nature portfolio

https://doi.org/10.1038/s43016-022-00493-z

Supplementary information

Profitability of climate-smart soil fertility investment varies widely across sub-Saharan Africa

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Profitability of climate smart soil fertility investment varies widely across sub-Saharan Africa

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Supplementary Discussion

Previous attempts to understand fertilizer use in Sub-Saharan Africa

Four approaches have been commonly used to understand fertilizer use in sub-Saharan Africa. These include agronomic trials, farmer-managed trials, mechanistic crop growth models, and observational farm surveys.

Agronomic trials are commonly used to compare two or more levels of fertilizer treatment while holding all other variables constant. Agronomic trials are typically characterized by small sample sizes, low variation in climate and soil conditions, and a limited number of fertilizer treatment doses from which a crop response curve can be derived. Some agronomic trials incorporate additional management practices into their design, such as crop variety or irrigation, through a factorial design. Beyond variables that are explicitly incorporated into a factorial design, it can be difficult to capture the interactions between fertilizer and other variables, either because the other variables are not recorded or because they do not vary within the trial dataset. Because one cannot fully identify the contributions of different interactions between fertilizer and other variables to the local average treatment effect, a fertilizer response parameter derived from an agronomic trial has limited validity outside of its trial setting. Measures of agronomic response to fertilizer on maize in East Africa range considerably, between 5 and 25 kg of maize per kg nitrogen applied [1]. Another concern with estimating fertilizer response using agronomic trial data is that, often, research stations are not representative of farmers' fields [2]. Yield responses are typically higher in experimental stations than on farmers' fields due to higher use of complementary inputs, more intensive weeding, and optimal timing of planting and fertilization, which could bias fertilizer response upwards in experiment stations relative to farmers' fields [1, 3]. Other studies have found that crop nutrient responses can be larger in depleted soils, where nutrients are limiting [4, 5]. If nutrients are more likely to be limiting on farmers' fields than on experiment stations, then the fertilizer response at experiment stations will be biased downwards relative to farmers' fields. Given the challenges posed by extracting away important interactions, limited variation in treatment and in trial conditions, and possible differences between farmer fields and experiment stations, agronomic trials do not lend themselves to externally valid estimates of crop response to fertilizer.

Farmer-managed trials, which call for side by side comparison between different fertilizer treatments on a large number of farms, offer an approach to estimating the key parameters of a fertilizer response function where fertilizer is experimentally assigned and the underlying agroclimatic conditions vary between farms. Data from a farmer-managed trial in Malawi show that moderate fertilizer application (35 kg/ha of nitrogen fertilizer), approximately doubles maize yields versus unfertilized farmer plots [6]. Using the same underlying farmer-managed trials, other researchers estimated a fertilizer response function that suggests the marginal returns to nitrogen are increasing with precipitation, decreasing with high temperatures (proxied by growing degree days 30C+), and also that nitrogen has positive complementarities when applied with other nutrients such as sulfur [7]. Despite their advantages in incorporating farm level heterogeneity and the realities of farmer management, farmer-managed trials present two key challenges. The first is that model farmers who participate in research trials do not represent the farming population as a whole. Typically, they are better educated, more affluent, more closely tied in with the extension system, and may differ in other characteristics [7, 8]. Fertilizer response parameters generated from model farm trials tend to be smaller in magnitude than those from experimental trials, most likely because even model farmers are likely to be more constrained than agronomists [3]. Another challenge with farmer-managed trials is that they typically run for only one to two growing seasons, so it is virtually impossible, without structural assumptions, to identify the effects on fertilizer response of interactions between time-invariant characteristics, such as soil type, and time varying characteristics, such as temperature and precipitation.

Fully mechanistic crop growth models, which predict crop yields given a daily set of assumptions encompassing the growing conditions and inputs applied, offer a third approach to measuring crop response to fertilizer. These models are generally highly sensitive to their data inputs (e.g., timing of fertilizer application, daily rainfall, and solar radiation). Furthermore, crop models do not obviate the need for good data to measure fertilizer response, as crop models must be calibrated to local conditions. Mechanistic crop growth models underlie estimates of returns to input use in the Global Agro-Ecological Zones assessments and the Harvest Choice platform [9–11]. Using multiple criteria, including maize potential as forecasted through crop models, soil type, slope, and land cover, sites for maize intensification are prioritized in East Africa [12]. Crop growth models incorporate spatial sources of heterogeneity related to physical production, but do not incorporate prices or spatial analysis of price variation, nor do they consider uncertainty associated with seasonal weather variation.

Observational farm surveys, which typically use cross-sectional variation in growing conditions to estimate the parameters of a crop production function, offer a final approach for estimating the parameters of a crop production function. The most important limitation of this approach is that the decision to use fertilizer is not randomly assigned and is likely correlated with unobservable farmer and plot characteristics, such as farmer ability, farm gate prices, and soil quality, which then can bias estimates of crop response to fertilizer use. Fertilizer response parameters estimated using observational data tend to be smaller than those estimated using agronomic trial or farmer trial data [3]. A recent comparison of nitrogen use efficiency measures derived from surveys with those from agronomic trials in Malawi suggests that farmer management practices, such as weeding, crop rotation, and timing and intensity of inorganic fertilizer application, can explain why nitrogen responses are lower on farmer fields than in research stations [13].

Economists usually address the endogeneity of fertilizer adoption either by using panel survey data and including farmer fixed effects, thus accounting for all time-invariant farm level characteristics that could affect both fertilizer adoption and yields. [14] use multiple waves of household survey data in Tanzania to estimate maize fertilizer response in Tanzania, conditional on crop management practices, soils, and rainfall. Then they simulate farm revenue for different fertilizer usage rates over stochastic rainfall and price realizations. [15] use Ethiopian observational data and control for plot level fixed effects to document how limits in farmers' ability to cope, *ex post*, with a failed harvest can be a stronger deterrent to fertilizer use than limits in farmers' ability to secure credit to purchase fertilizer. The demonstrated interplay between risk and adoption highlights a downfall of using observational data to estimate the returns to fertilizer use because the decision to use fertilizer is confounded by historic climate conditions in the farmer's location. It also highlights the importance of understanding the probability of crop failure is critical to predicting farmers' willingness to adopt fertilizer. Furthermore, in observational studies, variables like yields, plot size, soil characteristics, and plot level rainfall are measured with error, either due to misreporting or misperceptions, which can lead to biased testing of hypotheses related to productivity or technology adoption [16].

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