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RESEARCH

Technology Use, Maize Productivity, and Weather in West Africa

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Abstract
This paper presents estimates of the association between maize yield and weather using survey data from Ghana, Mali and Nigeria, allowing for the possibility that farmers' choices about agricultural technology may themselves depend on weather. We find that the association between yield and weather varies substantially according to these choices. We then use our estimates to forecast the change in yield under alternative weather change scenarios. All of these scenarios envisage an increase in temperature, but some envisage a rise in rainfall while others envisage a fall. In almost all scenarios, there is a substantial fall in productivity. In the absence of adaptation measures, weather change is likely to substantially reduce farm income in all three countries.

Keywords Weather · Technology use · Maize productivity · West Africa

JEL Classification C13 · C31 · Q12 · Q54

MSC Codes 62P12 · 62P20

Introduction

Maize is among the most important agricultural commodities produced in Africa. It serves as the staple food crop for more than 300 million Africans, the majority of whom fall below the poverty line. The crop is widely grown across sub Saharan Africa, where it occupies 25 million hectares of land and provides 20% of the calorific intake of half of the population, as well as being an important source of carbohydrates, protein, fats, minerals and vitamins

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(Badu-Apraku and Fakorede 2017). In 2009, per capita consumption of maize in Africa was more than four times that of Asia (International Maize and Wheat Improvement Center 2014).

Maize farmers in West Africa are generally smallholders producing under rain-fed conditions; their yields are typically very much lower than the international mean, and they are very vulnerable to climate change (Cairns et al. 2013; Tesfaye et al. 2018). The relatively low yields in West Africa can be attributed to unfavorable climate, low soil fertility, inadequate crop protection, and low use of agricultural inputs. High temperature can slow the ability of crops to uptake and utilize carbon dioxide for photosynthesis, which in turn depresses leaf development, facilitates early leaf senescence during grain filling, prevents silk elongation and induces ovule abortion. It can also reduce maize productivity by inhibiting root functioning and stunting plant growth. Low rainfall can reduce maize productivity by inducing stomatal closure and facilitating the production of abscisic acid as a result of difficulties in transpiration. (See Badu-Apraku and Fakorede (2017) and Lobell et al. (2011) for discussions of these points.)

While the economies of Africa are not the main cause of climate change, they have already been affected by it. There is a serious risk that these effects will worsen as climatic stresses interact with non-climatic factors and increase the vulnerability of the agricultural sector, particularly in semiarid regions of the continent where exposure to climate change is high and adaptive capacity is low. Sub-Saharan Africa has been warming at an average rate of 0.5 °C per century, and available data indicate that Africa will warm faster than other parts of the world; under some scenarios, temperature in maize-growing regions are predicted to rise by over 2 °C by 2050. The forecast increase in temperature in West Africa over 2020–2100 is between 3 °C and 6 °C. Maize-producing areas are predicted to become warmer, and heat is expected to replace drought as the most important stressor affecting maize productivity. There is much more uncertainty about changes in rainfall in West Africa, but extreme rainfall events such as storms and floods are predicted to become more frequent and severe.[1] Climate change poses a serious food security risk for millions of smallholder farmers who cultivate maize in already fragile tropical agricultural systems in Africa. The maize plant is more sensitive to high temperature than other crops (Tesfaye et al. 2015); there is evidence that 50% of the variation in maize yields is caused by variations in climate (Cairns and Prasanna 2018), and it is estimated that climate change could reduce maize yields in semiarid areas by up to 10 million tons per annum. In West Africa, maize farmers are vulnerable to increases in temperature, especially when such increases are accompanied by a decline in rainfall.

There is therefore interest in agricultural technologies that could mitigate the effects of climate change on smallholder agriculture (Di Falco et al. 2011). The use of improved varieties of maize that are tolerant to heat and drought is a potentially important adaptation mechanism (Cairns et al. 2013), as is the increased use of inorganic fertilizer, although there is some concern that climate change will limit the effectiveness of fertilizer in increasing the yield of improved maize varieties (Tesfaye et al. 2015).

In this paper, we present estimates of the association of maize yield with temperature and rainfall using farm-level survey data from Ghana, Mali and Nigeria, allowing for the possibility that farmers' choices about agricultural technology may themselves depend on the weather. The first part of our analysis identifies the factors determining whether maize farmers use (i) inorganic fertilizer and (ii) improved hybrid maize varieties (IMV) instead of open-pollinated varieties; these factors include local temperature and rainfall, household

[1] See Cairns et al. (2013), Niang et al. (2014), and Tesfaye et al. (2018) for further information about these predictions.

characteristics, whether the farm has been contacted by an agricultural extension agent, and whether it is a member of a co-operative farming association. The second part of our analysis estimates the association of farm-level maize yields with temperature, rainfall, and household characteristics, allowing the size of these associations to vary according to whether the farm uses fertilizer and/or IMV. These analyses form the basis of forecasts of the change in maize yields under eight alternative scenarios. The forecasts pertain to changes in maize yields for (i) farms which currently operate in average climatic conditions, (ii) farms which currently operate in moderately mild conditions, and (iii) farms which currently operate in moderately severe conditions. The forecasts in case (i) are based on estimated yields on farms that currently experience the conditions that would be experienced by the average farms after climate change; the forecasts in cases (ii-iii) are constructed in an analogous way.

All eight scenarios involve a rise in temperature; some involve a fall in rainfall, but others involve a rise in rainfall. We find that under the most pessimistic scenarios (with a large rise in temperature and a fall in rainfall), there is likely to be a very large fall in maize yields, and even under most of the optimistic scenarios (with a moderate rise in temperature and a rise in rainfall), maize yields can still be expected to fall. The consequence of climate change for maize productivity in these three countries is therefore likely to be more serious than in the world as a whole, for which a moderate decline in productivity is forecast (Haile et al. 2017).[2]

The rest of the paper is organized as follows. Section "Literature Review" reviews research on the determinants of farmer choices and maize yields in Africa, Section "Our Data" describes the dataset, Section "Methods" presents our statistical method, Section "Results" presents the results, and Section "Conclusion" concludes.

Literature Review

The research presented in this paper involves modeling both farmers' choices about technology (whether to apply inorganic fertilizer and whether to use IMV instead of an open pollinated variety) and maize yields per hectare conditional on these choices. Most of the existing African literature presents evidence on either one or other of these things. Moreover, when models of maize yield do control for fertilizer or seed variety choice, these are typically included as linearly separable terms, whereas we allow the association of yield with temperature and rainfall to depend on the choices. In this section, we review the literature on farmers' choices and then the literature on maize yield.

Evidence on Fertilizer Use in Africa

Whether rainfall increases or reduces inorganic fertilizer use will depend on whether they are complements or substitutes in the maize production function. We could not find any literature explicitly addressing the question of complementarity versus substitutability, but a few African studies using farm-level data implicitly address the question by modelling fertilizer use conditional on rainfall. These studies employ a variety of different modeling

[2] We note that some studies (for example Coulibaly et al. 2020) classify Ghana and Nigeria as countries facing a low level of climate change risk relative to the average for Africa. Our results do not contradict this classification: it is possible that other countries in Africa face even higher levels of risk.

approaches. Some researchers just use a Probit model to estimate the association of rainfall (and other factors) with the probability of inorganic fertilizer use; other researchers model both the probability of fertilizer use and the quantity of fertilizer applied per hectare, if data on such quantities are reliable. Estimates of the association of quantity with rainfall are based either on a Tobit model or on a Hurdle model, although the latter requires a plausible exclusion restriction to identify the parameters in the quantity equation.

Several authors report a significant association of the probability of fertilizer use with rainfall, although the magnitude of the association is difficult to ascertain because these authors either (i) report only regression coefficients, not marginal effects, or (ii) fit a quadratic model and report separate marginal effects on rainfall and rainfall squared. We could not find any paper that reported informative marginal effects, i.e. plots of the probability of fertilizer use conditional on the level of rainfall. Nevertheless, Zerfu and Larson (2011) report a significantly positive association of the probability of fertilizer use with rainfall in Ethiopia, which suggests that inorganic fertilizer and rainfall are complements. This result is probably consistent with the Ethiopian study of Alem et al. (2010), who report a positive coefficient on rainfall and a negative coefficient on rainfall squared. Although Alem et al. do not discuss the distribution of their rainfall data, rainfall would have to be twice its mean level for the estimated association to be negative. Using Tanzanian data, Heisse and Morimoto (2023) also find a positive coefficient on rainfall and a negative coefficient on rainfall squared. These authors do report enough information about the rainfall distribution to ascertain that the association is significantly positive at all rainfall levels. This contrasts with the results of Ricker-Gilbert et al. (2011), who report a significantly negative association of the probability of fertilizer use with rainfall in Malawi.

Among these studies, only Alem et al. and Ricker-Gilbert et al. model the association of the quantity of fertilizer with the rainfall level: Alem et al. use a Tobit model while Ricker-Gilbert et al. report results from both a Tobit model and a Hurdle model. In all cases, there is a significantly positive association of quantity with rainfall. Ricker-Gilbert et al. do not discuss why rainfall might reduce the probability of fertilizer use but increase the quantity of fertilizer on those farms that do use it. Taking a different approach, Naseem and Kelly (1999) model country-level average levels of fertilizer use in an African panel dataset. They find a significantly positive association with rainfall, but rainfall is measured as an index that is not described in detail, so the magnitude of the association is again difficult to ascertain. Overall, there is more evidence for the complementarity of inorganic fertilizer use and rainfall than there is for substitutability, but this may not be a common feature of all countries and all parts of the production function.

Of the studies cited above, only Heisse and Morimoto (2023) include temperature as an explanatory variable, finding a significantly negative association of the probability of fertilizer use with temperature. The Probit function is linear for temperatures below 28 degrees centigrade, the reported marginal effect implying that each extra degree reduces the probability of fertilizer use by about four percentage points.

Evidence on Crop Variety Choice in Africa

Several studies have employed Probit or Multinomial Logit models to explore the association of climate variables with farmers' choices about crop varieties. However, these studies are difficult to compare directly with our own, because either (i) marginal effects are not reported, or (ii) the choice variable is defined differently, or (iii) the climate variables are defined differently. For example, Deressa et al. (2009) find that the probability of selecting new varieties in Ethiopia is positively associated with temperature and negatively associated with rainfall, but they do not report marginal effects. Mukarumbwa and Taruvinga (2023) find that the adoption of GM varieties of maize in South Africa is positively associated with rainfall; they do report marginal effects, but they do not report the units in which rainfall is measured. Using data from Ethiopia, Kenya, Tanzania and Uganda, Kom et al. (2022) find a negative association of the probability of selecting improved varieties with a recent decrease in rainfall and with high temperature, but both of these factors are defined as binary variables; the marginal effects are 0.38 and 0.14 respectively. Using data from Ethiopia and Tanzania, Shikuku et al. (2017) find that the probability of selecting new short-cycle crop varieties is positively associated with both delayed rainfall and erratic rainfall; the marginal effects are 0.45 and 0.24 respectively. Taken together, these results include both positive and negative associations of the selection of non-traditional varieties of crop with rainfall, and both positive and negative associations with temperature; they are therefore inconclusive.

Evidence on Maize Yield

A number of studies report estimated associations between maize yield and climate variables in Africa, using either farm-level or country-level data. These studies employ a variety of different methods and functional forms, so making direct comparisons between them is often difficult. Using farm-level data from Tanzania, Rowhani et al. (2011) fit a linear model of yield per hectare as a function of rainfall, temperature, rainfall squared and temperature squared. They find yield to be a positive but concave function of rainfall, and a negative and approximately linear function of temperature. Using these results, they report forecasts for (i) a 20% increase in rainfall and (ii) two degree increase in temperature. The increase in rainfall is forecast to increase the average yield by 5% while the increase in temperature is forecast to reduce the average yield by 20–30%. Using farm-level data from Morocco, Achli et al. (2022) fit a linear model of yield per hectare as a function of growing-season rainfall, estimating that a 1 mm increase in rainfall leads to an increase in yield of about 20 kg per hectare. Given the different units of measurement and the limited information about sample distributions in these two papers, it is not possible to make a direct comparison of the estimated sizes of the effects. Jayanthi et al. (2013) report a positive and significant association between maize yield and rainfall in Malawi, but rainfall is measured as a standardized index, which limits comparison with other studies. Both Epule and Bryant (2014) and Sounders et al. (2017) find no significant rainfall or temperature effects in Cameroon. Atiah et al. (2022) report a *negative* association between maize yield and rainfall in Ghana, with no significant association between yield and temperature. The absence of other covariates in their model means that these results may be fragile, although very high rainfall may reduce yields because of waterlogging.

Perhaps the most comprehensive study of maize yield and climate using country-level panel data is Blanc (2012). The dependent variable in this study is the log of mean yield in an individual country in Sub-Saharan Africa in a particular year, and the explanatory variables include mean rainfall, rainfall squared, temperature, temperature squared. The model also includes country fixed effects, so the results are to be interpreted as estimates of the association between inter-temporal variation in climate and inter-temporal variation in maize yield, averaged across all countries in Sub-Saharan Africa. This contrasts with the farm-level results, which are based on variation across space. The results include plots of predicted log yield at (i) mean temperature (24.3 degrees) and different rainfall levels, and (ii) mean rainfall (1,057 mm) and different temperatures. The association of log yield with temperature is approximately linear, with each 0.1°rise in temperature leading to a reduction in yield of about 7%. The rainfall plots are non-linear, the curve becoming flat when rainfall reaches about 1,000 mm. Below this level, each 10 mm increase in rainfall is associated with an increase in yield of about 4%. We emphasize these results because they are the most comprehensive in any African study that we are aware of, and we will report our initial results in a similar way.

Our Data

Data on maize yields and household characteristics for individual farms come from a 2013 survey of Ghanaian, Malian and Nigerian households. The survey was implemented by each country's national agricultural research system (NARS) with funding from the International Institute of Tropical Agriculture (IITA). The NARS researchers (including two of the authors of this paper) first consulted with government agencies responsible for agriculture in the three countries. They confirmed which regions of Ghana and Mali (and which states of Nigeria) have maize as a major food crop. The survey was designed to be representative of farms in these regions and states.[3] Two maize-producing districts were randomly selected from each region, ten maize-producing communities were randomly selected from each district, and ten maize-producing households in each community were randomly selected for interview. In order to ensure consistency in interpretation, a member of the questionnaire drafting team from IITA was involved in the training of enumerators (mostly NARS staff) in each country. Ghana, Mali and Nigeria are three out of the four main West African countries for adaptive trials and dissemination of maize technologies developed by the IITA (the other country is Benin).

The study produced responses relating to farm and household characteristics from 2,089 out of the 2,200 households selected, and data relating to maize yield were obtained from 1,872 households.[4] Across all farms, the logarithm of maize yield is approximately normally distributed. Measuring yield in kilograms per hectare, the mean of this distribution is 6.27, i.e. the geometric mean of the yield is equal to $\exp(6.27) \approx 530$ kg/ha. The Supplementary Materials include further descriptive statistics and provide information about the locations selected in each country. Two farm characteristics central to our analysis are whether inorganic fertilizer is applied to fields (which is the case on 70% of the farms) and whether the farm uses IMV (which is the case on 24% of the farms). Overall, 22% of farms use both fertilizer and IMV, 28% use neither, 48% use fertilizer only, and just 2% use IMV only. The two choices are highly correlated, since farms not using fertilizer are very unlikely to use IMV.

Temperature and rainfall data were obtained from the El Tiempo database (see http://www.tutiempo.net/clima). Our statistical model employs mean annual temperature and rainfall figures for 2013, which are available for 121 distinct geographical units across the three countries; these units are larger than communities but smaller than districts. Figures 1 and 2 illustrate the sample distributions of temperature in degrees centigrade and rainfall in millimetres. Almost all farms in our sample experience mean temperatures

[3] For the sake of brevity, we will refer to "Ghanaian, Malian and Nigerian maize yields," but this is more properly described as "yields in the major maize-producing regions of Ghana and Mali and states of Nigeria." It is farms in these regions and states that form the population from which we are sampling.

[4] The yield distribution is broadly consistent with the distribution in other data sources: see for example Ragasa et al. (2014).

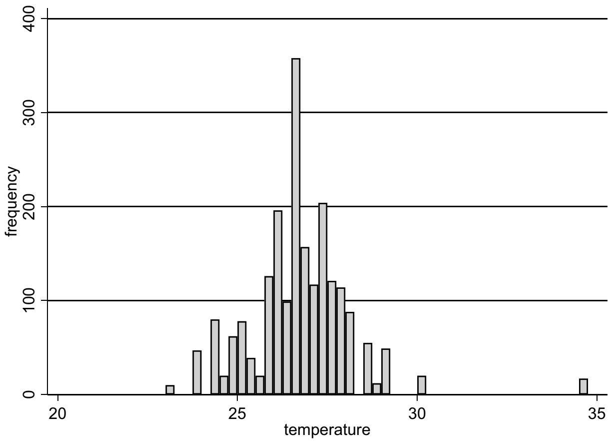


Fig. 1 Histogram for temperature

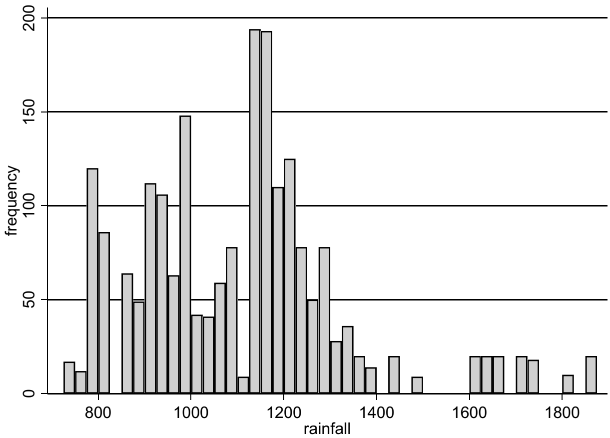


Fig. 2 Histogram for rainfall

between 24ºC and 28ºC and mean rainfall between 800 mm and 1,600 mm, although there are a few outliers.[5]

When modelling the association of the choice to use inorganic fertilizer (or IMV) with temperature and rainfall, it will be important to control for other farm and household characteristics that might be associated with these choices. First, inorganic fertilizer (or the use of IMV) could be a complement or a substitute for a number of other inputs in the production process, including soil quality, mechanisation, herbicides, and the number of people in the household. Previous studies have found significant associations of the probability of fertilizer use with soil quality (e.g. Marenya and Barrett 2009) and household size (e.g. Zerfu and Larson 2011). We include the following control variables; for our purposes, it is not necessary to make any assumptions about the shape of the production function, so we have no priors about the signs of the coefficients on these variables.[6]

[5] Omission of the outliers (observations below 24º, above 28º, below 800 mm, or above 1,600 mm) makes no substantial difference to our results.

[6] If these characteristics were completely uncorrelated with temperature and rainfall then it would not be necessary to control for them, but in fact the correlations are not exactly equal to zero. Descriptive statistics for all of the control variables appear in the Supplementary Materials.

- *soil* = 1 if the household head states the farm's soil quality is high; otherwise *soil* = 0. In a model of decision-making, perceived quality is likely to matter more than actual quality.
- *tractor* = 1 if a tractor is used on the farm; otherwise *tractor* = 0.
- *herbicide* = 1 if herbicide is used on the farm; otherwise *herbicide* = 0.
- *size* is the number of people in the household.

In principle, it is possible to use continuous variables measuring the intensity of the use of other factor inputs, for example, the number of hours of tractor use or litres of herbicide per hectare. However, farmers' recall about these quantities is likely to be less reliable than information about whether the inputs have been used at all.

Second, the technology choices of many maize farmers in Africa are constrained by the limited information available to them: see for example Mastenbroek et al. (2021). Information about fertilizers or IMV may be more readily available to households with young, male heads: younger individuals may be more open to new information, and males (who are in the majority) are likely to communicate more readily with each other than with females. Previous studies have found significant associations of the probability of fertilizer use with both age (e.g. Ricker-Gilbert et al. 2011) and gender (e.g. Alem et al. 2010). We include the following two control variables.

- *female* = 1 if the household head is female; otherwise *female* = 0.
- *age* is the age of the household head in years.

Finally, information may be more readily available when the household head has access to a co-operative association or to an extension programme. Co-operative associations are one of the main channels through which information about inorganic fertilizer and maize varieties is disseminated (Awunyo-Vitor et al. 2016), so association membership is likely to influence these technology choices. Antwi-Agyei and Stringer (2021) discuss of the role of West African agricultural extension in facilitating the adoption of new technologies, and Nkonya et al. (1997) discuss evidence on the association of IMV and fertilizer adoption with extension agent activity elsewhere in Africa. We include the following two control variables.

- *association* = 1 if the household head belongs to is a farmers' co-operative association, otherwise *association* = 0.
- *extension* = 1 if the household head has had contact with an agricultural extension agent; otherwise *extension* = 0.

Methods

Modelling technology selection

First, we fit a model of the probability of fertilizer and IMV use conditional on temperature ($temp_i$), rainfall ($prep_i$), contact with an extension agent ($extension_i$), membership of a co-operative association ($association_i$), and the six other household characteristics (x_i^k).[7] It is possible that there exists some unobserved heterogeneity across farms that is correlated with both fertilizer use and IMV use: in particular, farms not using fertilizer, for whatever reason, are very unlikely

[7] We also include a country fixed effect.

to use IMV. Therefore, in order to avoid biased parameter estimates, it is preferable to model the two choices simultaneously. This can be achieved using a Multinomial Probit model (MNP) or a Bivariate Probit model (BVP). In the MNP, there is a separate regression equation for three out of the four possible combinations (neither fertilizer nor IMV; fertilizer only; IMV only; both fertilizer and IMV): the probability of the fourth combination is implicit, because the four probabilities must sum to one. In the BVP, there two regression equations: one for the probability of fertilizer use and one for the probability of IMV use, from which the probabilities of the four different combinations can be inferred. With two equations instead of three, the BVP is more restrictive, but if the restrictions are valid then it is more efficient. The restrictions cannot be tested directly, because imposing them on the MNP produces a singular covariance matrix (Weeks and Orme 1999); for this reason, we fit both types of model to our data.[8] Fortunately, the two approaches produce very similar results. Given the similarity of the results and the relative parsimony of the BVP, we report the BVP results in the main text. The Supplementary Materials contain a comparison of the BVP and MNP results. The BVP takes the following form.

$$\begin{aligned} \mathrm{E}\left[fert_i^*\right] = {} & \alpha_0 + \alpha_1 \cdot temp_i + \alpha_2 \cdot prep_i + \alpha_3 \cdot temp_i \cdot prep_i + \alpha_4 \cdot \left(temp_i\right)^2 + \alpha_5 \cdot \left(prep_i\right)^2 \\ & + \alpha_6 \cdot extension_i + \alpha_7 \cdot association_i + \sum_{k=8}^{k=13} \alpha_k \cdot x_i^k \end{aligned}$$

$$fert_i^* = \mathrm{E}\left[fert_i^*\right] + \varepsilon_i ; fert_i = 1 \text{ if} fert_i^* > 0, \text{ otherwise } fert_i = 0 \tag{1a}$$

$$\begin{aligned} \mathrm{E}\left[imv_i^*\right] = {} & \beta_0 + \beta_1 \cdot temp_i + \beta_2 \cdot prep_i + \beta_3 \cdot temp_i \cdot prep_i + \beta_4 \cdot \left(temp_i\right)^2 + \beta_5 \cdot \left(prep_i\right)^2 \\ & + \beta_6 \cdot extension_i + \beta_7 \cdot association_i + \sum_{k=8}^{k=13} \beta_k \cdot x_i^k \end{aligned}$$

$$imv_i^* = \mathrm{E}\left[imv_i^*\right] + \eta_i ;\ imv_i = 1 \text{ if } imv_i^* > 0, \text{ otherwise } imv_i = 0 \tag{1b}$$

$$\left[\varepsilon_i, \eta_i\right] \sim \Phi[(0,0),(1,1),\rho]$$

Here, ε_i and η_i are error terms, Φ [.] is a multivariate normal distribution, and the α and β terms are parameters to be estimated. The coefficient ρ measures the degree of correlation of the two error terms, i.e. the extent to which unobserved heterogeneity in fertilizer preferences is associated with unobserved heterogeneity in IMV preferences. We allow the latent variables $fert_i^*$ and imv_i^* to be quadratic functions of temperature and rainfall, but otherwise the functions are linearly separable. Having fitted this model, we will be able to approximate the probability of each choice combination for different values of the explanatory variables. These joint probabilities are as follows.

$$\mathrm{P}_i^{11} = \Phi\left[\mathrm{E}\left[fert_i^*\right], \mathrm{E}\left[imv_i^*\right], \rho\right] : \text{ the farm uses both fertilizer and IMV} \tag{2a}$$

$$\mathrm{P}_i^{10} = \Phi\left[\mathrm{E}\left[fert_i^*\right], -\mathrm{E}\left[imv_i^*\right], \rho\right] : \text{ the farm uses fertilizer but not IMV} \tag{2b}$$

$$\mathrm{P}_i^{01} = \Phi\left[\mathrm{E}\left[fert_i^*\right], -\mathrm{E}\left[imv_i^*\right], \rho\right] : \text{ the farm uses IMV but not fertilizer} \tag{2c}$$

[8] Weeks and Orme (1999) propose a score test, but this proposal has not been peer reviewed and the method has not been widely adopted in the literature.

$$P_i^{00} = \Phi\left[-E\left[fert_i^*\right], -E\left[imv_i^*\right], \rho\right] \;:\; \text{the farm uses neither fertilizer nor IMV} \quad (2d)$$

We will be particularly interested in the association between each of the four estimated joint probabilities and the values of $temp_i$ and $prep_i$: these associations will underlie our predictions about the effects of climate change. We cannot capture any of the associations in a single coefficient, because the model is not linear. Instead, we will plot each estimated joint probability for a range of different values of $temp_i$ at the mean values of other covariates, and for a range of different values of $prep_i$ at the mean values of other covariates.

We will then construct predictions of the change in each of the joint probabilities under different climate change scenarios. These predictions are based on the assumption that farms experiencing a particular level of *temp* and *prep* in the future will eventually have the same probability of selecting a particular technology as do farms which currently experience that level of *temp* and *prep*. The scenarios are described in a later section of the paper: each scenario involves a certain change in mean temperature in West Africa ($\Delta temp$) and a certain change in mean rainfall ($\Delta prep$). These scenarios do not vary according to the current climate of a specific location, so we will consider three cases.

(i) A location which is currently at the 50th percentile of the temperature distribution in our sample ($temp_{50}$) and at the 50th percentile of the rainfall distribution ($prep_{50}$). We will refer to this location as "the 50th percentile case".
(ii) A location which is currently at the 25th percentile of the temperature distribution ($temp_{25}$) and at the 75th percentile of the rainfall distribution ($prep_{75}$). We will refer to this location – with an initially moderate climate – as "the 25th percentile case".
(iii) A location which is currently at the 75th percentile of the temperature distribution ($temp_{75}$) and at the 25th percentile of the rainfall distribution ($prep_{25}$). We will refer to this location – with an initially severe climate – as "the 75th percentile case".

In each case, we will consider the effect of the predicted changes in temperature and rainfall ($\Delta temp$ and $\Delta prep$) on the probability of fertilizer use and IMV use. Taking for example the 50th percentile case, we will first calculate the following quantities.

$$\begin{aligned} E\left[fert_{50}^*\right] &= \hat{\alpha}_0 + \hat{\alpha}_1 \cdot temp_{50} + \hat{\alpha}_2 \cdot prep_{50} + \hat{\alpha}_3 \cdot temp_{50} \cdot prep_{50} + \hat{\alpha}_4 \cdot \left(temp_{50}\right)^2 \\ &+ \hat{\alpha}_5 \cdot \left(prep_{50}\right)^2 + \hat{\alpha}_6 \cdot \overline{extension} + \hat{\alpha}_7 \cdot \overline{association} + \sum_{k=8}^{k=13} \hat{\alpha}_k \cdot \overline{x}^k \end{aligned} \quad (3a)$$

$$\begin{aligned} E\left[imv_{50}^*\right] &= \hat{\beta}_0 + \hat{\beta}_1 \cdot temp_{50} + \hat{\beta}_2 \cdot prep_{50} + \hat{\beta}_3 \cdot temp_{50} \cdot prep_{50} + \hat{\beta}_4 \cdot \left(temp_{50}\right)^2 \\ &+ \hat{\beta}_5 \cdot \left(prep_{50}\right)^2 + \hat{\beta}_6 \cdot \overline{extension} + \hat{\beta}_7 \cdot \overline{association} + \sum_{k=8}^{k=13} \hat{\beta}_k \cdot \overline{x}^k \end{aligned} \quad (3b)$$

$$\begin{aligned} E\left[fert_{50}^{\Delta}\right] &= \hat{\alpha}_0 + \hat{\alpha}_1 \cdot temp_{50}^{\Delta} + \hat{\alpha}_2 \cdot prep_{50}^{\Delta} + \hat{\alpha}_3 \cdot temp_{50}^{\Delta} \cdot prep_{50}^{\Delta} + \hat{\alpha}_4 \cdot \left(temp_{50}^{\Delta}\right)^2 \\ &+ \hat{\alpha}_5 \cdot \left(prep_{50}^{\Delta}\right)^2 + \hat{\alpha}_6 \cdot \overline{extension} + \hat{\alpha}_7 \cdot \overline{association} + \sum_{k=8}^{k=13} \hat{\alpha}_k \cdot \overline{x}^k \end{aligned} \quad (3c)$$

$$\begin{aligned} E\left[imv_{50}^{\Delta}\right] &= \hat{\beta}_0 + \hat{\beta}_1 \cdot temp_{50}^{\Delta} + \hat{\beta}_2 \cdot prep_{50}^{\Delta} + \hat{\beta}_3 \cdot temp_{50}^{\Delta} \cdot prep_{50}^{\Delta} + \hat{\beta}_4 \cdot \left(temp_{50}^{\Delta}\right)^2 \\ &+ \hat{\beta}_5 \cdot \left(prep_{50}^{\Delta}\right)^2 + \hat{\beta}_6 \cdot \overline{extension} + \hat{\beta}_7 \cdot \overline{association} + \sum_{k=8}^{k=13} \hat{\beta}_k \cdot \overline{x}^k \end{aligned} \quad (3d)$$

Here, $temp_{50}^{\Delta} = temp_{50} + \Delta temp$, $prep_{50}^{\Delta} = prep_{50} + \Delta prep$, hats denote fitted parameter values, and bars denote mean sample values. These four equations indicate (i) the current expected latent values of *fert* and *imv* for a farm at the 50th percentile of the temperature and rainfall distributions with the mean values of all other explanatory variables, and (ii) the expected latent values for such a farm after the predicted changes in temperature and rainfall. We will then substitute these latent values into the formulae in Eqs. (2a-2d). Estimated current probabilities of each outcome for farms at the 50th percentile can be produced by substituting $\mathrm{E}\left[fert_{50}^{*}\right]$ for $\mathrm{E}\left[fert_{i}^{*}\right]$ and $\mathrm{E}\left[imv_{50}^{*}\right]$ for $\mathrm{E}\left[imv_{i}^{*}\right]$. These probabilities are denoted P_{50}^{11},P_{50}^{10}, P_{50}^{01}, and P_{50}^{00}. Estimated probabilities of each outcome for these farms after climate change can be produced by substituting $\mathrm{E}\left[fert_{50}^{\Delta}\right]$ for $\mathrm{E}\left[fert_{i}^{*}\right]$ and $\mathrm{E}\left[imv_{50}^{\Delta}\right]$ for $\mathrm{E}\left[imv_{i}^{*}\right]$. These probabilities are denoted $\mathrm{P}_{50}^{\Delta 11}$, $\mathrm{P}_{50}^{\Delta 10}$, $\mathrm{P}_{50}^{\Delta 01}$, and $\mathrm{P}_{50}^{\Delta 00}$. The estimated changes in the probability of each outcome are $\mathrm{P}_{50}^{\Delta 11} - \mathrm{P}_{50}^{11}$, $\mathrm{P}_{50}^{\Delta 10} - \mathrm{P}_{50}^{10}$, $\mathrm{P}_{50}^{\Delta 01} - \mathrm{P}_{50}^{01}$, and $\mathrm{P}_{50}^{\Delta 00} - \mathrm{P}_{50}^{00}$. We will also calculate these quantities for the 25th percentile case and the 75th percentile case. It turns out that the change in the probability of using IMV but not maize ($\mathrm{P}_{c}^{\Delta 01} - \mathrm{P}_{c}^{01}$) is almost zero in all cases and all scenarios, so we will not report the change in this probability.

Modelling Maize Yield

The second stage in our modelling exercise is to fit a model of farm *i*'s maize yield ($yield_i$) conditional on temperature ($temp_i$), rainfall ($prep_i$) and the six other household characteristics (x_i^k). We will allow for the possibility that the relationship between yield and temperature / rainfall depends on the farmer's technology choice. (To our knowledge, there is no theory that predicts which technology choices are likely to lead to a greater sensitivity of yield to temperature or rainfall. However, in the absence of clear evidence that there is no such variation in sensitivity, it is prudent to accommodate this possibility. Not doing so could entail invalid parameter restrictions and biased parameter estimates.) The model is of the following form.

$$\log\left(yield_i\right) = \varphi_0^c + \varphi_1^c \cdot temp_i + \varphi_2^c \cdot prep_i + \varphi_3^c \cdot temp_i \cdot prep_i + \varphi_4^c \cdot \left(temp_i\right)^2 + \varphi_5^c \cdot \left(prep_i\right)^2 + \sum_{k=6}^{k=11} \varphi_k^c \cdot x_i^k + \upsilon_i \tag{4}$$

Here, υ_i is an error term and the φ^c terms are parameters to be estimated. It is possible that the relationship between the yield and the explanatory variables depends on whether the farm uses fertilizer or whether it uses IMV, so Eq. (4) will be fitted to three sub-samples, the superscript c distinguishing between the three cases. The sub-samples are as follows: observations for which $fert_i = 1$ and $imv_i = 1$ (i.e. $c = 11$), observations for which $fert_i = 1$ and $imv_i = 0$ (i.e. $c = 10$), and observations for which $fert_i = 0$ and $imv_i = 0$ (i.e. $c = 00$). Note that there are too few cases with $fert_i = 0$ and $imv_i = 1$ to fit the model to this sample. A priori, it is possible that technology choice is endogenous to maize yield, but we can test this conjecture by fitting the following model to each of the three samples.[9]

[9] If we were concerned only with modelling log(*yield*), then it would be preferable to use actual soil quality rather than perceived soil quality as a control variable. However, testing the exogeneity of decisions about fertilizer and IMV to maize yields requires that the control variables x^k in Eqs. (4–5) are the same as those in Eqs. (1a–1b). In principle, it is possible to include measures of both actual and perceived quality in all of the equations, but there would be a high level of multicollinearity between the two different measures. Equations (4–5) include perceived quality, acknowledging that this might entail some measurement error.

$$\log\left(yield_i\right) = \varphi_0^c + \varphi_1^c \cdot temp_i + \varphi_2^c \cdot prep_i + \varphi_3^c \cdot temp_i \cdot prep_i + \varphi_4^c \cdot \left(temp_i\right)^2 + \varphi_5^c \cdot \left(prep_i\right)^2 + \sum_{k=6}^{k=11} \varphi_k^c \cdot x_i^k + \lambda^c \cdot mills_i^c + \upsilon_i \tag{5}$$

Here, $mills_i^c$ is an Inverse Mills Ratio implicit in the estimates of the parameters in Eqs. (1a–1b): $mills_i^{11} = \mathrm{dP}_i^{11}/\mathrm{P}_i^{11}$, $mills_i^{10} = \mathrm{dP}_i^{10}/\mathrm{P}_i^{10}$, and $mills_i^{00} = \mathrm{dP}_i^{00}/\mathrm{P}_i^{00}$. If the parameter λ^c is significantly different from zero, then the null hypothesis of exogeneity can be rejected and estimates of the φ^c parameters should be based on Eq. (5). Otherwise, Eq. (4) is to be preferred, as the assumption of exogenous sample selection entails greater statistical efficiency.

Note that Eq. (5) is identified by the exclusion of $extension_i$ and $association_i$. In other words, we assume that together with the explanatory variables in Eq. (4) – which include, for example, herbicide and tractor use – fertilizer and IMV use fully capture the ways in which contact with an extension agent or membership of a farmers' association influences yield. The exclusion restriction would be invalid if there existed some other farm input that we could not measure, that affected yield, and that was influenced by contact with an extension agent or membership of a co-operative association. While we cannot entirely rule out such a possibility, we note that when we do fit Eqs. (4–5) to the data, none of the individual coefficients on the x^k variables is significantly different from zero: see Table S4 in the Supplementary Materials. This is because the different farm characteristics that we use as control variables are highly correlated with each other. (We have no need to test any hypotheses about the coefficients on the control variables, so the multicollinearity does not present a problem.) If there did exist an additional, unobservable input, the exclusion restrictions would only seriously bias our estimates if this input exhibited a level of correlation with the observable inputs that was much lower than the correlations between the observables. It is difficult to imagine what such an input would be.

Having estimated the φ^c parameters, we can then illustrate the association between yield and climate by plotting E[log($yield_i$)] for a range of different values of $temp_i$ at the mean values of other covariates, and for a range of different values of $prep_i$ at the mean values of other covariates. We will do this for each of the three technology combinations.

We will then estimate the change in expected yield under the eight different climate change scenarios, taking technology choice as given. In the 50th percentile case, the estimated change is equal to $\mathrm{E}\left[\log\left(yield_{50}^{\Delta c}\right)\right] - \mathrm{E}\left[\log\left(yield_{50}^{c}\right)\right]$, where the two expected values are calculated as follows.

$$\mathrm{E}\left[\log\left(yield_{50}^c\right)\right] = \hat{\varphi}_0^c + \hat{\varphi}_1^c \cdot temp_{50} + \hat{\varphi}_2^c \cdot prep_{50} + \hat{\varphi}_3^c \cdot temp_{50} \cdot prep_{50} + \hat{\varphi}_4^c \cdot \left(temp_{50}\right)^2 + \hat{\varphi}_5^c \cdot \left(prep_{50}\right)^2 + \sum_{k=6}^{k=11} \hat{\varphi}_k^c \cdot \overline{x}^k \tag{6a}$$

$$\mathrm{E}\left[\log\left(yield_{50}^{\Delta c}\right)\right] = \hat{\varphi}_0^c + \hat{\varphi}_1^c \cdot temp_{50}^{\Delta} + \hat{\varphi}_2^c \cdot prep_{50}^{\Delta} + \hat{\varphi}_3^c \cdot temp_{50}^{\Delta} \cdot prep_{50}^{\Delta} + \hat{\varphi}_4^c \cdot \left(temp_{50}^{\Delta}\right)^2 + \hat{\varphi}_5^c \cdot \left(prep_{50}^{\Delta}\right)^2 + \sum_{k=6}^{k=11} \hat{\varphi}_k^c \cdot \overline{x}^k \tag{6b}$$

We will also calculate these quantities for the 25th percentile and 75th percentile cases.

Finally, we will estimate the expected change in yield allowing for changes in technology choice. The expected value of log($yield$) after climate change is calculated as the sum over the three technology combinations of the probability of that combination times the expected yield for that combination. In the 50th percentile case, we use the following equation.

$$\mathrm{E}\left[\log\left(yield_{50}^{\Delta}\right)\right] = \mathrm{P}_{50}^{\Delta 11}\cdot\mathrm{E}\left[\log\left(yield_{50}^{\Delta 11}\right)\right] + \mathrm{P}_{50}^{\Delta 10}\cdot\mathrm{E}\left[\log\left(yield_{50}^{\Delta 10}\right)\right] + \mathrm{P}_{50}^{\Delta 00}\cdot\mathrm{E}\left[\log\left(yield_{50}^{\Delta 00}\right)\right] \tag{7a}$$

This quantity is compared to a corresponding baseline value, calculated as follows.

$$\mathrm{E}\left[\log\left(yield_{50}\right)\right] = \mathrm{P}_{50}^{11}\cdot\mathrm{E}\left[\log\left(yield_{50}^{11}\right)\right] + \mathrm{P}_{50}^{10}\cdot\mathrm{E}\left[\log\left(yield_{50}^{10}\right)\right] + \mathrm{P}_{50}^{00}\cdot\mathrm{E}\left[\log\left(yield_{50}^{00}\right)\right] \tag{7b}$$

Note that we have no expected yield estimates for the rare case of $fert_i = 0$ and $imv_i = 1$, and our comparison needs to make an adjustment for this. We scale both of the quantities by the probability of not being in the rare case and calculate the expected change in yield using the following formula.

$$\left(\frac{\mathrm{E}\left[\log\left(yield_{50}^{\Delta}\right)\right]}{1-\mathrm{P}_{50}^{\Delta 01}}\right) - \left(\frac{\mathrm{E}\left[\log\left(yield_{50}\right)\right]}{1-\mathrm{P}_{50}^{01}}\right)$$

This formula is also applied to the 25th percentile case and to the 75th percentile case.[10]

When reporting the estimates described above, a choice needs to be made about the way in which standard errors and confidence intervals are calculated. If our focus were on hypotheses about the association of maize yield with household characteristics, then it would be appropriate to allow for the clustering of errors at the levels of the household sample design, i.e. the community, district and region. However, our focus is on the association of maize yield with temperature and rainfall, which are reported at a different level of geographical aggregation (larger than a community but smaller than a district). The calculation of standard errors will therefore allow for clustering at this alternative level of aggregation.

Results[11]

Results for Technology Selection

Estimated coefficients and standard errors in the Bivariate Probit model (Eqs. (1a–1b)) appear in the Supplementary Materials. We are not directly interested in the association of technology choice with the explanatory variables other than *temp* and *prep*, but we note for future reference that the individual coefficients on both *association* and *extension* are significantly different from zero at the one percent level in the *imv* equation as is the coefficient on *association* in the *fert* equation. The four coefficients are jointly significant at the one percent level, as are the two *association* coefficients; the two *extension* coefficients are jointly significant at the five percent level.[12]

Our predictions about the changes in fertilizer and IMV use under the different climate change scenarios depend on our estimates of the effects of temperature and rainfall in

10 The standard errors for these estimates are computed using a bootstrap. However, we note as a caveat that since the estimates are based on separate regressions for technology selection and yield, the size of the confidence intervals may still have been underestimated (see Angrist and Pischke 2009).

11 All estimates were produced using Stata 15.

12 All four estimated coefficients are positive, indicating that both membership of a farmers' association and contact with an extension agent increase the probability of both inorganic fertilizer use and IMV use.

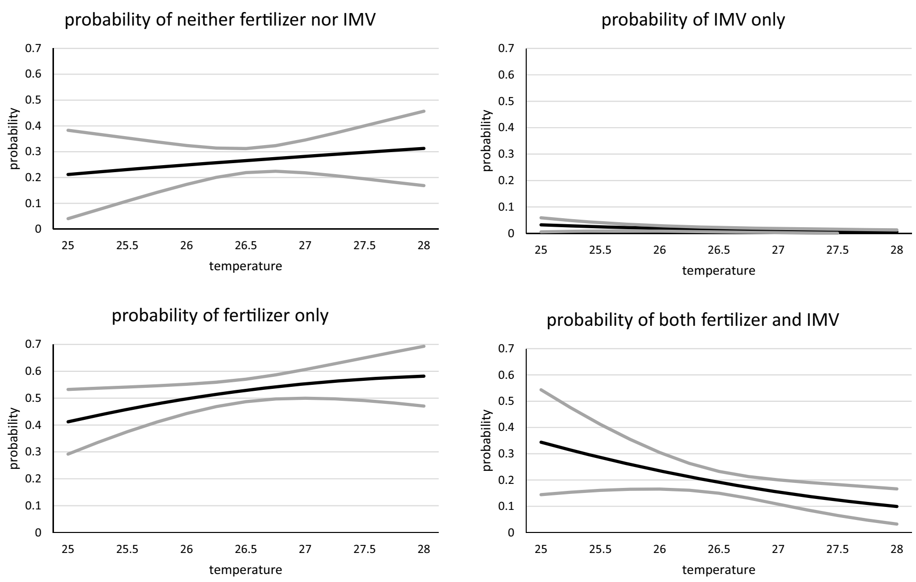


Fig. 3 The estimated association of technology choice with temperature (with 95 percent confidence intervals)

Eqs. (1a–1b). However, these relationships are not linear: the effect of a one degree or one percent change in temperature on these probabilities depends on the initial temperature; the same is true of rainfall. In order to provide an overview of the association of the probability of fertilizer and IMV use with temperature and rainfall, we will use charts that plot these probabilities against observed temperature and rainfall levels: these charts appear in Figs. 3 and 4.

Figures 3 and 4 show the estimated probability of each technology choice at different temperature and rainfall levels; in all cases, the estimates are for farms with mean values of all other characteristics. The 95% confidence intervals are constructed by applying the Delta Method to the standard errors on individual coefficients in Eqs. (1a–1b). It can be seen that the probability of using neither inorganic fertilizer nor IMV is positively associated with temperature but has no association with rainfall, while the probability of using both inorganic fertilizer and IMV is negatively associated with both temperature and rainfall. The probability of using just inorganic fertilizer is positively associated with both temperature and rainfall. The probability of using IMV only is always very low. The positive and negative associations are all significant at the five percent level but of moderate size. The largest associations are for rainfall and the probability of using inorganic fertilizer only (or using both inorganic fertilizer and IMV), but even in these cases, the change in probability between 800 mm and 1,650 mm is only about 30 percentage points.

The positive associations with using fertilizer only and the negative associations with using both inorganic fertilizer and IMV are of very similar magnitude. In other words, there is no strong association of inorganic fertilizer use with temperature or rainfall. By contrast, the probability of using IMV declines in both temperature and rainfall. Assuming that maize yields are (thought to be) higher at lower temperatures and higher rainfall levels, our results suggest that in the maize production function, IMV is a complement for low temperature but a substitute for high rainfall. This result accords with some existing studies but not with others: as noted in the literature review, there is evidence for a positive association of IMV

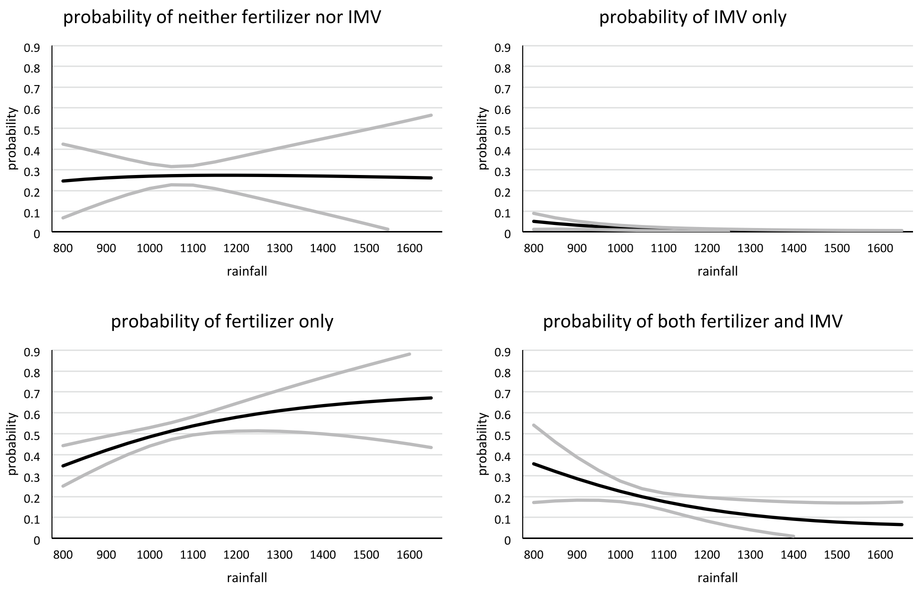


Fig. 4 The estimated association of technology choice with rainfall (with 95 percent confidence intervals)

use with temperature and/or rainfall in some studies and evidence for a negative association in others. We find no evidence for strong complementarity or substitutability with respect to inorganic fertilizer, which is not entirely surprising, given the contrasting results for fertilizer in the existing literature. There is a need for more research into the shape of the maize production function in Africa, and specifically into the conditions under which different inputs are treated as complements or substitutes. Taken together, the results of this study and of previous studies suggest that these conditions vary from one part of Africa to another.

We now turn to the climate change simulations. These simulations are based on eight alternative scenarios, which are listed in Table 1. All of the scenarios involve a rise in mean temperature, but scenarios 1–3 involve a rise in mean rainfall while scenarios 4–8 involve a fall in mean rainfall. Scenarios 2–3 are projections for West Africa in 2035 by the Intergovernmental Panel for Climate Change (IPCC), as discussed in Christensen (2013); scenario 1 is slightly more optimistic than these projections, with a smaller rise in temperature and a larger rise in rainfall. Scenario 4 is also an IPCC projection, with mean temperature rising by 1.5ºC and mean rainfall falling by four percent. Scenarios 5–8 represent outcomes that are either more or less extreme than this. Scenario 5 is the most pessimistic of all, with mean temperature rising by 2.0ºC and mean rainfall falling by ten percent, and scenario 4 is the next most pessimistic.[13] Figure 5 shows the predicted changes in the probability of using both inorganic fertilizer and IMV, neither inorganic fertilizer nor IMV, and fertilizer only. There are predictions for all eight scenarios in the 25th, 50th, and 75th percentile cases. In each case, the figures show the 95 percent confidence interval, which is constructed using the Delta Method.[14] Since the probability of using IMV only is always close to zero, we do not report results for this outcome.

[13] This scenario is still within the range of some climate change predictions: see for example Fitzpatrick et al. (2020).

[14] These calculations impose the restriction $\rho = 0$, but note that the correlation between the predicted probabilities with and without this restriction is greater than 0.98 in all cases.

Table 1 The different climate change scenarios

Scenario	Change in temperature	Change in rainfall
1	+0.5ºC	+15 percent
2	+0.7ºC	+8 percent
3	+0.9ºC	+1 percent
4	+1.5ºC	– 4 percent
5	+2.0ºC	– 10 percent
6	+0.5ºC	– 10 percent
7	+0.7ºC	– 4 percent
8	+0.9ºC	– 10 percent

The probability of using both inorganic fertilizer and IMV is a negative function of both temperature and rainfall. Moreover, the probability of using neither (or fertilizer only) is a non-negative function. It is therefore unsurprising that in all cases, scenarios 1–3, which involve rises in both temperature and rainfall, entail a decrease in the probability of using both inorganic fertilizer and IMV and an increase in the probability of the other outcomes. Across the three scenarios, the decreases are between five and seven percentage points (an effect which is significant at the five percent level), but do not vary substantially across the 25th percentile, 50th percentile and 75th percentile cases. Scenarios 4–8 involve a rise in temperature and a fall in rainfall, which have opposite effects on the probability of each outcome. However, except in scenario 6 (which has the largest rainfall change relative to temperature change), the temperature effects dominate, so there is still a fall in the probability of using both inorganic fertilizer and IMV. In scenario 6, the predicted changes are all very close to (and insignificantly different from) zero.

The most important qualitative result in this section is as follows. IMV use appears to be regarded as a complement to low temperature and a substitute for high rainfall in the maize production function, and almost all farms using IMV also use inorganic fertilizer. All climate scenarios involve a rise in temperature and therefore a fall in the predicted proportion of farms using IMV; rainfall effects are generally too small for it to matter whether rainfall rises or falls in a particular scenario. In this sense, climate change is predicted to lead to a greater frequency of traditional farming practices with just open-pollinated varieties of maize.

Results for Maize Yield

The first choice to make in modelling maize yield is between Eq. (4), with exogenous sample selection, and Eq. (5), with endogenous sample selection. When we fit Eq. (5) to the data, we find that none of the λ^c coefficients is significantly different from zero at the ten percent level.[15] The significance of the *association* and *extension* coefficients in Eqs. (1a–1b) means that Eq. (5) is identified, and the null hypothesis that sample selection is exogenous cannot be rejected. Further results in this section are based on estimates using Eq. (4).

The association of maize yield with temperature and rainfall is illustrated in Figs. 6 and 7. Figure 6 shows that yield is negatively associated with temperature on farms using both inorganic fertilizer and IMV, on farms using just inorganic fertilizer, and on farms using neither. (The

[15] This is the case whether or not we use a Bonferroni correction to correct for multiple hypothesis testing.

sample size for farms using only IMV is too small to produce a reliable estimate.) The effect is strongest on farms using neither inorganic fertilizer nor IMV. On such farms, the difference between log(*yield*) at 25º and log(*yield*) at 28º is about 1.7, i.e. the yield on the hottest farms is only about 20% as large as the yield on the coolest ones.[16] The effect is weakest on farms using inorganic fertilizer only, where the difference between log(*yield*) at 25º and log(*yield*) at 28º is about 0.5, i.e. the yield on the hottest farms is about 60% as large as the yield on the coolest ones.[17] Figure 7 shows that yield is positively associated with rainfall on farms using inorganic fertilizer only, but this is the only case with a significant positive association. On these farms, the difference between log(*yield*) at 1,650 mm and log(*yield*) at 800 mm is about 0.7, i.e. the yield on the driest farms is about 50% as large as the yield on the wettest ones.[18]

Comparing our results with those in the paper where African temperature and rainfall effects on maize yield are most comprehensively reported (Blanc 2012), our largest temperature effect (when neither inorganic fertilizer nor IMV is used) is roughly equal to the effect for all farms reported by Blanc. Blanc's results imply that a 0.1º rise in temperature leads to fall in yield of about 7%, while our results imply that the figure is around 6%. Our largest rainfall effect (when only inorganic fertilizer is used) is roughly equal to the effect for all farms reported by Blanc, although Blanc's function is more convex. This is despite the fact that Blanc's results are based on time-series variation and ours are based on cross-sectional variation. Comparison with the other papers discussed in the literature review is restricted by the limited detail in the results reported in these papers.

We now turn to the climate change simulations for log(*yield*) using Eqs. (6a–6b). Simulations for farms with different technology choices appear in Fig. 8; these simulations assume that no farm changes its decision about the use of fertilizer or IMV. Scenarios 1–3 involve a rise in both temperature and rainfall, and on farms using inorganic fertilizer only, these two effects offset each other, so the predicted change in yield is very close to (and insignificantly different from) zero. On other farms, where the temperature effect dominates, there is a predicted fall in yield, although this effect is only significantly different from zero on farms using neither inorganic fertilizer nor IMV. On such farms, the predicted fall in log(*yield*) is about 0.4, i.e. yield is predicted to fall by about one third.[19] There is little variation across the 25th, 50th and 75th percentile cases. Scenarios 4–8 involve a rise in temperature and a fall in rainfall. In all cases, yield is predicted to fall, and in most cases, this effect is significant at the five percent level. As one might expect, the effects are largest in the maximally pessimistic scenarios 4–5. Here, the effects are largest on farms using either both inorganic fertilizer and IMV or neither: log(*yield*) on such farms is predicted to fall by 0.6–0.8 under scenario 4 and by 0.8–1.0 under scenario 5. On farms using inorganic fertilizer only, log(*yield*) is predicted to fall by 0.2–0.3 under scenario 4 and by 0.4–0.5 under scenario 5. On farms using both inorganic fertilizer and IMV, the effects at the 75th percentile are larger than the effects at the 25th percentile. On other farms, this difference is reversed, but neither difference is statistically significant. Predicted effects are smaller under the less pessimistic scenarios 6–8, but even here, the smallest effect – under scenario 7 with farms using inorganic fertilizer only – is a decline in log(*yield*) of 0.15.

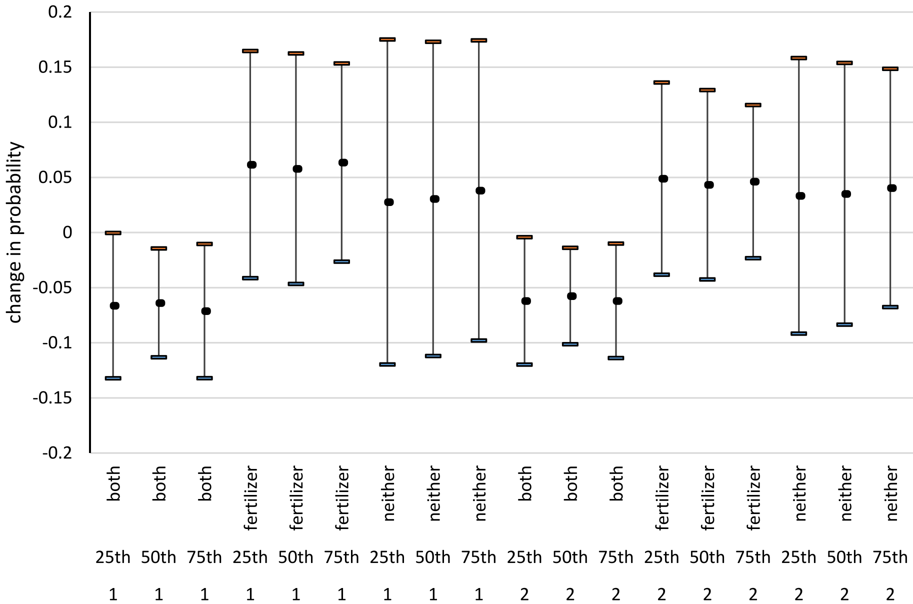
Finally, Fig. 9 shows predicted changes in yield allowing for changes in technology choice, using Eqs. (7a–7b). In the maximally optimistic scenario 1, the fall in mean

[16] Because exp(-1.7) $\approx$ 0.2.

[17] Because exp(-0.5) $\approx$ 0.6.

[18] Because exp(-0.7) $\approx$ 0.5.

[19] Because exp(-0.4) $\approx$ 0.67.



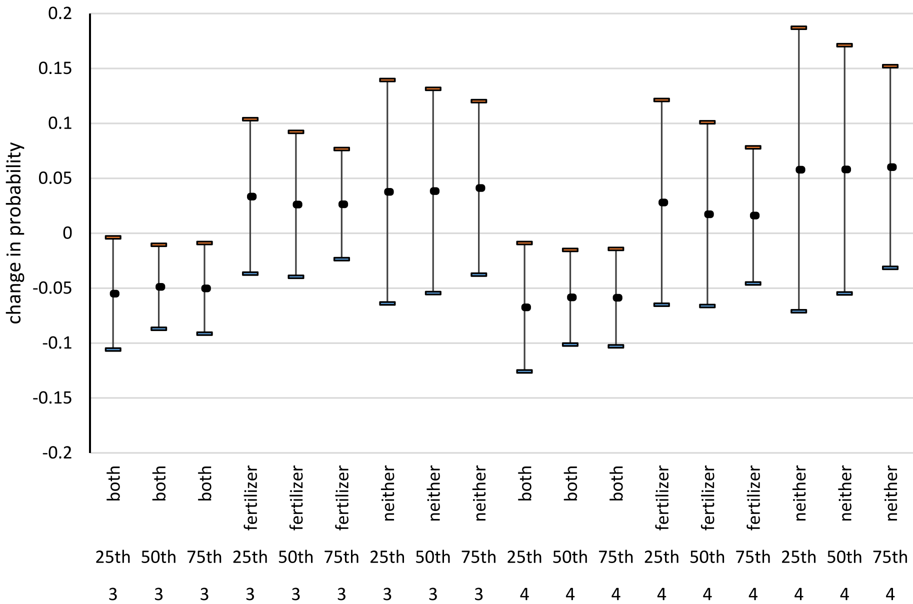


Fig. 5 The vertical axes in the figure measure the change in the probability of a farm (i) using *both* fertilizer and IMV, (ii) using fertilizer only, and (iii) using *neither* fertilizer nor IMV under different climate change scenarios. Estimates with 95 percent confidence intervals are shown for farms in the 25th, 50th and 75th percentile cases. The upper chart shows results for climate scenarios 1 and 2; the lower chart shows results for climate scenarios 3 and 4. The vertical axes in the figure measure the change in the probability of a farm (i) using *both* fertilizer and IMV, (ii) using fertilizer only, and (iii) using *neither* fertilizer nor IMV under different climate change scenarios. Estimates with 95 percent confidence intervals are shown for farms in the 25th, 50th and 75.th percentile cases. The upper chart shows results for climate scenarios 5 and 6; the lower chart shows results for climate scenarios 7 and 8

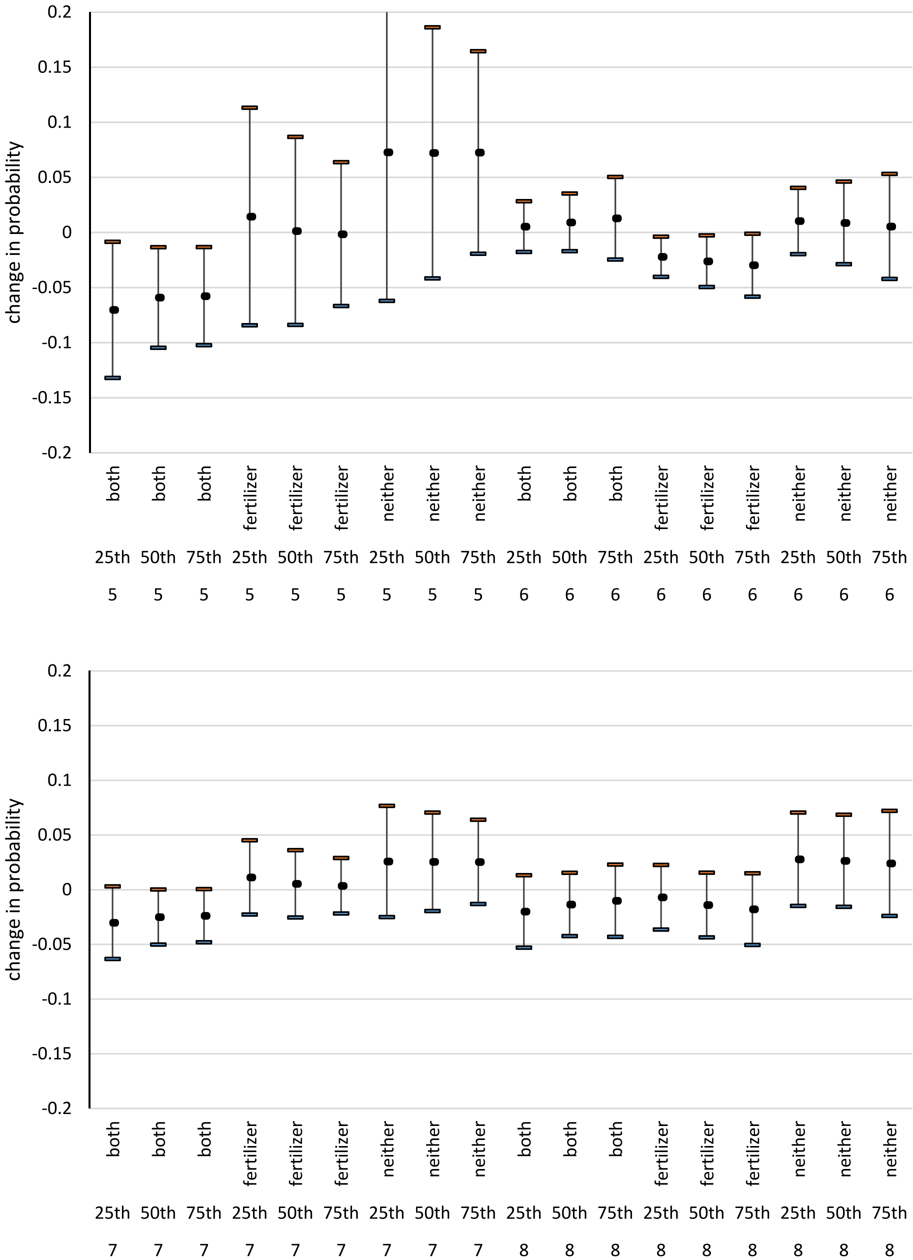


Fig. 5 (continued)

log(*yield*) is very small and insignificantly different from zero. Under this scenario, the predicted increase in the frequency of fertilizer-only farms (Fig. 5), combined with the relatively small effect of climate change on such farms (Fig. 8), means that negative climate change effects are mitigated. Under all other scenarios, log(*yield*) is predicted to fall; under

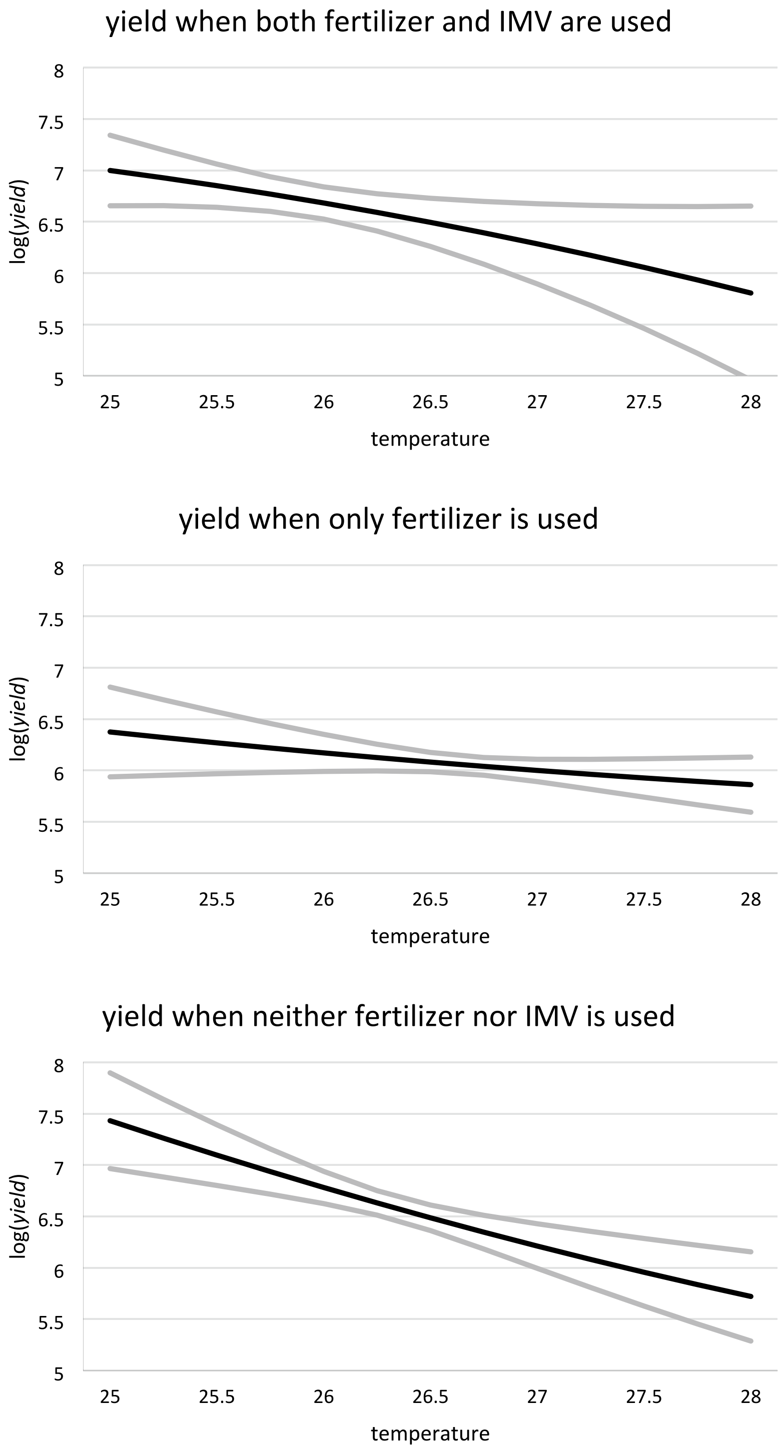


Fig. 6 The estimated association of log(*yield*) with temperature. (with 90 percent confidence intervals)

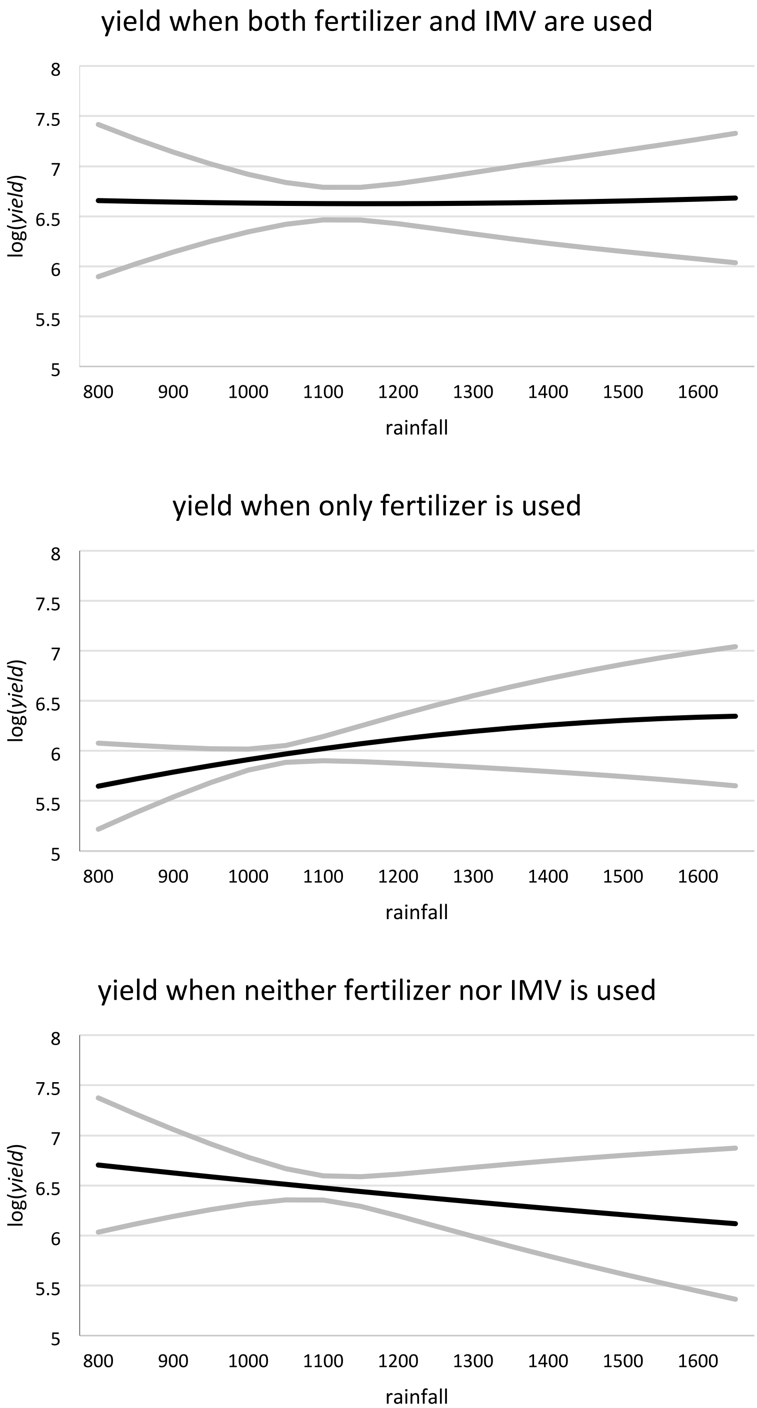


Fig. 7 The estimated association of log(*yield*) with rainfall. (with 90 percent confidence intervals)

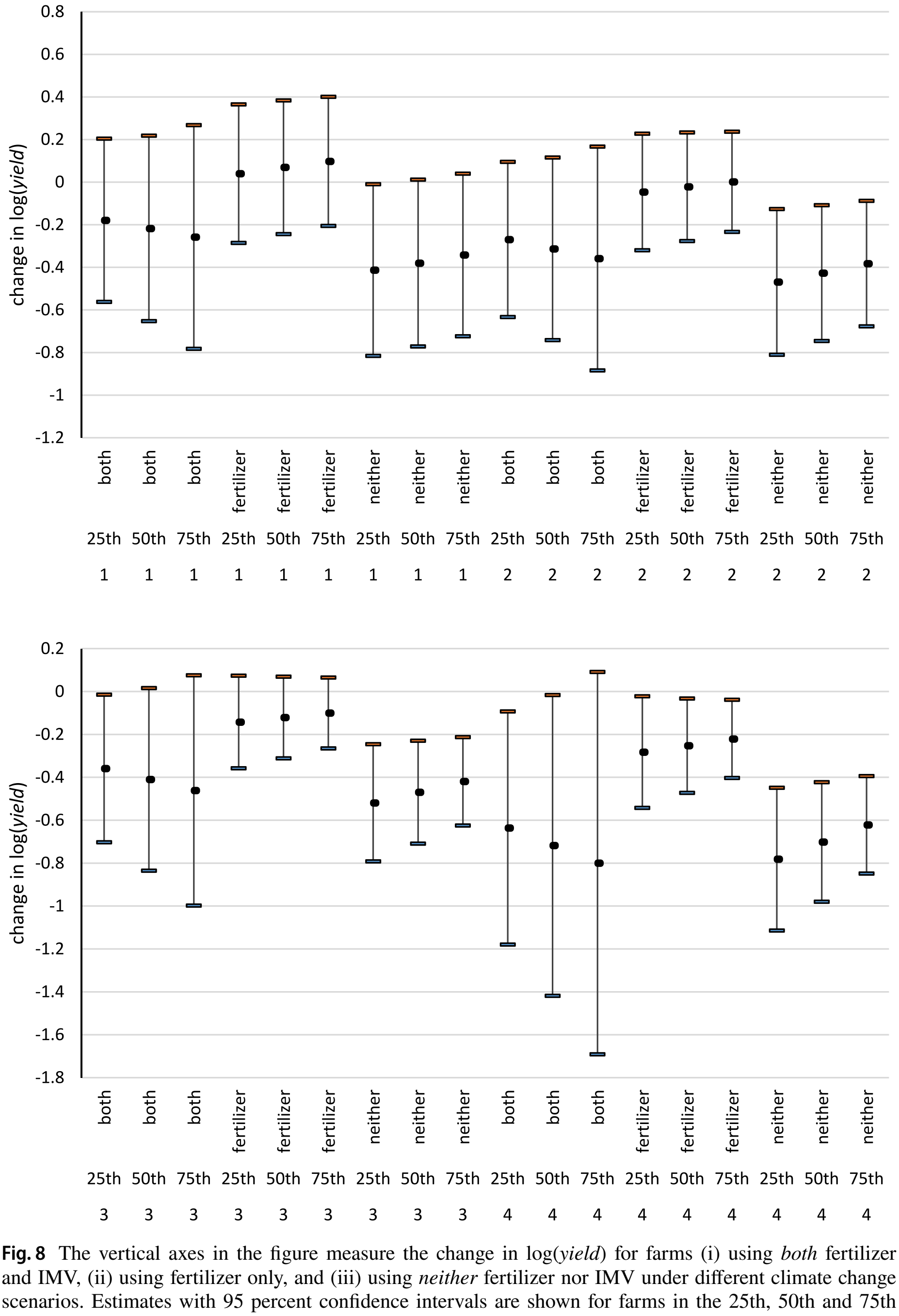


Fig. 8 The vertical axes in the figure measure the change in log(*yield*) for farms (i) using *both* fertilizer and IMV, (ii) using fertilizer only, and (iii) using *neither* fertilizer nor IMV under different climate change scenarios. Estimates with 95 percent confidence intervals are shown for farms in the 25th, 50th and 75th percentile cases. The upper chart shows results for climate scenarios 1 and 2; the lower chart shows results for climate scenarios 3 and 4. The vertical axes in the figure measure the change in log(*yield*) for farms (i) using *both* fertilizer and IMV, (ii) using fertilizer only, and (iii) using *neither* fertilizer nor IMV under different climate change scenarios. Estimates with 95 percent confidence intervals are shown for farms in the 25th, 50th and 75th percentile cases. The upper chart shows results for climate scenarios 5 and 6; the lower chart shows results for climate scenarios 7 and 8

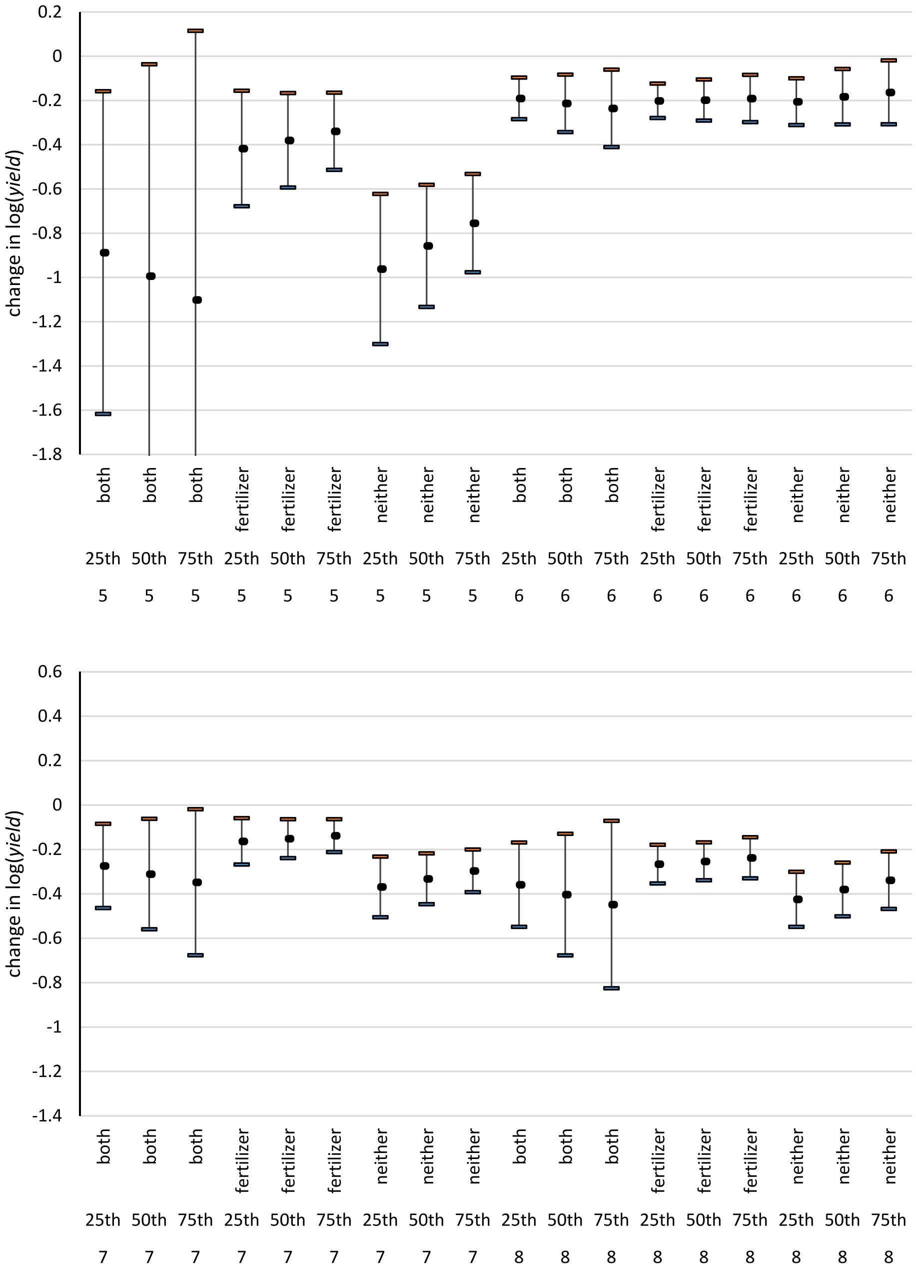


Fig. 8 (continued)

scenarios 3–8, this decline is significantly different from zero at the five percent level. Under the maximally pessimistic scenario 5, log(*yield*) is predicted to fall by 0.5–0.6 (i.e. yield is predicted to fall by around 50 percent). Even with a moderate increase in temperature and little change in rainfall (scenarios 3 and 7), log(*yield*) is predicted to fall by 0.2

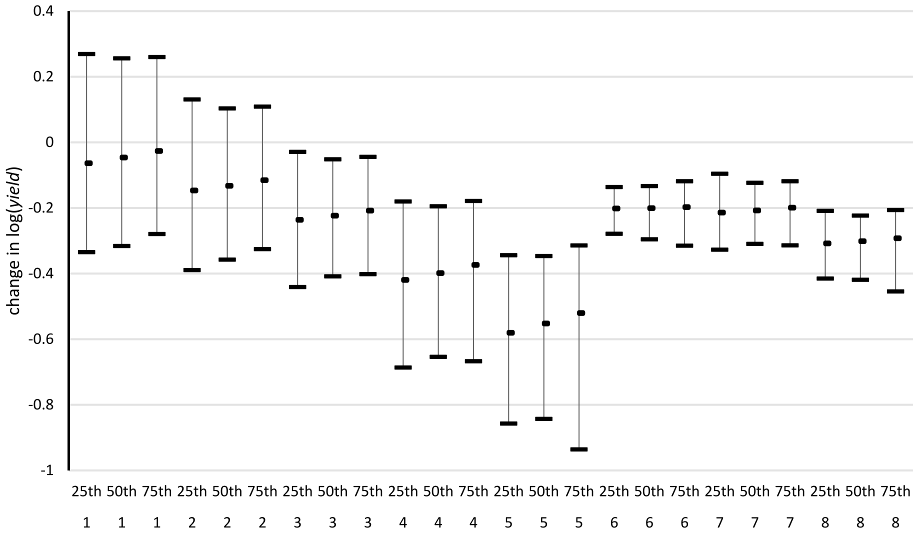


Fig. 9 The vertical axis measures the change in estimated log(*yield*) under different climate change scenarios (1–8), allowing for changes in technology choice. Estimates with 95 percent confidence intervals are shown for farms in the 25th, 50th and 75th percentile cases

(i.e. yield is predicted to fall by around 20 percent). In no case is there any substantial variation in these estimates across the 25th, 50th and 75th percentile cases.

Our results indicate that under plausible alternative scenarios for climate change, mean Ghanaian, Malian and Nigerian maize yields are likely to fall. Only under the most optimistic scenario (scenario 1) is there no substantial fall in yield; other scenarios entail large losses for maize farmers and represent a serious risk to the Ghanaian, Malian and Nigerian economies.

Conclusion

This study presents new evidence on the relationship between temperature, rainfall, technology use and maize yields in Ghana, Mali and Nigeria. Maize is a major staple food crop in these countries, but productivity is already constrained by stresses such as drought, and mean yields are far below the world mean. We estimate the association of maize yield with temperature and rainfall conditional on a range of farm characteristics, including whether the farm uses inorganic fertilizer and/or IMV, and allow for the fact that the probability of using inorganic fertilizer and IMV may itself depend on temperature and rainfall.

We find that temperature and rainfall have some influence on farm choices: farms in warmer, wetter conditions are somewhat less likely to use IMV, and choices about IMV use do affect our predictions about the effect of climate change on yield. However, the main source of uncertainty in our predictions is that mean rainfall is predicted to rise under some climate change scenarios and fall under others. In the most optimistic scenario, with a moderate increase in mean temperature accompanied by a large increase in mean rainfall, no substantial change in yield is predicted. In other scenarios, with either a moderate increase or a reduction in mean rainfall, large decreases in yield are predicted. Climate change therefore represents a very substantial risk to West Africa. These results reflect evidence on the sensitivity of maize yields to climate in other parts of Africa (see for example Abera et al 2018; Mulungu et al. 2021; Omoyo et al. 2015; Shi and Tao 2014), and there is a pressing need to mitigate this risk.

One part of mitigating risk will be to understand better the relationship between farmers' decision-making processes and the production functions that they face. Results here (and in previous studies) indicate that publicly subsidised interventions such as extension programmes and farmer associations raise the uptake of agricultural innovations such as inorganic fertilizer and IMV use, and the sensitivity of yield to temperature appears to be highest on farms using neither. However more detailed quantitative and qualitative data will be required for a comprehensive understanding of this issue.

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Declarations

Competing Interests The authors declare no competing interests.

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