

The Role of Active Soil Carbon in Influencing the Profitability of Fertilizer Use: Empirical Evidence from Smallholder Maize Plots in Tanzania

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Abstract

We use recent plot-level panel data from Tanzanian smallholder farmers to investigate maize yield responses to inorganic fertilizer under variable production conditions. We find that the marginal product of nitrogen is strongly conditioned by soil organic carbon and rainfall levels. These results highlight important sources of variation in the returns to fertilizer investments across plots and smallholder farmers in the region. When farmgate prices for maize and fertilizer are incorporated into calculations of economic returns, we find that the profitability of fertilizer use is strongly dependent upon farmgate price ratio assumptions: under our most optimistic agronomic response estimates, while 71% of our sample has an AVCR greater than 1.5 at a maize-nitrogen price ratio of 0.15, that share drops to 30% at a price ratio of 0.12 and 2% at a price ratio of 0.09. Our findings provide insights into the low levels of commercial fertilizer use in Tanzania and elsewhere in the region, and suggest that raising active carbon stocks in smallholder systems should be a strategic priority for sustainable development.

Motivation

Staple crop yields in sub-Saharan Africa (SSA) remain very low by international standards, with yield gaps on the order of 80% (van Ittersum et al. 2017). Inorganic fertilizer is widely agreed to be the technology with the greatest potential to raise yields in SSA's smallholder systems (Vanlauwe et al., 2014; Holden 2018). Nitrogen is the main constraining nutrient for cereal crop performance across most environments, both in terms of yield level and yield stability (Vanlauwe et al., 2011). Indeed, nitrogen has been identified as one of the grand challenges of the 21st Century given its pivotal role in food production, and nowhere is this more important than in sub-Saharan Africa where a strong negative relationship has been observed between soil nitrogen balances and population density (Drechsel et al., 2001). Yet the relatively low uptake of nitrogen fertilizers by SSA smallholders indicates important constraints, which are not yet fully understood.

The large spatial heterogeneity in fertilizer usage in SSA (Sheahan & Barrett 2017) suggests that both market factors (e.g. farmgate crop/fertilizer price ratios) as well as environmental factors (such as soil and rainfall) may play an important role. Yield response – i.e. the marginal or average physical product of fertilizer – is often low and highly variable for smallholder staples producers, resulting in low levels of profitability of fertilizer use when farm-gate crop and fertilizer prices are applied (Xu et al., 2009; Marenja & Barrett, 2009; Sheahan et al., 2013; Jayne & Rachid, 2013; Liverpool-Tasie et al., 2017; Burke et al., 2017; Koussoube & Nauges, 2017).¹¹See Jayne et al. (2018) for a recent review of over 20 studies estimating the profitability of applying inorganic fertilizer on maize in various African locations. Relatedly, fertilizer is not profitable for many farmers even where the *average* benefits are positive and relatively large, given

differences in management ability and other factors that vary across plots and households (Suri, 2011). Fertilizer responses in many areas may be limited by depleted soil organic matter (Marenja & Barrett, 2009, Dreschel et al., 2001), soil acidity (Burke et al., 2017), and other factors. Risk-averse farmers are especially likely to forgo expected gains in the face of uncertainty around the performance or profitability of a given technology (Emerick et al., 2016; Magruder, 2018). Disentangling the patterns of fertilizer responses may help us to better understand how to design area-, household-, and plot-specific interventions to overcome constraints to the profitable use of fertilizer in African smallholder production systems.

This study identifies key soil-related drivers of maize yield and maize yield response to nitrogen fertilizers for Tanzanian smallholders. Our particular emphasis is on organic carbon, a particularly important component of soil fertility (Lal 2006; Nord & Snapp 2020). We use two-wave panel data on farmer-managed plots in 25 maize-producing districts in Tanzania. In addition to the standard farmer-, farm- and community-level characteristics typically included in such analyses, our dataset features well-measured yields (through yield sub-plot crop cuts at harvest time), plot-level soil chemical analysis, and detailed plot-level agronomic management information. We find that estimated maize yield response to N is similar to other empirical studies from the region based on farmer-managed fields and that they are strongly conditioned by both rainfall and soil organic carbon stocks. Our production function estimates indicate that the marginal product of nitrogen increases by 25% when moving from the 25th to the 75th percentile of available carbon in our sample. Furthermore, the variability around these expected returns are high. After factoring in local input and output prices, profitability assessments indicate relatively low returns to fertilizer investments: less than half of the sample have $AVCR > 2$ under our most favorable estimation results and very conservative estimates of farmgate price ratios. Our results also highlight differences in conclusions about the profitability of fertilizer use on farmers' own fields and management conditions vs. studies relying on farm trials and demonstration plots (e.g., Jama et al., 2017), which tend to benefit from researcher management protocols that many smallholder farmers may not be able to replicate (Snapp et al., 2014). Our results highlight the importance of considering the factors that condition fertilizer response (and profitability) from the farmer's standpoint when designing agricultural intensification programs and investment strategies. Our analysis concludes that agricultural intensification strategies based on raising the intensity of fertilizer use are unlikely to lead to widespread adoption if the variation in agronomic and economic returns is not accounted for and if the sources of low active soil carbon are not also addressed.

The rest of this paper is organized as follows. After describing our setting, data and empirical estimation strategy, we present estimation results for agronomic and economic returns to fertilizer investments, in turn. We discuss these results and their implications for sustainable intensification strategies, concluding with key messages for policymakers and recommendations for further research.

Empirical framework

Context

Tanzania is one of the largest countries in Eastern and Central Africa, and an important source of the region's maize production. However, most of this production comes from smallholders who have relatively low levels of productivity, and few of which use modern inputs such as fertilizer. As such, raising maize yields has been an important investment and policy target for the country and its partners in recent years. Tanzania is representative in many ways of the maize-based farming systems found elsewhere in the region, in terms of its agroecologies and range of biophysical endowments, the predominant production characteristics of its smallholder farmers, and the relatively low levels of market infrastructure development. At the same time, the heterogeneity of production characteristics found within Tanzania's maize growing areas bodes well for its value as a test case for evaluating variability of agronomic responses across key geographical characteristics (Nord & Snapp 2020).

Data

Farm household survey data were collected in Tanzania in 2016 and 2017 on 624 households, located in 25 districts (Figure 1). These districts are located in both the Southern Highlands and Northern zone, representing the most important maize growing areas in the country. Within each district, a stratified sampling frame was used that maximized soil type variability so as to be able to make broad inferences about crop response, and to identify survey localities (Walsh & Vågen 2006; Shepherd et al., 2015). Within each locality, a listing of all maize producing households was generated with the assistance of the local headman. From this listing, 24 households in each locality were randomly selected. Data were collected on household demographics, farm and non-farm economic portfolios, land holdings and productive assets, and other characteristics. Within each farm household, basic information was collected for each plot managed by the household (e.g. land use status, production decisions). In addition, very detailed agronomic management information was collected for household's most important maize plot (henceforth the farm's "focal plot"). This plot was identified by the farmer as the plot which generated the most maize production, and which received the most managerial effort.

Nitrogen and other macronutrient supplies were calculated from the various fertilizer blends farmers reported using. To account for implausible values, we replaced application rates exceeding 700 kg ha⁻¹ of N with that value, which was tantamount to winsorizing at the 99th percentile of N application rates for fertilizer users, and which follows the protocols used by Liverpool-Tasie et al. (2017) and Sheahan and Barrett (2017).

Maize yields on focal plots were measured using crop cuts from three 5x5 meter quadrants, calculated at 12.5% grain moisture content. Soil characteristics from these plots were measured from samples taken at quadrant locations at 0-10 and 10-20 cm depths. Soil organic carbon is largely conditioned by topography and soil parent material; however, once a field is converted to agriculture, active soil organic matter fractions largely determine soil productivity, and this is markedly influenced by farmer practices (Zingore et al., 2008). Developments in laboratory assays to monitor 'active' soil organic matter fractions have highlighted the value of permanganate oxidizable carbon as an early indicator of management influence on soil organic carbon (Culman et al., 2012). Total soil organic carbon also provides insights regarding sustainable soil management, although at a slow timestep (five to ten years). For this work, permanganate oxidizable carbon (POXC) was determined on a ground (1mm sieve) sub-sample, oxidized with 0.02 M KMnO₄, and subsequently absorbance was read at a wavelength of 550nm (ibid.). To address potential measurement error, and under the assumption that the soil properties of interest here (particularly soil active carbon) are relatively stable, we use the average measure across the two years for each plot in our regression work.

Rainfall was measured as the sum of dekadal values recorded for the main growing season, using the CHIRPS dataset (Funk et al., 2017). Rainfall variability was measured as the coefficient of variation on the dekadal observations within a season.

Estimation strategy

The intent of this paper is to understand the agronomic and economic returns to nitrogen fertilizer applications in smallholder maize production. In keeping with agronomic and agricultural economic literature, we frame maize yield (y) as a function of fertilizer application rates (F), other agronomic management decisions (M), and other exogenous conditioners (G).

$$y = f(F, M, G) \quad (1)$$

Because farmers in Tanzania use a variety of fertilizer blends, we integrate these decisions by decomposing each blend into its macronutrient content, i.e. nitrogen (N), phosphorous (P) and potassium (K). Other management factors include improved maize seed, maize-legume intercropping (common in the southern highlands), organic matter integration via compost, manure and crop residue retention, plant spacing, weeding, fallowing, terracing and erosion control structures, and herbicide and pesticide applications. Other exogenous conditioners include slope, rainfall, rainfall variability and the presence of disease or striga (witchweed).

We adopt a flexible polynomial functional form, allowing for quadratic terms and interactions between variables. In this approach, we follow similar empirical studies (e.g. Burke et al., 2017, Sheahan et al., 2013, Xu et al., 2009). This flexibility is important in enabling us to investigate how yield response to nitrogen is conditioned by other factors. We may generalize this function as:

$$y_{it} = \alpha + \beta_1 N_{it} + \beta_2 N_{it}^2 + \beta_{10} \mathbf{X}_{it} + \beta_{11} N_{it} * \mathbf{X}_{it} + u_{it} \quad (2)$$

where N is nitrogen, our primary input of interest, i indexes plots, t indexes observations over time, and where, for convenience, we have subsumed $\mathbf{M}$ and $\mathbf{G}$ in the vector $\mathbf{X}$. As indicated earlier, *a priori* hypotheses include the possibility of positive interactions between nitrogen, soil organic carbon and rainfall, after controlling for other factors.

A key consideration is the possibility that unobserved factors may possibly bias our estimation results. Concretely, we may decompose the residual in equation 2 as:

$$u_{it} = o_{it} + c_i + \epsilon_{it} \quad (3)$$

where o represents unobserved time-varying factors, c represents unobserved time-constant factors, and ϵ is a randomly distributed error term. Time-varying unobservables may include soil moisture, nutrient status or other factors which are often missing from empirical studies (or poorly measured). Time-constant unobservables may include farmer ability or plot biophysical characteristics which change little from year to year, but which may affect both fertilizer usage and yield outcomes. Finally, correlation between model covariates and the stochastic error term may be an additional source of bias.¹¹ Burke et al. (2017) provide a useful, detailed discussion of these issues and corresponding identification strategies in survey data settings.

In the present study, we argue that our dataset does a better job at controlling for time-varying plot and plot-management factors than is typically the case in empirical studies, and therefore unobserved o_{it} is unlikely to be a major issue. Our larger concern is with time-invariant unobserved farmer and plot-level heterogeneity which are likely to upwardly bias our results if not addressed (e.g. under the assumption that more able farmers are more likely to use fertilizer than less able farmers). To address this, we estimate models with the Mundlak-Chamberlain device (i.e. the Correlated Random Effects model (Wooldridge 2010), as well as a Fixed Effects estimator.

Results

Descriptive statistics

Summary statistics on our dataset are reported in Table 1. The average farm size is 3.3 hectares, and is comprised of 4 plots. Most of our sample consists of farms in the 1-4 hectare range, which is typical for smallholder systems in the region. Only 7% had a single plot, and 14% had more than 5 plots. The mean and median focal plot sizes are 0.85 and 0.51 ha, respectively. Thirteen % of our sample farms are managed by female household heads.

Yields in our sample are somewhat higher than the national averages reported elsewhere for Tanzania, with a median value of 2.7 tons/ha. This reflects the fact that the focal plot is not a random maize plot, but the most important and generally most productive plot available to the farmer. Furthermore, because our sample districts were selected on the basis of being important maize producing districts, maize yields in our sample likely reflect more favorable production conditions than a nationally representative sample. This sample orientation notwithstanding, only about a third of sample uses fertilizer on these plots.¹¹ Sheahan & Barret (2017) estimate that 17% of Tanzanian farm households use fertilizer, drawn from the nationally representative 2011 wave of the LSMS-ISA data. Mather et al. (2016), using three waves of the LSMS-ISA data, find similar national-level estimates, but note higher levels of fertilizer use by maize farmers in the zones covered by our survey: 31-37% of maize plots in the Southern Highlands and 16% of maize plots in the Northern zone. Of these fertilizer users, there is considerable variability in fertilizer application rates, with a

median rate of 56 kg ha⁻¹ of nitrogen (somewhat below regional recommendations).²² Sheahan and Barrett (2017) found that fertilizer users applied an average of 32kg/ha in the nationally representative LSMS-ISA data for Tanzania in 2011. The higher application rates we find for fertilizer users in our sample reflects our sample design, as noted above, as well as the fact that fertilizer use in our sample is dominated by high analysis Urea (46%N) and was often applied to very small maize plots.

Agronomic returns to nitrogen

Production function coefficient estimates are shown in Table 2 (we show only a subset of estimation results; full results are reported in the supplementary materials). We show six alternative specifications. In each of these, the dependent variable is maize yield, measured in kg ha⁻¹ during the maize production season. Nitrogen, as expected, shows a strong positive and non-linear influence on yield outcomes. Specifications (1) and (2) use pooled OLS (POLS), and only differ in the interaction term: the first specification interacts N with active carbon alone, while the second specification interacts N with active carbon and log rainfall for that growing season. Specifications (3) and (4) incorporate the Mundlak-Chamberlain device – i.e. the correlated random effects (CRE) model – to address unobserved heterogeneity, but are otherwise similar to the first two specifications. Specifications (5) and (6) use Fixed Effects estimation to address unobserved heterogeneity, but are otherwise similar to the other specification pairs. All models are cluster robust at the household level and include controls for plot, household and community characteristics (including distance to markets), detailed plot management controls, a year indicator, and, in the POLS and CRE models, time-invariant controls for the 75 districts in the sample.

Coefficient estimates (Table 2) are fairly consistent across all specifications, although they differ somewhat in magnitude. Results correspond with the expected positive returns to N applications, but at diminishing rates. Interaction terms – N*POXC and N*POXC*log(rainfall) – are significant under all three estimators, indicating that the agronomic efficiency of N is conditioned by active carbon and rainfall, as hypothesized. The coefficients on active carbon and its interaction term is highly significant in all models, even where the individual coefficient for active carbon is not significant at conventional levels. The estimated impacts of rainfall and rainfall variability are positive and negative, respectively, as we would expect.

Average marginal effects are shown for N and POXC in Table 3. The marginal effects for N are our estimates of marginal physical product (MP). These estimates differ somewhat across specifications, being somewhat higher under FE compared with POLS and CRE models. The range in MP estimates of 10-16 (additional kgs of maize yield per additional kg of N) are similar to those found elsewhere in the region: 8 kg in Nigeria (Liverpool-Tasie et al., 2017), 16 kg for Zambia (Xu et al., 2009), 17 kg for Kenya (Marenja & Barret, 2009), 23 to 25 kg for Uganda (Matsumoto & Yamano, 2013), 21 to 25 kg for Malawi (Harou et al., 2017), 19 kg for Burkina Faso (Koussoubé & Nauges, 2017). Our results are somewhat higher than Mather et al. (2016) found for Tanzania using LSMS-ISA data (7-8kg). However, their data included all plots and production in marginal areas, and was based on farmer estimates, rather than crop-cut measures. Because our sample focuses on the most productive maize plots of farmers in Tanzania’s maize producing belt, we would expect somewhat higher levels of productivity than for the entire population of smallholders in the nation.

In the analysis that follows, we focus on the results of the Fixed Effects regression, as the model which has the most plausible controls for unobserved time-invariant heterogeneity which may otherwise bias our results. However, we may note that all our results (i.e. limited agronomic and economic returns to fertilizer) are even stronger when based on the other model estimates, which indicate lower agronomic use efficiencies. We return to this point in the discussion.

Table 4 illustrates the diminishing expected MP of nitrogen at different levels of active carbon (10th, 25th, 50th, 75th, and 90th percentile, respectively), holding other factors constant, focusing on the Fixed Effects model results. The direct impact of moving from 337 ppm (the 25th percentile of our sample) to 696 ppm (75th percentile) implies an increase in MP by 20-25 percentage points, depending upon the specification (i.e. whether or not log rainfall enters via an interaction). Moving from the 10th to the 90th percentile of the

active carbon distribution is associated with even larger changes in MP: 43-55 percentage points.

Given the uncertainty that farmer face in production environments, these expected changes in MP are not at all trivial. Recall that rainfall variability also affects response. Because rainfall is a stochastic variable, the large impact it has on yields, even after controlling for other factors, indicates the magnitude of uncertainty in yield outcomes for farmers operating in these areas.

As a complement to our MP estimate, we computed the average physical product (AP) of N, calculated as the difference between the estimated difference in yields resulting from zero fertilizer and yields resulting from 200 kg ha⁻¹ of nitrogen (the level at which MVCR=1, on average, when using a farmgate maize-nitrogen price ratio of 0.15), with other sample values as observed. The distribution of MP and AP estimates across the sample is shown in Table 5. These results indicate substantial variability in agronomic response across the sample. As an illustration, a farmer at the 75th percentile of the MP distribution has an expected MP that is 40% larger than that of a farmer at the 25th percentile.

Economic returns to nitrogen

To translate these agronomic responses into profitability terms, we calculate and summarize a number of relative measures of economic returns on the basis of alternative maize-nitrogen price ratios. In our farm survey data, the farmer-reported input and output prices were exceedingly noisy and it was not possible to coherently interpret the variability of responses within a given area. Data entry problems cannot be ruled out, but we may also note the wide variety of fertilizer acquisition and maize sales channels: farmers buy and sell at very different quantities, in different types of markets, at different distances from their homestead. For this reason, we base the profitability analysis in this paper on a set of representative wholesale prices based on different sources of local market price information for Tanzania: data on the average maize wholesale prices in regional markets was taken from FEWSNet for the 2014-2018 period. Data on the average unsubsidized commercial price of urea (generally the cheapest source of N) for all local Tanzanian markets reporting prices for 50kg bags during the 2014-2018 period was obtained AfricaFertilizer.org. The price for nitrogen was inferred from the urea price, based on the 46% N content of urea, as is standard practice in this type of analysis. Based on these data, we define a representative market price ratio, as well several indicative farmgate price ratios (Table 6). The representative maize/nitrogen market price ratio of 0.22, based on 0.27 and 1.22 USD/kg for maize and nitrogen respectively. These values are very similar to those used in other studies of fertilizer profitability for Tanzanian maize farmers (e.g. Kihara et al., 2016). However, such a market price ratio fails to account for last mile transfer costs incurred by farmers, in which effective prices of inputs increase (as the farmer needs to add transport costs to the market price paid) and the effective prices of marketed output decline (as the farmer must discount transfer costs between the farm and the market from the market price received).³³ Note that this situation does not change when marketing is done locally via traders. In that case, the trader's margins will include transfer costs between the village and market, plus intermediation fees. Thus, we further define farmgate price ratios from the baseline market price ratio, based on transfer costs of 0.006 USD/kg/km at 5,10,15 and 20 kilometers distance, respectively, between the wholesale market and the farmgate, resulting in decreasing price ratios of 0.18, 0.15, 0.12, and 0.09. The transfer cost assumption here is based on the empirical finding of Benson et al. (2012). Our resulting farmgate price ratios are in the range of those calculated by Mather et al. (2016) from LSMS-ISA data for Tanzania (which range from 0.19-0.14).

The marginal value-cost ratio (MVCR) is computed as the MP multiplied by the input-output price ratio, while the average value-cost ratio (AVCR) is the AP multiplied by the input-output price ratio. An AVCR value exceeding 1 indicates profitability, strictly speaking, although an AVCR value of 2 is often used as a shorthand criterion for gauging the economic attractiveness of an investment from the perspective of a risk-averse farmer. Similarly, while an MVCR value of 0 indicates the optimal input level for a risk-neutral farmer (because marginal returns are zero), MVCR values of 1 or greater are often used as more reasonable indicators of acceptable minimum marginal returns, under assumptions of risk-aversion and imperfectly observed production or transactions costs.

Table 7 summarizes these measures for the different price ratio assumptions, using the estimation results from the FE model with $N*POXC*\log(\text{rainfall})$ interactions (column 6 in table 2). This specification produces the highest estimated agronomic response of maize to N. As such, these results may be taken as an upper bound to the actual profitability of fertilizer in our survey area.

Results indicate relatively low rates of profitability, regardless of the assumption: the average MVCR ranges from 2.85 (at the market price ratio of 0.22) to 1.116 (when the farmgate price ratio is 0.09). While most farmers apply at rates below the economically efficient rate for a risk-neutral farmer (i.e. where $MVCR=0$), the share of farmers with $MVCR>1$ drops notably with price ratio reductions, and the share of farmers with $MVCR>2$ drops even faster. As discussed elsewhere (e.g. Sheahan et al., 2013; Xu et al., 2009), an MVCR of 2 may be a more appropriate “optimal” level of input usage, under the assumption that a risk-averse farmer will require a marginal return of at least this magnitude.

AVCR estimates show similar cross-sectional variability, with mean values ranging between 2.60 (at price ratio=0.22) to 1.06 (at price ratio=0.09). It is common to use an AVCR of 1.5 or 2 as a minimal threshold of profitability sufficient to incentivize risk-averse smallholder farmers to use fertilizer, to account for risk aversity and unobserved transactions costs in production and marketing (e.g. Xu et al., 2009; Sheahan et al., 2013). While most farmers in the sample have AVCR estimates exceeding 1, the share with AVCR estimates exceeding 1.5 or 2 is very sensitive to price ratio assumptions: at a price ratio of 0.15 only 71% and 22% of our sample has an AVCR exceeding 1.5 and 2, respectively. Our results suggest that under even moderate uncertainty about farm gate prices, the magnitude of the MVCR and AVCR estimates may be insufficient to motivate farmers to make risky fertilizer investments.

These findings suggest that even where agronomic returns are positive and of magnitudes generally considered conducive to investment, the incorporation of “last mile” transportation costs may quickly attenuate the economic attractiveness of these investments (e.g., Minten et al., 2013). The implications of economic remoteness have been well described (e.g. Minten & Stifel, 2004; Chamberlin & Jayne, 2013). Adding uncertainty around the actual costs of last mile transportation (which is the reality for many farmers in rural Tanzania) will only magnify the disincentivizing effects of these transfer costs on fertilizer investments. The fact that active soil carbon is an empirically important driver of agronomic responses may help to target attention to where these market remoteness effects may be especially magnified. Figure 2 shows the AVCR calculated at a price ratio of 0.15 as a non-parametric function of active carbon. This graph illustrates that at lower levels of soil carbon the agronomic use efficiency of nitrogen is likely to be insufficient to be an attractive investment for risk averse farmers, even in average rainfall years. When we additionally consider the estimated impacts on profitability of seasonal rainfall (Figure 3), we can clearly see the sensitivity of expected profitability calculations to stochastic factors.

Discussion

Our results indicate that while the marginal and average agronomic returns to inorganic fertilizer use are generally positive, there are strong variations in these returns over our sample. We have shown that both early-season rainfall and available soil carbon are important conditioners of yield responses to nitrogen. Building on these agronomic response estimates, our economic analysis has stark implications. Even under relatively modest assumptions of last-mile transportation costs, the inclusion of estimated farmgate prices in relative profitability calculations reduces the attractiveness of fertilizer investments for a large share of our sample.

Our findings are likely to overestimate Tanzanian smallholders’ agronomic responses to fertilizer use and hence their economic incentives to use fertilizer, for several reasons. First of all, our sample consists of farmers in Tanzania’s maize belt, where agroecological conditions are generally more favorable than in most other parts of the country. Secondly, the fact that this analysis is based on focal plots, rather than on all plots, means that our analysis cannot be taken as representative of all maize production conditions, but rather of

preferential conditions within the smallholder maize system. Farmer preferential allocation of maize crops to higher fertility, adequate soil organic carbon status field has been well documented (Mhango et al., 2013; Tittonell et al., 2008). As such, our estimates of agronomic and economic returns to fertilizer use are likely an upward bound on the true values for the system. Problems with acute soil organic carbon depletion and other soil fertility issues are likely to be much worse on average over the farming system as a whole.

Thirdly, our analysis uses the most favorable production function estimates, i.e. those resulting from the Fixed Effects estimation. Profitability analysis using the POLS and CRE estimators is even less profitable on average (although in most other respects estimation results are remarkably consistent). When we re-run the same economic analysis using the estimates of agronomic returns generated from the POLS and CRE estimation results, the share of farmers for with MVCr and AVCr estimates exceeding 2 is much lower.¹¹ For example, Table 7 shows that 71% of the sample has estimated AVCr values greater than 1.5. When we use POLS and CRE estimates corresponding to columns 2 and 4 in Table 2 as the basis of the calculation, the corresponding share of the sample with AVCr values great than 1.5 is just 13% and 1%, respectively.

Fourth, our estimates of farmgate maize/nitrogen price ratios, upon which profitability estimates critically depend, are conservative and likely to overestimate the ratio for many farmers. Our price ratio assumptions are somewhat higher than those used in other empirical analysis in the region. Sheahan et al. (2013) find an average maize/nitrogen price ratio of 0.083 for Kenya. Matsumoto and Yamano (2011) find ratios of 0.063-0.075 in Kenya and 0.044-0.027 in Uganda. The price ratio assumptions we employ in our analysis are likely to be optimistic; many farmers in Tanzania are likely to regularly face less-favorable farmgate price ratios. As such, our profitability analysis is likely biased upwards.

Finally, our results highlight important sources of uncertainty in both agronomic and economic returns to fertilizer investments. We see this particularly in the role of seasonal rainfall and rainfall distribution parameters in the production functions, but may also note that the large uncertainty around input, output and transportation prices faced by farmers means that calculating expected returns on fertilizer investments is highly uncertain even under optimal biophysical production contexts. The fact that soil carbon stocks have such a strong effect on yield responses in our sample is all the more striking given these considerations. What this means is that even for the most productive smallholders, the agronomic and economic returns to fertilizer use are quite variable, which would further impede the incentives of risk averse farmers to incur high capital outlays on fertilizers.

Taken together, these results indicate that efforts to spur fertilizer usage by smallholder farmers in Tanzania should not focus exclusively on blanket agronomic targets, which are based on average responses over large areas, but rather should carefully consider localized response rates. This is in alignment with conclusions from other studies, e.g. Nord & Snapp (2020), who studied soil fertility variability in the same geography. Investments in extension and promotion of integrated use of organic management practices in combination with fertilizer are urgently required if maize based systems are to be productive, which has clear implications for reform of input based agricultural subsidies (Lal 2006; Adowla et al., 2019). Such policies will often miss the mark, as there is growing evidence – including this study – regarding the accumulation of soil carbon as being necessary to raise yield responses sufficiently for nitrogen fertilizer to be economically attractive. This may be particularly valid for risk adverse farmers in areas facing high transport costs to regional input and output markets. Implications are also stark in the face of highly variable weather and a changing climate, complementary investments in soil organic carbon can help buffer risk (Williams et al., 2016). Our analysis suggests that agronomic returns to nitrogen will have to increase substantially in order to offset the low and variable price margins that smallholder farmers typically face in countries like Tanzania.

Conclusions

Many areas of smallholder cultivation in sub-Saharan Africa have been systematically experiencing reductions in soil organic carbon levels, particularly where continuous maize cultivation without legume rotations and/or

application of inorganic or organic fertilizer is common (Shepherd & Soule, 1998; Drechsel et al., 2001; Tittonell et al., 2005; Lal 2006; Marenja & Barrett 2009). Soil organic carbon stocks are known to affect plant uptake of nutrient supplies, and figure into low-responsiveness of yields to nitrogen supply in some areas. Farmers in such areas are much less likely to find fertilizer investments to be economically attractive, regardless of how well fertilizer markets are performing.

This paper has assembled evidence on the ways in which maize yield responses to inorganic fertilizer are affected by soil organic carbon and other factors. We have shown that the marginal product of nitrogen is positively associated with both soil organic carbon stocks (measured as active carbon), as well as by seasonal rainfall. When farmgate prices for maize and fertilizer are incorporated into calculations of average and marginal cost-benefit ratios, we find that economic returns – as measured by MVCr and AVCr – drop drastically over price-ratio ranges that are representative of those likely faced by many smallholders in Tanzania. For example, assuming a price ratio of 0.15, only 22% of farmers could utilize fertilizer profitably (using $AVCr > 2$). However, even under more favorable assumptions, the high year-to-year variability around these expected returns would discourage many farmers from investing in fertilizer even if it were profitable to do so on average across all years. Our results indicate that the sensitivity of fertilizer profitability to such outcome uncertainty will be to be particularly acute in areas of depleted organic matter.

An important implication of our analysis is the importance of investments and policy interventions which address the systematic depletion of soil organic carbon stocks. This study adds to the growing evidence that cereal crop response to fertilizer requires that attention be paid to soil health, as indicated by active soil carbon. There have been previous calls by soil scientists and economists for integrated soil fertility management to complement inorganic fertilizer, yet few previous studies have examined this at scale. Our research, conducted across a broad range of soil types and market contexts across Tanzania, reasserts the urgency of this proposition to better inform discussions of how to stimulate fertilizer investments by African smallholders. Farmer incentives to make such investments will be promoted by efforts to raise the agronomic efficiency of fertilizer sufficiently for fertilizer to be profitable.

References

- Adolwa, I.S., Schwarze, S. & Buerkert, A. (2019). Impacts of integrated soil fertility management on yield and household income: The case of Tamale (Ghana) and Kakamega (Kenya). *Ecological Economics* , 161, pp.186-192. <https://doi.org/10.1016/j.ecolecon.2019.03.023>
- Benson, T., Kirama, S.L. & Onesmo, S. (2012). The Supply of Inorganic Fertilizers to Smallholder Farmers in Tanzania: Evidence for Fertilizer Policy Development. International Food Policy Research Institute (IFPRI) Discussion Paper 01230. Washington, DC: IFPRI. <http://dx.doi.org/10.2139/ssrn.2197893>
- Benson, T., & Mogues, T. (2018). Constraints in the fertilizer supply chain: evidence for fertilizer policy development from three African countries. *Food Security*, 10 (2018), p.1479–1500. <https://doi.org/10.1007/s12571-018-0863-7>
- Burke, W.J., Jayne, T.S. & Black, J.R. (2017). Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics* , 48(1), pp.115-126. <https://doi.org/10.1111/agec.12299>
- Culman, S., Snapp, S.S., Schipanski, M.E., Freeman, M.A. Beniston, J., Drinkwater, L.E., . . . Wander, M.M. (2012). Permanganate oxidizable carbon reflects a processed soil fraction that is sensitive to management. *Soil Science Society of America Journal* , 76: 494-504. <https://doi.org/10.2136/sssaj2011.0286>
- Drechsel, P., Gyiele, L., Kunze, D. & Cofie, O. (2001). Population density, soil nutrient depletion, and economic growth in sub-Saharan Africa. *Ecological Economics* , 38(2), pp.251-258. [https://doi.org/10.1016/S0921-8009\(01\)00167-7](https://doi.org/10.1016/S0921-8009(01)00167-7)

- Emerick, K., de Janvry, A., Sadoulet, E. & Dar, M.H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review* , 106(6), pp.1537-61. <https://doi.org/10.1257/aer.20150474>
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... Michaelsen, J. (2017). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data* , 2:150066. <https://doi.org/10.1038/sdata.2015.66>
- Harou, A.P., Liu, Y., Barrett, C.B. & You, L. (2017). Variable returns to fertilizer use and the geography of poverty: Experimental and simulation evidence from Malawi. *Journal of African Economie s* , 26, 342-371. <https://doi.org/10.1093/jae/ejx002>
- Holden, S.T. (2018). Fertilizer and sustainable intensification in Sub-Saharan Africa. *Global Food Security* , 18, pp.20-26. <https://doi.org/10.1016/j.gfs.2018.07.001>
- Jama, B., Kimani, D., Harawa, R., Mavuthu, A. & Sileshi, G. (2017). Maize yield response, nitrogen use efficiency and financial returns to fertilizer on smallholder farms in southern Africa. *Food Security, Food Security* , 9, 577–593. <https://doi.org/10.1007/s12571-017-0674-2>
- Jayne, T. S., Mason, N. M., Burke, W. J., & Ariga, J. (2018). Review: Taking stock of Africa’s second-generation agricultural input subsidy programs. *Food Policy* , 75(2018):1-14. <https://doi.org/10.1016/j.foodpol.2018.01.003>
- Jayne, T.S. & Rashid, S. (2013). Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence. *Agricultural Economics* , 44(6), pp.547-562. <https://doi.org/10.1111/agec.12073>
- Kihara, J., Huising, J., Nziguheba, G., Waswa, B.S., Njoroge, S., Kabambe, V., ... Coulibaly, A. (2016). Maize response to macronutrients and potential for profitability in sub-Saharan Africa. *Nutrient Cycling in Agroecosystems* , 105, 171-181. <https://doi.org/10.1007/s10705-015-9717-2>
- Koussoubé, E. & Nauges, C. (2017). Returns to fertiliser use: Does it pay enough? Some new evidence from Sub-Saharan Africa. *European Review of Agricultural Economics* , 44(2), pp.183-210. <https://doi.org/10.1093/erae/jbw018>
- Lal, R. (2006). Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. *Land Degradation & Development* , 17(2), pp.197-209. <https://doi.org/10.1002/ldr.696>
- Liverpool-Tasie, L.S.O., Omonona, B.T., Sanou, A. & Ogunleye, W.O. (2017). Is increasing inorganic fertilizer use for maize production in SSA a profitable proposition? Evidence from Nigeria. *Food Policy* , 67, pp.41-51. <https://doi.org/10.1016/j.foodpol.2016.09.011>
- Marenja, P.P. & Barrett, C.B. (2009). State-conditional fertilizer yield response on western Kenyan farms. *American Journal of Agricultural Economics* , 91(4), pp.991-1006. <https://doi.org/10.1111/j.1467-8276.2009.01313.x>
- Mather, D., Minde, I., Waized, B., Ndyetabula, D. & Temu, A. (2016). The profitability of inorganic fertilizer use in smallholder maize production in Tanzania: Implications for alternative strategies to improve smallholder maize productivity (No. 1093-2016-88057). GISAIA Working Paper #4. No 245891, Food Security Collaborative Working Papers from Michigan State University, Department of Agricultural, Food, and Resource Economics. <http://DOI.org/10.22004/ag.econ.245891>
- Matsumoto, T. & T. Yamano. (2013). Maize, soil fertility, and the green revolution in East Africa. In Otsuka, K. & Larson, D.F. (Eds.), *An African green revolution: Finding ways to boost productivity on small farms* , Dordrecht: Springer. https://doi.org/10.1007/978-94-007-5760-8_9
- Marriot, E.E. & Wander, M. (2006). Total and labile soil organic matter in organic and conventional farming systems. *Soil Science Society of America Journal* 70:950–959. <https://doi.org/10.2136/sssaj2005.0241>
- Mhango, W., Snapp, S. S. & Kanyama-Phiri, G. Y. (2013). Opportunities and constraints to legume diversification for sustainable cereal production on African smallholder farms. *Renewable Agriculture and Food Systems* 28:234-244. <https://doi.org/10.1017/S1742170512000178>

- Ncube, P., Roberts, S., & Vilakazi, T. (2015). Study of Competition in the Road Freight Sector in the SADC Region - Case Study of Fertilizer Transport and Trading in Zambia, Tanzania and Malawi. (2015). CCRED Working Paper No. 3/(2015). <http://dx.doi.org/10.2139/ssrn.2716035>
- Nord, A., & Snapp, S. S. (2020). Documentation of farmer perceptions and site-specific properties to improve soil management on smallholder farms in Tanzania. *Land Degradation & Development*. First published:18 February 2020. <https://doi.org/10.1002/ldr.3582>
- Minten, B., Stifel, D., & Koro, B. (2013). The Last Mile(s) in Modern Input Distribution: Evidence from Northwest Ethiopia. *Agricultural Economics*, 44(6), 629-646. <https://doi.org/10.1111/agec.12078>
- Sheahan, M. & Barrett, C.B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy*, 67, pp.12-25. <https://doi.org/10.1016/j.foodpol.2016.09.010>
- Sheahan, M., Black, R., & Jayne, T.S. (2013). Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy*, 41, pp.39-52. <https://doi.org/10.1016/j.foodpol.2013.04.008>
- Shepherd, K.D., & Soule, M.J. (1998). Soil fertility management in west Kenya: dynamic simulation of productivity, profitability and sustainability at different resource endowment levels. *Agriculture, Ecosystems and Environment* 71, 131-145. [https://doi.org/10.1016/S0167-8809\(98\)00136-4](https://doi.org/10.1016/S0167-8809(98)00136-4)
- Shepherd, K.D., Shepherd, G., & Walsh, M.G. (2015). Land health surveillance and response: a framework for evidence-informed land management. *Agricultural Systems* 132:93-106. <https://doi.org/10.1016/j.agsy.2014.09.002>
- Snapp, S., Jayne, T.S., Mhango, W., Benson, T. & Ricker-Gilbert, J. (2014). Maize yield response to nitrogen in Malawi's smallholder production systems. MaSSP Working Paper 9, Washington, DC, International Food Policy Research Institute. <http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/128436>
- Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), pp.159-209. <https://doi.org/10.3982/ECTA7749>
- Theriault, V., Smale, M., & Haider, H. (2018). Economic incentives to use fertilizer on maize under differing agro-ecological conditions in Burkina Faso. *Food Security*. <https://doi.org/10.1007/s12571-018-0842-z>
- Tittonell, P., Vanlauwe, B., Leffelaar, P.A., Shepherd, K.D., & Giller, K.E. (2005). Exploring diversity in soil fertility management of smallholder farms in western Kenya: II. Within-farm variability in resource allocation, nutrient flows and soil fertility status. *Agriculture, Ecosystems and Environment* 110, 166-184. <https://doi.org/10.1016/j.agee.2005.04.001>
- Tittonell, P., Vanlauwe, B., Corbeels, M. & Giller, K.E. (2008). Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous smallholder farms of western Kenya. *Plant and Soil*, 313(1-2), pp.19-37. <https://doi.org/10.1007/s11104-008-9676-3>
- van Ittersum, M. K., van Bussel, L. G. J., Wolf, J., Grassini, P., van Wart, J., Guilpart, N., ... Cassman, K.G. (2016). "Can sub-Saharan Africa feed itself?" *Proceedings of the National Academy of Sciences*, 113(52), pp.14964-14969. <https://doi.org/10.1073/pnas.1610359113>
- Vanlauwe, B., Wendt, J., Giller, K.E., Corbeels, M., Gerard, B., & Nolte, C. (2014). A fourth principle is required to define conservation agriculture in sub-Saharan Africa: the appropriate use of fertilizer to enhance crop productivity. *Field Crops Research*, 155, pp.10-13. <https://doi.org/10.1016/j.fcr.2013.10.002>
- Walsh, M.G., & Vagen, T. (2006). LDSF Guide to Field Sampling and Measurement Procedures. The Land Degradation Surveillance Framework, World Agroforestry Centre, Nairobi, Kenya.
- Williams, A., Hunter, M.C., Kammerer, M., Kane, D., Jordan, N., Mortensen, ... A. Davis. (2016). Soil water holding capacity mitigates production downside risk and volatility in US rainfed maize: Time to invest in soil organic matter. *PLoS One*, 11(8): e0160974. <https://doi.org/10.1371/journal.pone.0160974>

Xu, Z., Guan, Z., Jayne, T.S., & Black, R. (2009). Factors influencing the profitability of fertilizer use on maize in Zambia. *Agricultural Economics*, 40 (4), 437-446. <https://doi.org/10.1111/j.1574-0862.2009.00384.x>

Zingore, S., Delve, R.J., Nyamangara, J., & Giller, K.E. (2008). Multiple benefits of manure: the key to maintenance of soil fertility and restoration of depleted sandy soils on African smallholder farms. *Nutrient Cycling in Agroecosystems*, 80(3), pp.267-282. <https://doi.org/10.1007/s10705-007-9142-2>

Conflict of Interest Statement

The authors declare that they have no known conflicts of interest in the preparation or publication of this research.

Tables

Table 1: Summary statistics of sample

Variable	units	25th	50th	50th	75th	75th	mean	mean
<i>farm/farmer characteristics</i>	<i>farm/farmer characteristics</i>							
farm size	ha	1.11	2.02	2.02	3.64	3.64	3.30	3.30
# of plots	count	2	3	3	4	4	4	4
focal plot size	ha	0.26	0.51	0.51	1.03	1.03	0.85	0.85
household size	members	4	5	5	7	7	6	6
farmer age	years	38	48	48	59	59	49	49
farmer education	years	8	8	8	8	8	7	7
female	binary	-	-	-	-	-	0.13	0.13
<i>focal plot characteristics</i>								
yield	kg ha ⁻¹	1,112	2,748	2,748	4,464	4,464	2,996	2,996
used fertilizer	binary	-	-	-	-	-	0.32	0.32
N (for fertilizer users)	kg ha ⁻¹	38	60	60	101	101	84	84
P (for fertilizer users)	kg ha ⁻¹	0	10	10	55	55	38	38
K (for fertilizer users)	kg ha ⁻¹	0	0	0	0	0	3	3
available carbon	ppm	341	472	472	632	632	513	513
total carbon	ppm	4,673	6,604	6,604	9,919	9,919	8,604	8,604
topsoil pH	pH	5.6	6.1	6.1	6.5	6.5	6.1	6.1
intercropped	binary	-	-	-	-	-	0.54	0.54
legume rotation	binary	-	-	-	-	-	0.09	0.09
compost	binary	-	-	-	-	-	0.01	0.01
manure	binary	-	-	-	-	-	0.19	0.19
crop residues retained	binary	-	-	-	-	-	0.06	0.06
herbicide	binary	-	-	-	-	-	0.01	0.01
pesticide	binary	-	-	-	-	-	0.01	0.01
improved seed	binary	-	-	-	-	-	0.33	0.33
n. weedings	count	1	2	2	2	2	1.57	1.57
disease	binary	-	-	-	-	-	0.12	0.12
striga	binary	-	-	-	-	-	0.03	0.03
fallowed w/in 3 years	binary	-	-	-	-	-	0.05	0.05
erosion control structures	binary	-	-	-	-	-	0.14	0.14
terraced	binary	-	-	-	-	-	0.04	0.04
sloped	binary	-	-	-	-	-	0.77	0.77

Variable	units	25th	50th	50th	75th	75th	mean	mean
rainfall	mm	322	383	383	759	759	528	528
rainfall CV	CV	0.49	0.65	0.65	0.85	0.85	0.66	0.66

Notes: Summary statistics calculated for the 553 observations recorded in year 2017.

Table 2: Production function estimates

		(1)	(1)	(2)	(2)	(3)
		POLS	POLS	POLS	POLS	CRE
N	N	9.430*** (2.764)	9.430*** (2.764)	9.180*** (2.821)	9.180*** (2.821)	7.474** (3.097)
N ²	N ²	-0.0155*** (0.00470)	-0.0155*** (0.00470)	-0.0153*** (0.00465)	-0.0153*** (0.00465)	-0.0133*** (0.00479)
POXC	POXC	0.438 (0.349)	0.438 (0.349)	0.432 (0.350)	0.432 (0.350)	0.483 (0.352)
N*POXC	N*POXC	0.00481*** (0.00172)	0.00481*** (0.00172)			0.00443** (0.00194)
N*POXC*log(rain)	N*POXC*log(rain)			0.000819** (0.000330)	0.000819** (0.000330)	
log(rain)	log(rain)	3,162*** (955.1)	3,162*** (955.1)	3,172*** (954.8)	3,172*** (954.8)	4,188*** (1,108)
CV(rain)	CV(rain)	-1,167 (875.1)	-1,167 (875.1)	-1,168 (874.4)	-1,168 (874.4)	-943.4 (907.6)
Observations	Observations	607	607	607	607	607
R-squared	R-squared	0.343	0.343	0.343	0.343	0.358
Estimator	Estimator	POLS	POLS	POLS	POLS	CRE
HH, farm & plot controls	Yes	Yes	Yes	Yes	Yes	Yes
Plot management controls	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak-Chamberlain controls	No	No	No	No	Yes	Yes
District fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable in all models is maize yield measured in kg ha⁻¹. N = nitrogen; POXC = active carbon; CV = coefficient of variation. Rainfall measured in 10-day periods during the growing season for the survey year. Standard errors are cluster robust at the household level. Significance denoted by * (p<0.1), ** (p<0.05) and *** (p<0.01). Full results shown in appendix (table A1).

Table 3: Partial effects of nitrogen and active carbon (estimates from Fixed Effects models)

	(1)	(2)
	Fixed Effects estimates w/ N*POXC interaction	Fixed Effects estimates w/ N*POXC*log(rainfall) interaction
MP at POXC=220 (10th pctlile)	13.20*** (3.921)	12.59*** (3.882)
MP at POXC=337 (25th pctlile)	14.09*** (3.936)	13.69*** (3.884)
MP at POXC=481 (50th pctlile)	15.20***	15.07***

	(1)	(2)
MP at POXC=696 (75th pctlile)	(3.979) 16.85***	(3.923) 17.11***
MP at POXC=954 (90th pctlile)	(4.088) 18.84***	(4.053) 19.57***
	(4.286)	(4.311)
Δ MP: 25th-75th POXC pctlile	20%	25%
Δ MP: 10th-90th POXC pctlile	43%	55%

Notes: Table shows partial effects of nitrogen (N) and active carbon (POXC) from Fixed Effects models in table 2. Standard errors are cluster robust at the household level. Standard errors are cluster robust at the household level. Significance denoted by * ($p<0.1$), ** ($p<0.05$) and *** ($p<0.01$).

Table 4: Partial effects of nitrogen at different levels of active carbon in sample (estimates from Fixed Effects models)

	(1)	(2)
	Fixed Effects estimates w/ N*POXC interaction	Fixed Effects estimates w/ N*POXC*log(rainfall) interaction
MP at POXC=220 (10th pctlile)	13.20*** (3.921)	12.59*** (3.882)
MP at POXC=337 (25th pctlile)	14.09*** (3.936)	13.69*** (3.884)
MP at POXC=481 (50th pctlile)	15.20*** (3.979)	15.07*** (3.923)
MP at POXC=696 (75th pctlile)	16.85*** (4.088)	17.11*** (4.053)
MP at POXC=954 (90th pctlile)	18.84*** (4.286)	19.57*** (4.311)
Δ MP: 25th-75th POXC pctlile	20%	25%
Δ MP: 10th-90th POXC pctlile	43%	55%

Notes: Table shows partial effects of nitrogen at 10th, 25th, 50th, 75th and 90th percentile of active carbon in the sample, from the Fixed Effects models reported in table 2. Standard errors are cluster robust at the household level. Standard errors are cluster robust at the household level. Significance denoted by * ($p<0.1$), ** ($p<0.05$) and *** ($p<0.01$).

Table 5: Distribution of MP and AP estimates

physical product	10th	25th	50th	75th	90th	mean	std.dev.
MP	7.77	11.35	13.65	15.84	18.22	12.87	5.46
AP	9.09	10.03	11.50	13.45	14.97	11.73	2.49

Note: MP and AP estimates come from the Fixed Effects model corresponding to column 5 in table 2. MP is calculated for each household using sample values. AP is calculated as the difference between the estimated difference in yields resulting from zero fertilizer and yields resulting from 200 kg ha⁻¹ of nitrogen (the level at which MVCr=1, on average, when using a farmgate maize-nitrogen price ratio of 0.15), with other sample values as observed.

Table 6: Maize and N price assumptions used in profitability calculations

Price ratios used for profitability analysis	maize (USD/kg)	nitrogen (USD/kg)	maize/N price ratio
wholesale price ratio: 0.22	0.27	1.22	0.22
farmgate price ratio: 0.18	0.24	1.33	0.18
farmgate price ratio: 0.15	0.21	1.44	0.15
farmgate price ratio: 0.12	0.18	1.55	0.12
farmgate price ratio: 0.09	0.15	1.66	0.09

Table 7: Profitability distributions under alternative maize-N price ratios

MVCR	10th	25th	50th	75th	90th	mean	std.dev.	MVCR>0	MVCR>1	MVCR>2
wholesale price ratio: 0.22	1.72	2.51	3.02	3.51	4.03	2.85	1.21	96%	94%	88%
farmgate price ratio: 0.18	1.40	2.05	2.46	2.86	3.29	2.32	0.99	96%	94%	77%
farmgate price ratio: 0.15	1.13	1.66	1.99	2.31	2.66	1.88	0.80	96%	92%	48%
farmgate price ratio: 0.12	0.90	1.32	1.58	1.84	2.12	1.49	0.63	96%	88%	16%
farmgate price ratio: 0.09	0.70	1.03	1.23	1.43	1.65	1.16	0.49	96%	78%	1%
AVCR	10th	25th	50th	75th	90th	mean	std.dev.	AVCR>1	AVCR>1.5	AVCR>2
wholesale price ratio: 0.22	2.01	2.22	2.55	2.98	3.31	2.60	0.55	99%	98%	90%
farmgate price ratio: 0.18	1.64	1.81	2.08	2.43	2.70	2.12	0.45	99%	95%	56%
farmgate price ratio: 0.15	1.33	1.46	1.68	1.96	2.18	1.71	0.36	98%	71%	22%
farmgate price ratio: 0.12	1.06	1.16	1.34	1.56	1.74	1.36	0.29	94%	30%	2%
farmgate price ratio: 0.09	0.82	0.91	1.04	1.22	1.35	1.06	0.22	56%	2%	0%

Note: Calculations based on the MP and AP estimates shown in table 5, against each of the price-ratio assumptions in table 6.

Figures

Figure 1: Survey locations

[Figure 1 here]

Figure 2: Estimated AVCR over distribution of active carbon in sample

[Figure 2 here]

Note: Vertical red lines indicate 10% and 90th percentiles of the distribution of POXC measures in the sample. AVCR estimates use AP estimates from the fixed effects model with N*POXC*log(rainfall) interaction (column 6 in table 2), and a farmgate maize-nitrogen price ratio of 0.15.

Figure 3: Estimated AVCR over distribution of seasonal rainfall in sample

[Figure 3 here]

Note: Vertical red lines indicate 10% and 90th percentiles of the distribution of seasonal rainfall totals in the sample. AVCR estimates use AP estimates from the fixed effects model with N*POXC*log(rainfall) interaction (column 6 in table 2), and a farmgate maize-nitrogen price ratio of 0.15.





