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Weather risk: how does it change the yield benefits of nitrogen fertilizer and improved maize varieties in sub-Saharan Africa?

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Abstract

The purpose of this research was to explore how weather risk affects the value of nitrogen fertilizer use and improved seed variety adoption to sub-Saharan African (SSA) maize farmers. It contributes to the literature by providing additional broad support for the hypothesis that low rates of fertilizer use and improved seed variety adoption can be attributed to the fact that the SSA landscape is heterogeneous, so fertilizer and improved seed are not always advantageous, especially when considering the potentially high cost to farmers of obtaining fertilizer and improved seed. The analysis finds a synergy between nitrogen fertilizer and improved seed varieties. While the benefits of nitrogen tend to increase overtime without improved seed varieties and the benefits of improved seed varieties tend to decrease overtime without nitrogen, combining the two provides more sustained productivity benefits. Therefore, securing both nitrogen use and improved seed variety adoption is important for promoting sustained maize productivity increases across much of SSA. The research also contributes to the literature by using a methodology for calculating willingness to pay bounds that assess the importance of farmers' risk tolerances as a barrier to fertilizer use or improved seed variety adoption.

JEL classifications: Q1, Q12, Q16

Keywords: Improved seed; Maize; Nitrogen fertilizer; Risk; Stochastic dominance; Sub-Saharan Africa

1. Introduction

Growth in maize yields in much of sub-Saharan Africa (SSA) has failed to keep pace with other developing and more developed regions of the world (Ray et al., 2012). A common explanation for poor growth is low levels of fertilizer use and improved seed variety adoption. But why is fertilizer use and improved seed variety adoption low? Answering this question generally for the adoption of more intensive production practices by developing country farmers has stimulated much research interest. A thoughtful review of early literature identified factors such as a lack of credit, labor, and physical capital; limited education, information, infrastructure and markets; small farm size; weak land tenure arrangements; and low risk tolerance as potential reasons (Feder et al., 1985). These themes have continued to develop in more recent literature. Foster and Rosenzweig (1995, 2010), Smale et al. (1995), Diagne and Demont (2007), and Kabunga et al. (2012) explore the effect of limited information, knowledge, and awareness on adoption. The importance of networks, farmer groups, social capital, and learning from others has received attention from Munshi (2004), Conley and Udry (2010), Weber (2012), Abebaw and Haile (2013), Wossen et al. (2015), and Ainembabazi et al. (2017). Chirwa (2005) and Byerlee and Heisey (1996) raise issues of market access, while credit constraints are highlighted in Smale et al. (1995) and Croppenstedt et al. (2003). Risks attributable to crop failures and subsistence concerns are further explored by Smale et al. (1995) and Dercon and Christiaensen (2011), while Duflo et al. (2011) introduce behavioral biases in decision making, particularly as related to impatience.

Another line of argument is that farms and farmers are heterogeneous making it false to presume that fertilizer and improved seed varieties are equally beneficial to everyone everywhere. Byerlee and Heisey (1996) argued the adoption of improved seed varieties plateaued because farmer preferences were not sufficiently considered in variety development, which survey results appear to support (e.g., Lunduka et al., 2012). While Duflo et al. (2008) found fertilizer and improved seed was

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profitable when used optimally, suboptimal use, including recommendations of the Ministry of Agriculture in Kenya, was found to be unprofitable. Suri (2011) and Kathage et al. (2012, 2016) explored profitability and yield concerns of fertilizer and improved seed varieties using farm level survey data from Kenya and Tanzania. Suri concludes that there are maize farmers that do not adopt improved seed varieties even though the returns are high because of the high cost of acquiring fertilizer and seed from distant distributors. She also finds some farmers switch back and forth between adoption and disadoption due to low returns. Kathage et al. (2016) finds that where productivity gains are high in Tanzania, farmers are typically aware of and adopt fertilizer and improved seed varieties, while awareness and adoption are low in regions with small productivity gains.

The purpose of this article is to build on two aspects of this previous research by exploring how weather risk can affect the yield benefits to maize farmers of improved seed varieties and nitrogen fertilizer across the widely heterogeneous SSA landscape. The heterogeneity of interest includes soils and climate, which is captured by using calibrated crop growth models to simulate yield distributions (at a resolution of 30 arc-minutes or about 60 km) for traditional and improved seed varieties with and without nitrogen fertilizer. Heterogeneity in a farmer's willingness to pay (WTP) for improved seed varieties or fertilizer due to heterogeneity in farmers' risk preferences is also an important consideration. To account for these heterogeneous risk preferences, the simulated yield distributions are compared using second-order stochastic dominance (SOSD; Rothschild and Stiglitz, 1970, 1971) in order to calculate bounds on the potential range of a risk averse farmer's WTP, which is most conveniently measured in terms of maize yield. These bounds make it possible to assess how improved seed varieties or nitrogen fertilizer affect the riskiness and desirability of maize yields to risk-averse farmers across the SSA landscape. Sensitivity analysis further explores how variations in the price of maize or cost of nitrogen fertilizer (also measured in terms of maize yields) affect the riskiness and desirability of maize yields to risk-averse farmers.

Four interesting results emerge from the analysis. First, the initial adoption of nitrogen fertilizer with traditional seed varieties clearly improves the yield distribution for risk-averse farmers on relatively modest portions of the SSA landscape, though the proportion of the landscape showing strict improvement increases with sustained fertilizer use. Second, the initial adoption of improved seed varieties without nitrogen fertilizer provides larger improvements to yield distributions for risk-averse farmers across a larger portion of the SSA landscape, but these improvements tend to diminish with sustained use. Third, the initial adoption of improved seed varieties and fertilizer provides large improvements in the yield distribution for risk-averse farmers across most of SSA, and these improvements tend to persist with sustained use. Finally, while the improvement in yield distributions from fertilizer and improved seed varieties for risk-averse farmers remain high across most of SSA even after taking into account the world price of maize and cost of nitrogen fertilizer, the value of these improvements are diminished or even completely lost in regions where limited market access effectively drives the price of maize down and cost of nitrogen fertilizer up.

The methods and results found herein contribute to the literature in multiple ways. Methodologically, the WTP bounds analysis in terms of maize yields provides a practical strategy for dealing with heterogeneous risk-averse farmer preferences, which will often be the case when analyzing landscape scale impacts of new technologies, practices, or policies. While Neill (1986) and Quiggin (2002) develop WTP bounds in a similar spirit to this article, Neill's dollar-denominated WTP bounds are for nonmarket goods without uncertainty and Quiggin's dollar-denominated WTP bounds are for ambient health risk reductions. Neither of these authors empirically assesses their proposed WTP bounds. Empirically, the article's results account for the riskiness of production due to weather, while also providing a more comprehensive continental scale analysis. Previous studies accounting for risk typically focus on a more limited scope of analysis (e.g., country or village level), while also making more restrictive assumptions regarding the characteristics of farmers' risk preferences (e.g., constant absolute or relative risk aversion). Alternatively, previous continental scale studies of the value of nitrogen fertilizer in SSA have not considered the riskiness of maize production due to unpredictable weather.

The next section of the article provides an overview of the conceptual framework that guides our calculation of the WTP bounds on which the subsequent analysis is based. We then describe the crop growth simulation model used to develop yield distributions across the SSA landscape. This description includes an accounting of the sources of necessary climate and soils information as well as model parameterization and calibration. The specific scenarios that are explored are introduced with the methods, while the sensitivity analysis is detailed within the context of the results. Conclusions reiterate key findings, offer policy insights, and review important caveats.

2. Bounding the WTP for better yields

Unpredictable weather makes maize farming inherently risky—how much will be produced is not known when seed is planted. This and other types of risk have a significant impact on farmer decisions such as the decision to adopt improved seed varieties or use fertilizer (for a review, see Hurley, 2010); though the magnitude, and sometimes the direction of the impact, can vary. This variation is typically divided into differences in the riskiness of production faced by farmers and differences in farmers' risk preferences. For farmers living and working in close proximity to each other, differences in the riskiness of production attributable to weather and other factors such as markets will be negligible, making risk preferences a key to understanding variation in farmers' decisions.

Differences in farmers' risk preferences across the SSA landscape make assessing the yield benefits of improved seed or

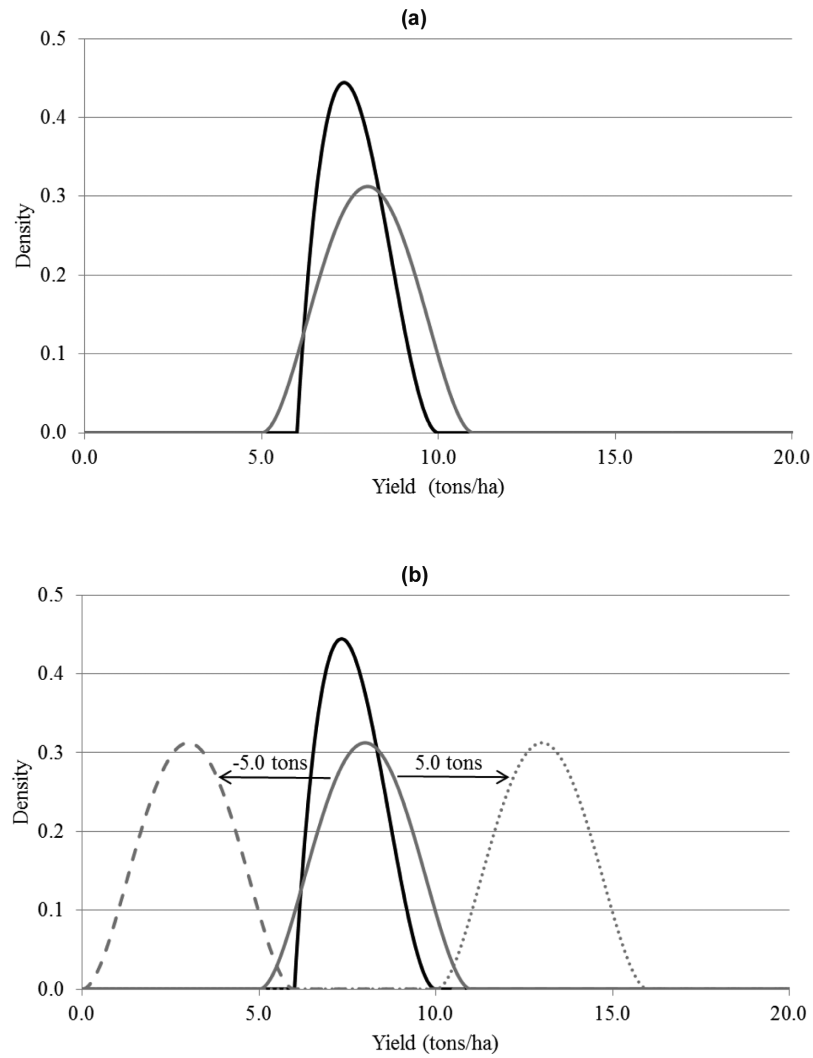
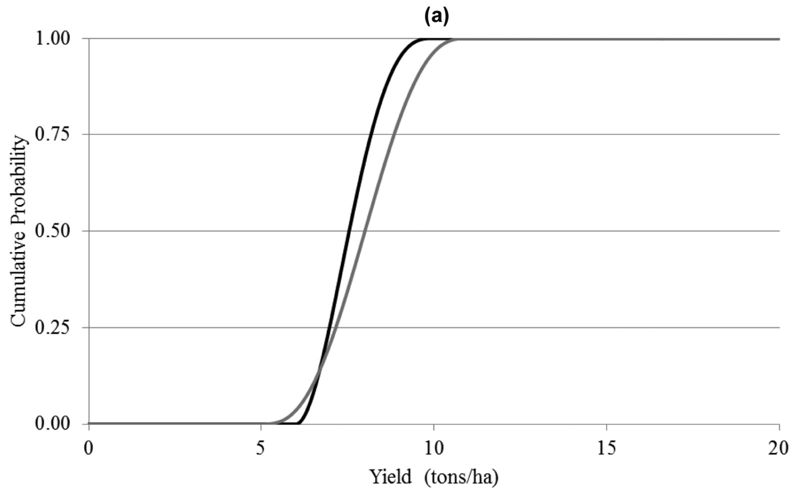


Fig. 1. Example yield density comparisons.
Note: The black solid density is a beta with $\alpha = 2$, $\beta = 3$, minimum = 6.0 tons/ha, and maximum = 10.0 tons/ha, resulting in a mean and variance of 7.6 and 0.64. The gray solid density is also a beta with $\alpha = 3$, $\beta = 3$, minimum = 5.0 tons/ha, and maximum = 11.0, so the mean and variance are 8.0 and 1.29.

fertilizer challenging because measuring these differences is not practical on such a broad scale. However, there are circumstances when differences in the riskiness of production are stark enough to render farmers' risk preferences irrelevant. Fig. 1 illustrates with a stark example. Fig. 1a shows two potential yield distributions represented by black and gray lines.[1] Suppose the black distribution represents the potential yield outcomes and likelihoods if a farmer plants a traditional seed variety. Alternatively, suppose the gray distribution represents the potential yield outcomes and likelihoods if an improved seed variety is planted. The way these two distributions are constructed, the average yield for the improved seed variety is higher than the average yield for the traditional seed variety. Alternatively, the lowest potential yields are actually associated with the improved seed variety and the variability of yield for the improved seed variety is higher than for the traditional seed variety. Is a farmer better off choosing the traditional or improved seed variety?

The answer to this question is not straightforward. While farmers are typically found to prefer higher average yields holding all else constant, they also tend to avoid the chance of really low yields or excessive yield variability. So, how would the yield distribution of the improved seed variety have to change to make the answer to this question obvious? Fig. 1b provides one answer. If the dotted gray line is the yield distribution with the improved seed variety, any farmer who prefers higher yields would choose to plant it instead of the traditional seed variety because they are assured a higher yield no matter what happens. Alternatively, if the dashed gray line is the yield distribution with the improved seed variety, any farmer who prefers higher yields would choose not to plant it because they are assured a

[1] For this illustrative example, the black distribution is a beta with $\alpha = 2$, $\beta = 3$, minimum = 6.0 tons/ha, and maximum = 10.0 tons/ha, which results in a mean and variance of 7.6 and 0.64. The gray distribution is also a beta distribution with $\alpha = 3$, $\beta = 3$, minimum = 5.0, and maximum = 11.0, so the mean and variance are 8.0 and 1.29.



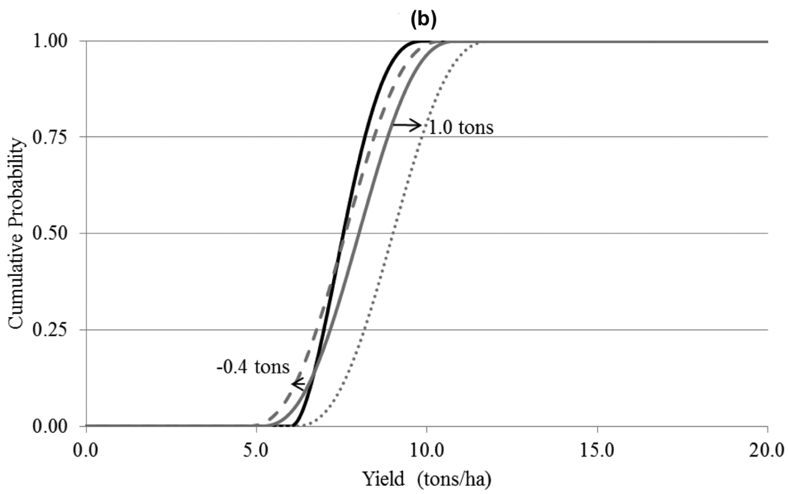


Fig. 2. Example yield cumulative distribution comparisons.
Note: The black solid cumulative distribution is a beta with $\alpha = 2$, $\beta = 3$, minimum = 6.0 tons/ha, and maximum = 10.0 tons/ha, resulting in a mean and variance of 7.6 and 0.64. The gray solid cumulative distribution is also a beta with $\alpha = 3$, $\beta = 3$, minimum = 5.0 tons/ha, and maximum = 11.0, so the mean and variance are 8.0 and 1.29.

lower yield than with the traditional seed variety. How much the gray distribution must shift right before it is clearly better than the black distribution and how much it has to shift left before the black distribution is clearly better provides bounds on how much improved seed must change the yield distribution either up or down so the risk preferences of farmers are no longer relevant for choosing between the alternative yield distributions.

These intuitive bounds are wide, which raises the question: Can we find similar bounds that are narrower and more informative? The answer to this question is yes if it is reasonable to presume farmers' preferences over alternative yield distributions can be characterized by the expected utility hypothesis and exhibit risk aversion.[2] That is, if y represents a random yield between y^L and y^U; $f^r(y)$ and $f^g(y)$ are the yield density functions for the traditional and improved seed varieties; $F^r(y)$ and $F^g(y)$ are the cumulative distribution functions for the traditional and improved seed varieties; and $U(y)$ is a twice differentiable, risk-averse utility of yield function, such that $U'(y) > 0$ and $U''(y) < 0$. The expected utility hypothesis implies that a farmer will weakly prefer the improved (traditional) seed variety if

$$\int_{y^L}^{y^H} U(y) f^g(y) dy \geq (\leq) \int_{y^L}^{y^H} U(y) f^r(y) dy. \tag{1}$$

[2] Actually, this result can be demonstrated for more general risk-averse preferences such as generalized Schur-concave preferences. The key assumption here is that the preferences can at least partially rank distributions according to second-order stochastic dominance (Rothschild and Stiglitz, 1970, 1971). We use the expected utility hypothesis to demonstrate this result with more broadly accessible arguments.

With these assumptions about a farmer's risk preferences, the bounds illustrated in Fig. 1b can be refined using SOSD (Rothschild and Stiglitz, 1970, 1971). How SOSD can be used to refine these bounds is illustrated in Fig. 2. Instead of comparing the density functions, SOSD compares the area under cumulative distribution functions. If the area under the black (gray) cumulative distribution function is larger or equal to the area under the gray (black) cumulative distribution function for all possible yields (i.e., $\int_{y^L}^{y} F^r(z)dz \geq (\leq) \int_{y^L}^{y} F^g(z)dz$ for all y where z is a variable of integration), then the improved (traditional) seed variety will be weakly preferred by farmers. For the example in Fig. 2b, the least amount the gray cumulative distribution can be shifted to the right and still satisfy the SOSD condition with the improved variety being preferred is 1.0 ton/ha. Alternatively, the least amount the gray cumulative distribution can be shifted to the left and still satisfy the SOSD condition with the traditional variety being preferred is 0.4 tons/ha. Note that these bounds are almost an order of magnitude narrower than the ones illustrated in Fig. 1b (1.4 vs. 10.0 tons/ha) and therefore are more informative.

The bounds in Figs. 1b and 2b assume farmers' maize production preferences depend exclusively on yield, which may be the case for subsistence farmers, but not for those who choose to market some or all of their maize, or are more reliant on purchased inputs. For farmers who market maize, volatile prices becomes another important source of risk. Taking price risk, production costs, and the amount of land devoted to maize production into account, Eq. (1) can be written in terms of a farmer's net maize returns instead:

$$\int_{\varepsilon}\int_{p>0}\int_{y^L}^{y^U} U\left(\left(py-c^g\right)A\right) f^g(y|\varepsilon)dyh(p|\varepsilon)dp\phi(\varepsilon)d\varepsilon \geq (\leq).$$

$$\int_{\varepsilon}\int_{p>0}\int_{y^L}^{y^U} U\left((py-c^r)A\right) f^r(y|\varepsilon)\,dyh(p|\varepsilon)\,dp\phi(\varepsilon)d\varepsilon, \qquad (2)$$

where $p > 0$ is the random maize price; $A > 0$ are maize hectares; $c^g \geq 0$ and $c^r \geq 0$ are the per hectare maize cost of production; ε is a stochastic vector, with probability density $\phi(\varepsilon) \geq 0$, of factors that can jointly influence the maize price and a farmer's yields; $h(p|\varepsilon) \geq 0$ is the probability density for the random maize price given the vector ε; and $f^k(y|\varepsilon) \geq 0$ with support $y^U \geq y \geq y^L$ is the probability density for the random yield of production alternative k given the vector ε.

The formulation of price and yield randomness in Eq. (2) permits the type of negative correlation between prices and yields that is consistent with the notion of a natural hedge. For example, the vector ε can be thought of as reflecting the regional temperature and precipitation conditions that result in widespread drought, low yields for most farmers, and maize price spikes due to low aggregate production. Alternatively, it can reflect optimal growing conditions in a region that produces high yields for most farmers, a glut in supply and subsequent price drop. It is also flexible enough to reflect a positive correlation between farm level yields and prices should they exist. Intuitively, the assumptions imply that an individual farmer's yield and production is not significant enough to directly affect the realized market price, while the realized maize price does not directly affect an individual farmer's yield. Given the typically small scale of maize production and lack of availability of price risk management tools (e.g., future contracts) in SSA, these assumptions seem reasonably innocuous.

With Eq. (2), we can ask how much maize per hectare would a risk-averse farmer be willing to give up/pay (WTP) to plant the improved seed variety? Since $U((py - c^k)A)$ is strictly increasing in y, the answer to this question is the w that satisfies

$$\int_{\varepsilon}\int_{p>0}\int_{y^L}^{y^U} U\left(\left(p\,(y-w)-c^r\right)A\right) f^g\,(y|\varepsilon)\,dyh\,(p|\varepsilon)\,dp\phi\,(\varepsilon)\,d\varepsilon$$

$$= \int_{\varepsilon}\int_{p>0}\int_{y^L}^{y^U} U\left(\left(py-c^r\right)A\right) f^r\,(y|\varepsilon)\,dyh\,(p|\varepsilon)\,dp\phi\,(\varepsilon)\,d\varepsilon. \qquad (3)$$

A lower bound for the w that makes any risk-averse farmer prefer the improved variety and an upper bound for the w that makes any risk-averse farmer prefer the traditional variety can be derived using SOSD (see Supplementary Online Appendix A for the derivation of these bounds):

$$wtp^{LB} = \max_{w}\left\{w : \int_{y^L}^{y} F^r\,(z|\varepsilon)\,dz \geq \int_{y^L-w}^{y-w} F^g\,(z|\varepsilon)\,dz \text{ for all } y \geq \min\left\{y^L - w,\, y^L\right\} \text{ and } \varepsilon\right\} \text{ and} \qquad (4)$$

$$wtp^{UB} = \min_{w}\left\{w : \int_{y^L-w}^{y-w} F^g\,(z|\varepsilon)\,dz \geq \int_{y^L}^{y} F^r\,(z|\varepsilon)\,dz \text{ for all } y \geq \min\left\{y^L - w,\, y^L\right\} \text{ and } \varepsilon\right\}$$

where $F^k(z|\varepsilon)$ is the conditional cumulative distribution of yield for alternative k given ε. The bounds in Eq. (4) depend only on the conditional yield distributions. However, if farm level yields are independent of market prices, these bounds will only depend on the unconditional cumulative yield distributions $F^g(z)$ and $F^r(z)$.

3. Yield distributions

Using WTP bounds to assess the yield benefits of nitrogen fertilizer or improved seed varieties when farmers face

Table 1
Willingness to pay bound (maize ton/ha) descriptive statistics

	Year 1		Year 10	
	Upper bound	Lower bound	Upper bound	Lower bound
	From traditional without to traditional with 40 kg/ha N			
Mean	0.22	0.09	0.48	0.25
Standard deviation	0.42	0.27	0.60	0.46
Median	0.00	0.00	0.17	0.00
Interquartile range	0.18	0.00	0.91	0.39
[Min, Max]	[−0.11, 2.39]	[−0.79, 1.65]	[−0.14, 2.85]	[−1.62, 2.05]
Clearly better (%)	27.1		48.8	
Clearly worse (%)	2.6		5.2	
	From traditional without N to improved without N			
Mean	2.17	1.18	1.16	0.50
Standard deviation	1.74	1.54	1.20	1.02
Median	1.97	0.73	0.73	0.26
Interquartile range	2.79	1.98	1.39	0.77
[Min, Max]	[−1.03, 8.81]	[−2.92, 7.68]	[−1.20, 7.01]	[−2.92, 6.61]
Clearly better (%)	81.2		74.4	
Clearly worse (%)	1.6		4.2	
	From traditional without N to improved with 40 kg/ha N			
Mean	2.94	1.85	2.56	1.67
Standard deviation	1.69	1.69	1.31	1.42
Median	2.74	1.76	2.48	1.73
Interquartile range	2.20	2.54	1.82	2.17
[Min, Max]	[−1.03, 9.34]	[−3.23, 7.39]	[−1.23, 7.50]	[−2.92, 6.74]
Clearly better (%)	88.4		88.6	
Clearly worse (%)	0.3		0.3	
Million hectares	24.8			
Cells	3,854			

Note: Descriptive statistics are weighted by maize hectares.

unpredictable weather requires information on yields for traditional and improved seed varieties with and without nitrogen fertilizer under a range of possible weather outcomes as well as information on the factors that jointly affect a farmer's yield and price. While the necessary information could be obtained from a panel of field experiments and survey data, the field and survey data we are aware of is lacking in terms of geographical and temporal extent for our purpose. Therefore, to gain insight across all of SSA where crop production takes place, we chose to develop yield distribution information using crop growth models and the distribution of historical weather outcomes assuming that maize prices and a farmer's yields are independent.

The crop model used to simulate maize growth and yield was the CERES-Maize model (Jones et al., 1986) which is one of a suite of models in the Decision Support System for Agrotechnology Transfer (DSSAT) v4.5 (Hoogenboom et al., 2015; Jones et al., 2003). The CERES-Maize model describes daily phenological development and growth in response to environmental factors (soils, weather, and management). Modeled processes include the duration of growth stages; growth of vegetative and reproductive plant parts; extension growth of leaves and stems; senescence of leaves; biomass production, and partitioning among plant parts, and root system dynamics; and yield and yield components of maize. The model includes subroutines to simulate nutrients (nitrogen and phosphorus) and water balances in soil and plants, giving it the capacity to simulate the effects of nutrient deficiency and soil water deficit on photosynthesis and pathways of carbohydrate movement in the plants.

In this study, the DSSAT model was used to simulate rainfed maize yield across SSA at a resolution of 30 arc-minute (about 60 km at the equator) for rainfed maize growing areas identified by the Spatial Allocation Model (SPAM) (You and Wood, 2006). The primary data needed to run DSSAT includes weather, soil, maize variety characteristics, and information on farmers' management practices representing the modeling unit area. The weather data variables include daily solar radiation, maximum and minimum temperatures, and precipitation, typically obtained from the nearby weather station for field-scale studies. For this regional study, we used AgMERRA, a global gridded weather data set (Ruane et al., 2015) that has global-scale baseline weather data for 1981–2010 (30 years). For the soil data, DSSAT requires detailed soil property information for each layer, which can be measured *in situ* for field-scale studies. For this regional-scale study, we used the HC27 Generic Soil Profile Database (Koo and Dimes, 2013), which was developed using the reanalysis of ISRIC-WISE International Soil Profile Dataset (Batjes, 1995) converted to a DSSAT-compatible format (Romero et al., 2012) and resampled to the 30 arc-minute resolution based on the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009). For

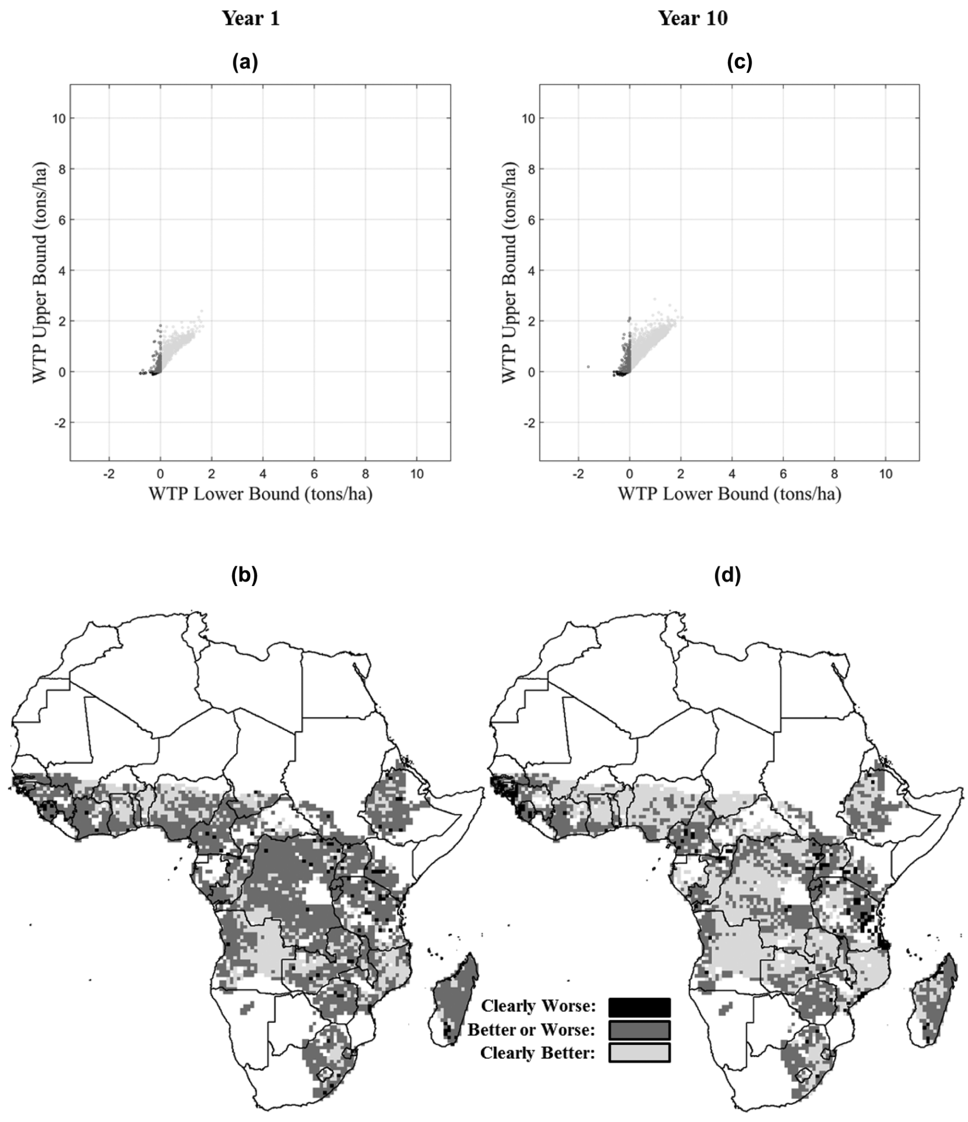


Fig. 3. Willingness to pay bounds (maize ton/ha) for switching from the traditional variety without nitrogen fertilizer to the traditional variety with 40 kg/ha of nitrogen fertilizer in year 1 (panels (a) and (b)) and 10 years (panels (c) and (d)) after adoption.

each grid cell, a monthly planting window was defined using the resampling of the Generic Rainfed Crop Calendar data on 5 arc-minute grids obtained from CCAFS (http://ccafs-climate.org). Within the planting month, DSSAT was set to simulate seed planting when the available soil moisture in the top 10 cm layer is above 10%.

While the model is capable of simulating balances of nitrogen and phosphorus, only the nitrogen balance was simulated. This is due to the predominant role of nitrogen fertilizer in crop productivity potential in SSA overall (Zhang et al., 2015) and the agronomic characteristics of nitrogen (i.e., its relatively higher mobility and generally more immediate yield responses in maize when compared to phosphorus), as well as the lack of detailed phosphorus data to appropriately initialize the phosphorus balance subroutine. Hence, the overall simulated yields from the model maybe overestimated in the areas where soil phosphorus is severely limiting for maize cultivation and not managed by applications of phosphorus fertilizer. For the nitrogen fertilizer input, 40 kg/ha of nitrogen was split applied at 50:50 (i.e., 20 kg/ha each of nitrogen) on the planting date and 10 days before flowering.

The CERES-Maize Model also requires plant genetic coefficients that are calibrated and evaluated using experimental data. The genetic coefficients for the improved maize varieties used in this study were obtained from previous International Maize and Wheat Improvement Center (CIMMYT) work that calibrated and evaluated benchmark maize varieties developed for specific maize mega environments in Africa (Tesfaye et al., 2015). The coefficients for the traditional varieties were taken from two old maize varieties that belong to the Katumani

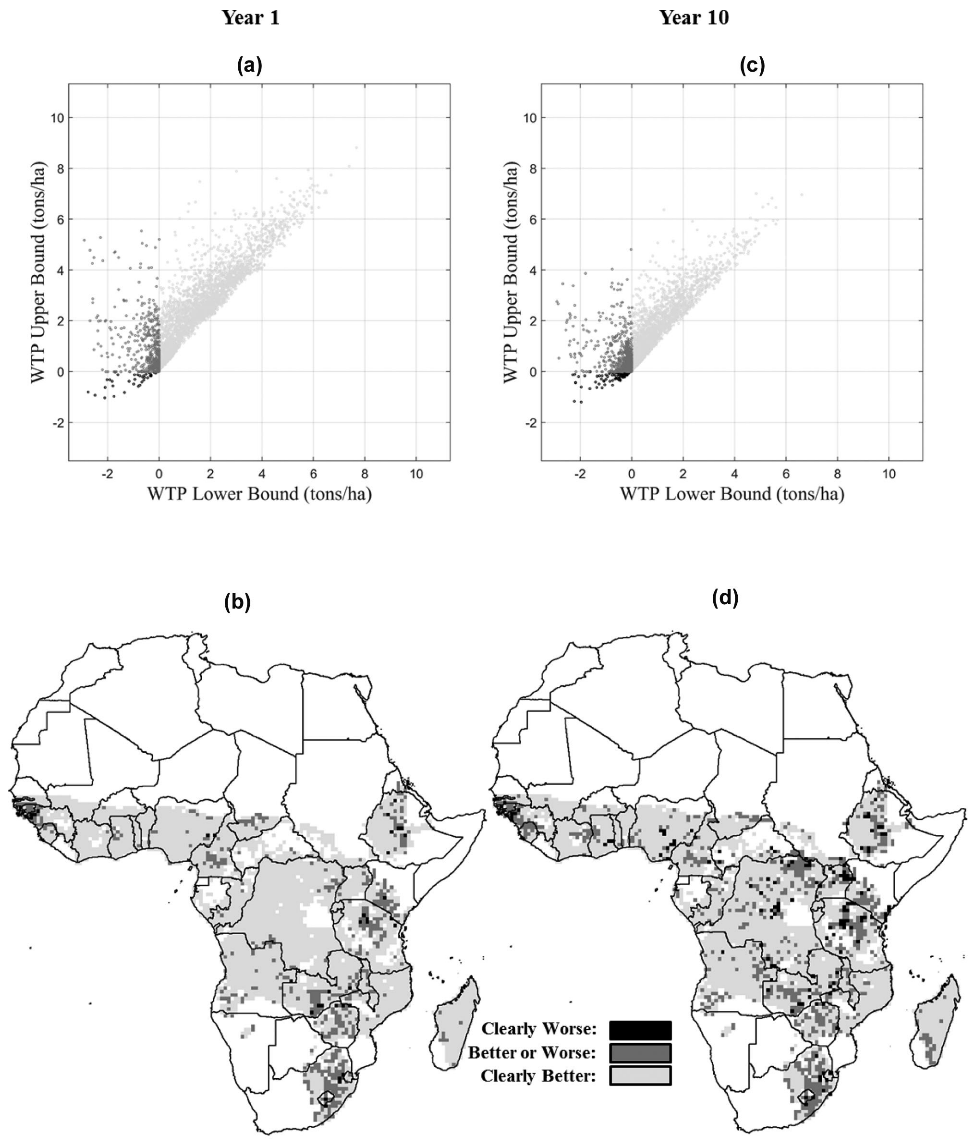


Fig. 4. Willingness to pay bounds (maize ton/ha) for switching from the traditional variety without nitrogen fertilizer to the improved variety without nitrogen fertilizer in year 1 (panels (a) and (b)) and 10 years (panels (c) and (d)) after adoption.

Composite with long and short maturity length.[3] They have been commonly grown by African farmers for more than 15 years.

The CERES-Maize Model's accounting for soil water and nutrient balances within and between cropping seasons makes it possible to run multiyear sequential simulations that capture both the short- and long-run effects of production on soil nutrient dynamics and yields, which is particularly important in low input cropping systems that can mine soils of important nutrients over time. These multiyear sequential simulations were repeated for different weather histories in order to construct plausible, temporally correlated short- and long-run yield distributions. Specifically, for each grid cell, the CERES-Maize Model was used to produce thirty different 10-year sequential simulations, referred to as replications. What differed between each replication was the weather sequence that was used. These different weather sequences were constructed from the available daily weather data from 1981 to 2010, by creating a loop from 2010 back to 1981 and then sampling all 30 unique weather sequences in this loop (see Table B1 in the Supplementary Online Appendix B). Ten yield distributions were then created from these 30 simulations—one yield distribution for each simulated year.

[3] To explore the sensitivity of our results to our choice of the traditional seed variety, we used two different varieties parameterized for the DSSAT model denoted as CM1509 and CM1510, whose genetic coefficient values are included in the Supplementary Online Appendix B (Table B3). Results for CM1509 are reported here, while the same figures and tables for CM1510 can be found in Supplementary Online Appendix B.

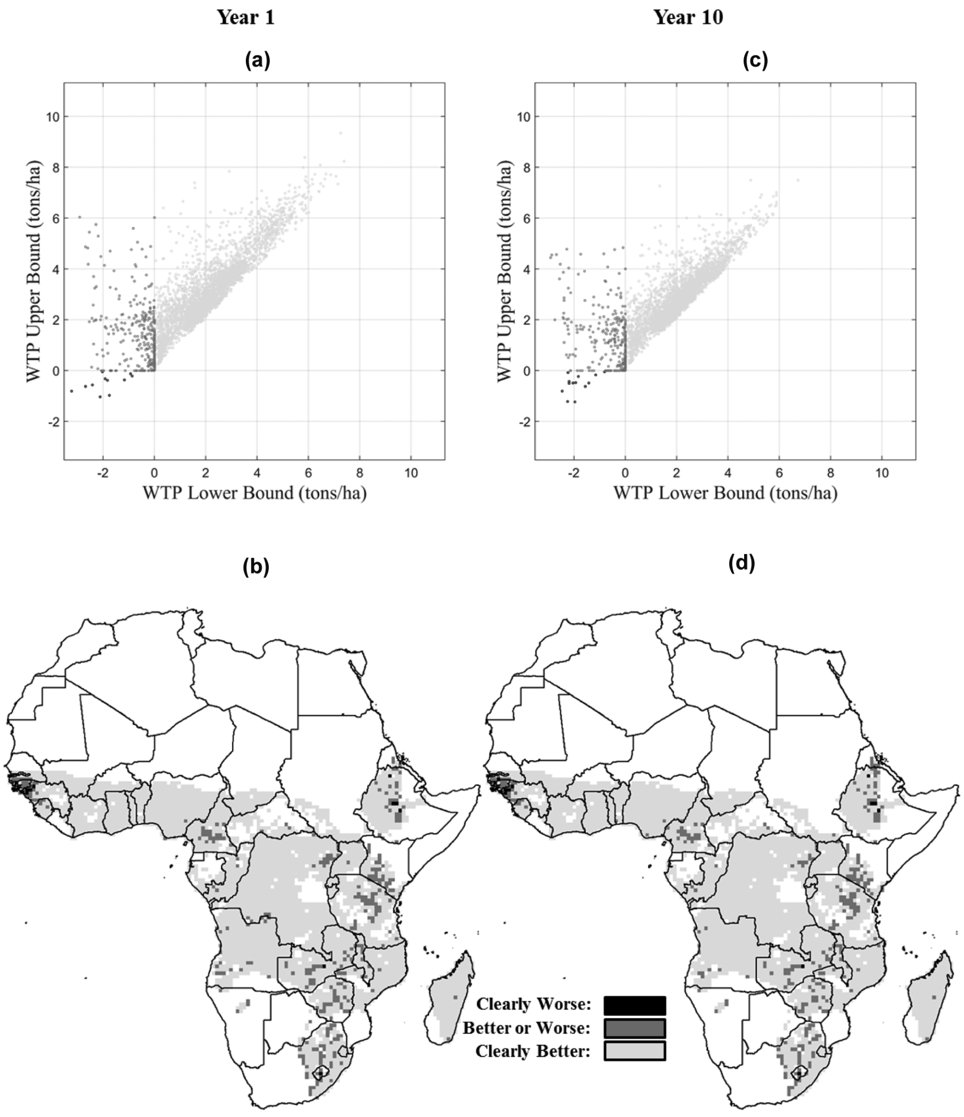


Fig. 5. Willingness to pay bounds (maize ton/ha) for switching from the traditional variety without nitrogen fertilizer to the improved variety with 40 kg/ha of nitrogen fertilizer in year 1 (panels (a) and (b)) and 10 years (panels (c) and (d)) after adoption.

In summary, for each of the 3,854 30 arc-minute grid cells in SSA with some maize production in 2005, the CERES-Maize Model is used to simulate 10-year cropping histories for 30 different 10-year weather histories with an improved and traditional seed variety, with and without 40 kg/ha of nitrogen fertilizer. These simulations were used to construct yield distributions for improved and traditional seed variety, with and without 40 kg/ha of nitrogen fertilizer for each year in the 10-year cropping history. Yield distributions for year 1 and year 10 in the cropping history were used to construct WTP bounds for each cell comparing (i) improved and traditional seed varieties without nitrogen fertilizer, (ii) traditional seed varieties with and without 40 kg/ha of nitrogen fertilizer, and (iii) improved seed varieties with 40 kg/ha of nitrogen fertilizer and traditional seed varieties without nitrogen fertilizer.

4. Results

The first set of results compares the estimated yield distribution for the traditional variety with and without nitrogen, the improved and traditional varieties without nitrogen, and the improved variety with and the traditional variety without nitrogen. These distributional comparisons focus on yields, while ignoring any cost of nitrogen fertilizer or improved seed varieties (i.e., $c^r = 0$ is assumed). Therefore, we follow-up these results with a sensitivity analysis that shows how the added cost of fertilizer relative to the price of maize changes the reported yield benefits.

Table 1 reports the WTP bound descriptive statistics. Figs. 3, 4, and 5, panels (a) and (c), plot these WTP bounds (the upper bound on the vertical and lower bound on the horizontal axis) for

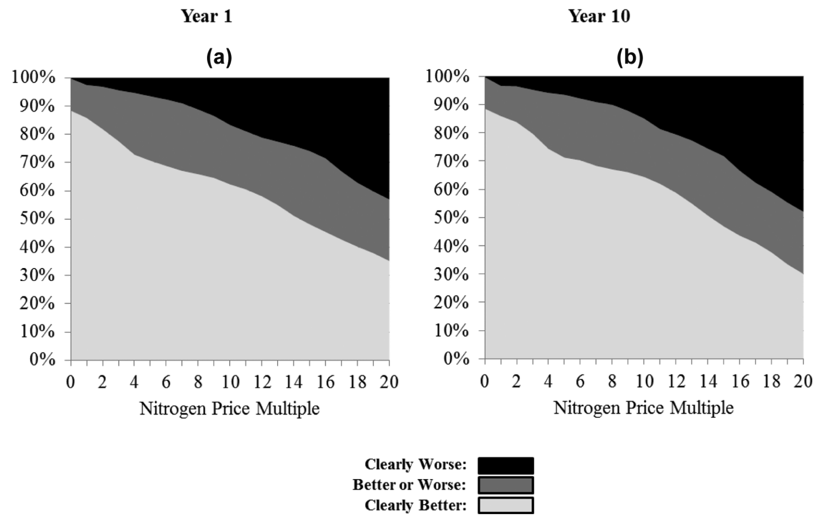


Fig. 6. Sensitivity analysis for willingness to pay bounds (maize ton/ha) when switching from the traditional variety without nitrogen fertilizer to the improved variety with 40 kg/ha of nitrogen fertilizer at a price multiple of 122 kg/ha in year 1 (panel (a)) and 10 years (panel (b)) after adoption.

a 1- and 10-year cropping history for each 30 arc-minute cell. The points in Figs. 3, 4, and 5, panels (a) and (c), are colored in black to indicate farmers are clearly worse off with nitrogen, improved seed varieties, or both; light gray to indicate farmers are clearly better off with nitrogen, improved seed varieties, or both; and dark gray to indicate that farmers' are better or worse off depending on their individual specific risk preferences. The geographic distribution of these black, light gray, and dark gray points are shown in Figs. 3, 4, and 5, panels (b) and (d), for the 1- and 10-year cropping histories.

The top third of Table 1 and Fig. 3 address the question of how adding nitrogen fertilizer to traditional seed varieties affects yield distributions across SSA. The results are different between the initial year and 10th year of repeated use. In the initial year, nitrogen fertilizer use is clearly the best option on only 27.1% of the 24.8 million hectares of maize cropland. After 10 years, nitrogen use is clearly the best option on 48.8% of the maize cropland. The increase in the yield benefits of nitrogen fertilizer with sustained use are illustrated in the shifting geographic extent of dark gray in Fig. 3b to light gray in Fig. 3d, which is particularly evident in Angola, Congo, and Nigeria. As might then be expected, the average and median bounds on the WTP increase as the years of nitrogen fertilizer use increases. The improvements to sustained use are not uniformly positive, however, as the percentage of cropland that is clearly worse increases from 2.6% to 5.2%. Visually, this result is most apparent in Cameroon and Eastern Tanzania where the geographic extent of dark gray in Fig. 3b yields to black in Fig. 3d. A possible explanation for these results is that without nitrogen fertilizer, traditional maize varieties tend to mine naturally occurring soil nitrogen. Adding nitrogen fertilizer helps to stop (or at least slow this mining) in most regions, which improves soil productivity in future years (e.g., Nkonya et al., 2005).

The middle third of Table 1 and Fig. 4 address the question of how switching from traditional to improved seed varieties without adding nitrogen fertilizer affects yield distributions across SSA. Again, the results are different between the initial and 10th year of adoption, but the difference is now in the opposite direction. In the first year, improved seed varieties are clearly better on 81.2% of maize cropland, falling to 74.4% after 10 years of repeated use. Furthermore, after 10 years, improved seed varieties result in clearly worse yield distributions on about 4.2% of maize cropland as compared to only 1.6% in the first year of adoption. Geographically, the deterioration of the benefits to the adoption of improved seed varieties is most apparent in Eastern and South Eastern SSA. A possible explanation for these results again relates to mining naturally occurring soil nitrogen. A target of improved maize breeding is nitrogen use efficiency. Switching to varieties with greater nitrogen use efficiency, makes it possible to utilize more nitrogen annually, which becomes problematic overtime if there is no supplemental nitrogen to bolster naturally occurring nitrogen. Comparing the results in the top and middle third of Table 1, and Figs. 3 with 4, the yield distribution benefits of switching to improved seed varieties appear larger than using nitrogen fertilizer with traditional seed varieties even after 10 years of adoption.

The bottom third of Table 1 and Fig. 5 address the question of how switching to improved seed with 40 kg/ha of nitrogen fertilizer affects yield distributions across SSA. The key result that supports our hypothesis regarding the importance of supplemental nitrogen for avoiding nitrogen mining, particularly with improved seed varieties, is that the improved seed varieties with nitrogen initially leads to improvements in the yield distributions across almost the entire landscape, and these improvements appear largely maintained even after 10 years.

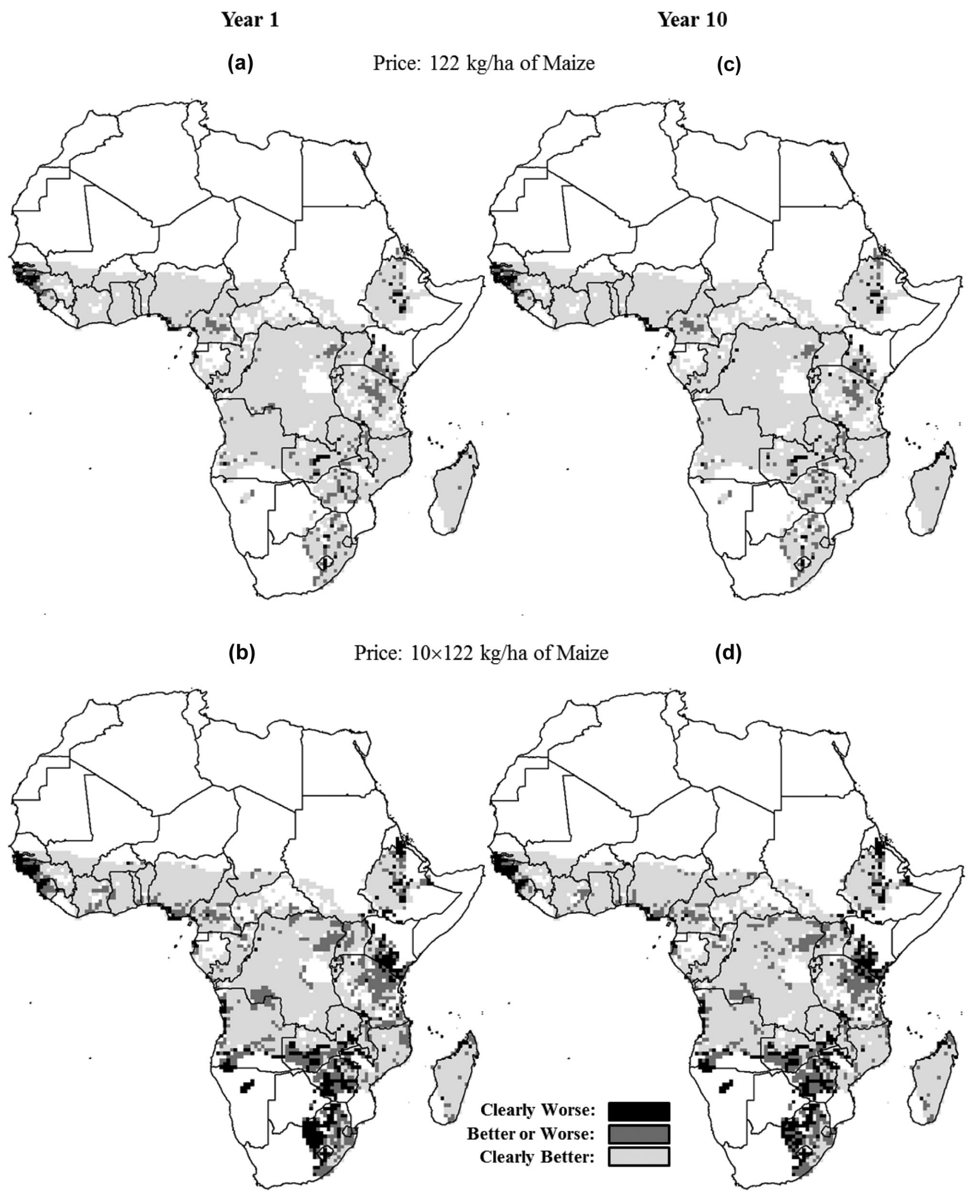


Fig. 7. Sensitivity analysis for willingness to pay bounds (maize ton/ha) when switching from the traditional variety without nitrogen fertilizer to the improved variety with 40 kg/ha of nitrogen fertilizer at a price of 122 kg/ha and 10 × 122 kg/ha of maize in year 1 (panels (a) and (b)) and 10 years (panels (c) and (d)) after adoption.

The results in Table 1 and Figs. 3–5 show how fertilizer and improved seed varieties can affect yield distributions across SSA without considering the potential added cost of more intensive production to farmers. To take these costs into account, we determine how much additional maize (ton/ha) would be needed to cover the cost of 40 kg/ha of nitrogen given maize and fertilizer prices. The monthly average world maize price ranged from 0.15 to 0.33 \$/kg with an average of 22.3 \$/kg between June 2009 and April 2016 (IFPRI, 2016). The price of urea between 2010 and 2014 reported in FAO (2015) ranged from 0.289 to 0.421 \$/kg. Using a urea price of 0.35 \$/kg, maize price of 0.25 \$/kg, and taking into account urea is 46% nitrogen, the cost of 40 kg/ha of nitrogen fertilizer in terms of maize is 122 kg/ha.

Given the maize price of fertilizer, we can determine if any change in the yield distribution due to using fertilizer and improved seed is enough to cover the cost of fertilizer by comparing this price to the lower WTP bound. If the lower WTP bound is larger than the price, there is a large enough improvement in the yield distribution to cover the cost of fertilizer (assuming no transportation or other costs). Alternatively, if the upper WTP bound is lower than this price, there is not a large enough improvement in the yield distribution to cover the cost of fertilizer. For a price between the WTP bounds, the result is indeterminate, again depending on a farmer's specific risk preferences. The results of this analysis are reported in Fig. 6, which illustrates the sensitivity of our results in terms of the proportion of cropland with clearly better and clearly worse yield distributions as the 122 kg/ha maize price of nitrogen fertilizer is scaled between 0 and 20 times. Fig. 6 further illustrates these results geographically for nitrogen fertilizer prices of 122 and 10×122 kg/ha maize.

Fig. 5, panels (b) and (d), are virtually indistinguishable from Fig. 7, panels (a) and (c). The reason for such a small difference is found in the lower third of Table 1, which shows the mean WTP bounds are more than an order of magnitude larger than the maize price of nitrogen fertilizer. Similarly, the standard deviations of the WTP bound are much larger than the price. This suggests that the material cost of fertilizer, given world prices, is not substantial compared to the potential yield benefits it could provide with improved seed varieties across much of SSA. However, Fig. 7, panels (b) and (d), show that if actual fertilizer (and improved seed variety) costs substantially outpace the material costs due to transportation and other factors (e.g., see Minten et al., 2013), then the yield benefits of the adoption of fertilizer and improved seed varieties can be dissipated by these costs over a broad landscape.

5. Conclusions

The purpose of this research was to explore how weather risk affects the value of nitrogen fertilizer use and improved seed variety adoption to SSA maize farmers. Empirically, it contributes to the literature by providing additional and broader support for the hypothesis that low rates of fertilizer use and improved seed variety adoption can be explained by the fact that the SSA landscape is heterogeneous, so fertilizer use and improved seed variety adoption is not always advantageous, especially when considering the potentially high cost to farmers of obtaining fertilizer and improved seed.

Methodologically, it contributes WTP bounds to the literature that can be used to assess the importance of farmers' risk preferences as potential barriers to fertilizer and improved seed variety adoption. While this methodology was applied to fertilizer and improved seed in SSA maize production using simulated yield distributions, its applicability can be extended to comparing other technology bundles or policy prescriptions in other regions of the world, using benefit metrics other than yield, and using distributions generated from survey or experimental as well as simulation data.

The analysis points to important synergies between nitrogen fertilizer and improved seed varieties that are particularly interesting from a policy perspective. While the benefits of nitrogen use tend to increase overtime without improved seed varieties and the benefits of improved seed varieties tend to decrease overtime without nitrogen, combining the two provides larger and more sustainable productivity benefits. Therefore, from a policy perspective, securing both nitrogen use and improved seed variety adoption is important for promoting sustained maize productivity gains across much of SSA. It is also interesting to note that the yield benefits of improved seed varieties tend to be larger than the yield benefits of using nitrogen fertilizer, particularly in the earlier years of adoption. This result suggests that securing higher levels of adoption may be obtained by sequentially introducing farmers to improved seed varieties before encouraging the use of nitrogen fertilizer because farmers are more likely to see larger improvements faster and with less additional effort.

Two caveats of our analysis are its focus on yield and use of simulated yield distributions. Depending on a farmer's commercial versus subsistence orientation, maize yield may not be the only or most important factor guiding behavior, which means maize yield may not be the best metric or most informative metric for analysis. While we show that it is possible to include price risk in the analysis, this requires yield distributions to be estimated conditionally on factors that influence farmer's yields and prices when yield and prices are not independent.

The advantage to using crop growth models to simulate yield distributions is that they can be systematically and cost effectively applied across a wide area. The disadvantage is that they are inherently limited in the extent to which they can capture idiosyncratic differences in the production environment and farmers' management practices across a widely heterogeneous landscape. It should also be noted that the models do not capture all the abiotic and biotic constraints that crops will face in the field. This study focused on two broadly important abiotic constraints, water and nitrogen. The yields estimated from the model should be considered achievable assuming other constraints are well managed. While both experimental trial and farmer survey data offer obvious alternatives for generating yield distributions that will be more sensitive to these idiosyncratic differences, experimental trial data are relatively costly to generate, especially on a landscape level, and survey data, in addition to being costly, can be hopelessly confounded by various socioeconomic factors. Therefore, alternative strategies for characterizing yield distributions are not without their own caveats.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supporting Information