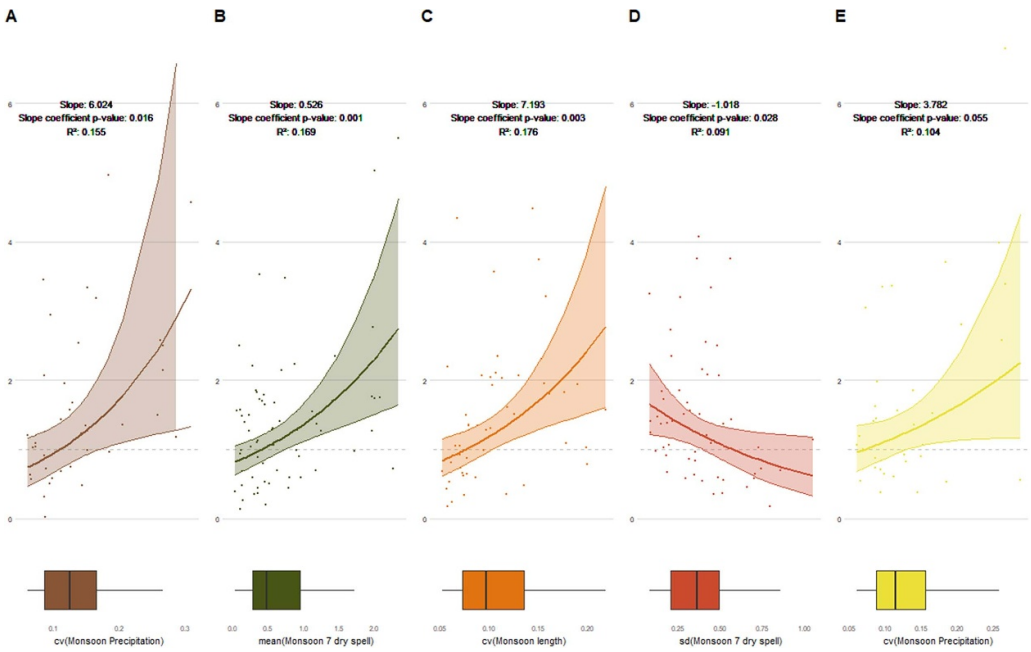

Figure 4. Relationship between climate indices, and the variability of rice yields compared to cassava (A), maize (B), millet (C), sorghum (D), and yams (E) yields variability, after removing areas where irrigated rice predominates (i.e. more than 80% of irrigated rice areas), identified from SPAM2000. Climatic indices are selected based on the AIC criteria. Selected best indices are the normalized variability of monsoon precipitation (CV (monsoon precipitation)) or of monsoon length (CV (monsoon length)), the average or standard deviation of dry spells occurrences mean (monsoon seven dry spell) and sd (monsoon seven dry spell). Median relationship (bold lines) and 95% confidence intervals are computed based on model (5). Boxplot represents the distribution of the observed values of corresponding climate indices. Note that the time-periods on which these relationships are computed may vary between crops. Grey horizontal dotted lines indicate SD ratios equal to one (rice yield variability is equal to that of another crop species) with values above one indicating higher variability of rice yields (or lower stability) in comparison to alternative crops. AIC criteria, slope value and significance and R2 are informed for each model independently.

precipitation, monsoon duration, or occurrence of 7 d dry spell events (p-value = 0.0159 for cassava, p-value = 6×10^{-4} for maize and $p = 0.0027$ for millet; see table S12). This impact of monsoon precipitation variability is the highest for rice yield variability relative to millet: for a 0.1 unit increase in relative variability of monsoon duration (i.e. the coefficient of variation of interannual monsoon duration), the yield variability difference is doubled.

4. Discussion and conclusion

Here, we show that, on average over the entirety of West Africa, alternative food crops yields tend to be more stable than rice. This stability difference is significant for millet and sorghum but not for maize, yams and cassava; these differences are somewhat affected by the inclusion or not of predominantly irrigated areas (figure 1). This pattern and its robustness are heterogeneous across latitude (figure 2). Fewer areas are characterized by rice yields significantly more stable than any alternative crop also cultivated in these administrative regions (figure 2). While the areas characterized by more stable rice yields are located in diverse climatic regions, the areas where alternative crops have more stable yields than rice tend to be located in the climatic regions where these crops are mostly cultivated (figures 2, 3 and S14). For example, sorghum and millet tend to have more stable yields than rice in the Sahelian and Soudanian areas, whereas cassava, tubers and yams yields tend to be more stable in the Guinean areas (figure 3). This remains true when excluding irrigated areas (figure 2). Monsoon precipitation variability and mean dry spell occurrence explain a small part of these yields' variability differences (figure 4).

The robustness of our results may suffer from two types of impediments. The 1st ones pertain to the quality and availability of the data and the second, to the statistical methods on which we base our analysis. This study relies on statistical data collected by the FAO according to national declarations. Hence, the consistency of the data depends on national survey or estimation methodologies (which sometimes includes indirect estimates from harvested or planted areas and corrections based on cropping conditions, com pers). Note though, that our initial data treatment and selection procedure addresses such possible heterogeneities (see section 2). We also compared our dataset with data from alternative sources to assess the consistency of our yield standard deviations estimates. We relied on simulated rice and maize from a global gridded yield dataset [50] and qualitatively compared the distribution of yield variability estimated from these data to (a) the ones estimated from our administrative level 1 data and (b) national estimates from USDA [51] and FAOSTAT [16] datasets (see figure S15). We find that the mean standard deviations measured from [50] are similar to the ones estimated with administrative level 1 data when grouped by countries. Yield variability distribution estimated from [50] noticeably tends to be narrower. This is perhaps due to the fact that [50] simulations are based on a secondary disaggregation from national and satellite data, i.e. the subnational variability is estimated. Yield standard deviations estimated from the aggregation of administrative level 1 time-series are similar to the ones estimated at national level with FAOSTAT and USDA yield data. Mean yield variability tends to be smaller at national level than at subnational level (see figure S15): yield interannual variability tends to decrease when the area of the geographical units studied increase, consistent with previous findings [52, 53]. Note that despite our efforts, we did not succeed in collecting data over the totality of West Africa (for data availability see figure S16, e.g. no data is available for the western part of the Guinean sub-region). Finally, SDRs are based on normalized detrended yields. Note that detrending or the detrending method chosen has little to no effect on our estimates since the time-span of yield time-series is rather short (see table S2 and figure S4). Climate indices are also associated with uncertainties in particular regarding observed precipitation datasets for observation-poor regions such as West Africa [54, 55]. Satellite retrievals are useful in that context, especially when corrected with *in situ* observations, but also present some challenges [56]. Different datasets can be used in order to characterize observational uncertainties [57], but there is no other available dataset at the high spatial and temporal resolution needed in this study.

The estimated yield variability differences we find here may be due to the fact that the areas encompassed by rice cultivation cover the entire West African sub-continent, i.e. there is an absence of geographical specialization for rice while on the other hand, traditional crops are cultivated in narrower agroecological areas. These differences may also be the result of a stronger adaptation to precipitation variability or more broadly, higher resistance of traditionally cropped species such as millet and sorghum in arid and semi-arid areas [25, 42] or tuber species such as yam and cassava in more humid areas [58]. Sorghum and millet farmers are, for example, known to develop strategies designed to cope with precipitation uncertainty [59]. A small negative impact of monsoon precipitation variability on the rice to sorghum SDR measured here, tends to support this hypothesis.

The width of administrative level 1 regions typically spans from 100 km in the Guinean region to 1000 km in the Sahelian region. The regions studied are composed of a large diversity of cropping systems

(e.g. different types of soil, hygrometric conditions, topography). West African rice cropping systems can be classified according to local hydrological and topographic conditions and water management practices. The most commonly found rice cropping systems are rainfed upland systems (about 43% of the total west African rice area in 1990–2000), followed by rainfed lowland and irrigated lowland systems (40% and 12%, respectively) [23]. The relative proportion of these systems varies spatially [23]. The effects of monsoon characteristics on the relative stability of rice to alternative crop species is significant but small (i.e. from about 9% to less than 18%). This means that the bulk fraction of the differences in stability between rice and alternative crop species is due to other factors. Topographic conditions (i.e. plateaus, hydromorphic slopes, valley bottom, floodplains, rivers, lagoons and deltas) cropping systems (in particular water management practices) and agronomic factors (e.g. fertilizers, pesticides or crop cultivars) certainly explain part of these differences. The effects of these factors may be direct (e.g. precipitation accumulation in valley bottom) or indirect (increased yield average and variance through fertilization). Note that results with and without areas with predominant irrigation reveal negligible to small effects on our conclusions. Geographically explicit information on the use of fertilizers and pesticides would obviously be needed to formally test the response of yield variability to increased input use. A unified database at the scale of West Africa would be very relevant to precisely evaluate the direct and indirect effects of agronomic practices on the relative stability of rice. Such a database may be built from, national and subnational statistics, field or farm scale surveys and quantitative expert elicitation.

Our results suggest that, at constant production systems, expanding West African rice production may impact the stability of the caloric supply mix produced in this region. This stability may be enhanced or hindered depending on regional stability and climatic specificities. For example, rice production may be enhanced in the areas where rice yield stability is significantly higher. Similarly, we have shown that alternative food crops may, for some species-regions combinations, improve the relative stability of the regional caloric supply, including when climatic conditions are less favorable. In terms of imports, the three biggest rice suppliers of West Africa (i.e. India, Thailand and Vietnam) tend to have a higher relative stability (see figure S17) which may give them a competitive advantage. But, the relationship between domestic production stability and the stability of exports is complex and perhaps nonlinear as exports are the result of public policies which depend on domestic or global economic shocks. Hence, our results advocate for an explicit account of yield stability in West African rice expansion scenarios and supply strategies.

Data availability statement

The data that support the findings of this study are available from the authors upon reasonable request.

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Conflict of interest

The authors declare no competing interests

Author contributions

T B A, P D and D M framed the study. M D built the yield database. J B computed the climatic indicators. M D analyzed the data with the support of T B A, D M, P D and J B. M D and T B A wrote an initial version of the manuscript. All co-authors discussed the results and wrote the final version of the paper.

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