Feed the Future Innovation Lab for Food Security Policy

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UNDERSTANDING FERTILIZER EFFECTIVENESS AND ADOPTION ON MAIZE IN ZAMBIA

By

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Food Security Policy *Research Papers*

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EXECUTIVE SUMMARY

As populations continue to rise and land becomes scarcer in Africa's rural areas, there is increasing urgency for farmers to adopt land management practices that sustainably raise land and labor productivity. Considerable effort has focused on promoting inorganic fertilizers, but it is increasingly recognized that smallholder farmers' demand for fertilizer can be depressed by soil conditions that reduce crop response to and the profitability of fertilizer use. This article quantifies the impacts of soil characteristics on maize response to fertilizer in Zambia using a nationally representative sample of 1,453 fields. In addition to economic and farm management surveys, composite soil samples were collected and analyzed for several characteristics at the Zambia Agricultural Research Institute. Soil's role in agricultural production and fertilizer efficiency is more nuanced than most economic literature has acknowledged. We believe ours is the first model in economic literature that simultaneously allows for the effects of multiple soil characteristics. We estimate critical threshold effects on yield response to fertilizer to be between pH levels of 5.4 and 5.6, soil organic matter levels of 1.2-1.4%, and find significant soil texture—and cation exchange—related thresholds. Depending on these soil characteristics, average maize yield response estimates range from insignificant (0) to 5.7 maize kg per fertilizer kg. We estimate fertilizer use on maize is not profitable at commercial prices for the majority of Zambian farmers (under current practices). Even ignoring transfer costs, about 80% of fertilized maize fields still have an estimated average value-cost-ratio for fertilizer less than one at commercial prices. To the best of our knowledge, the flexibility of our model and data with this scope of geography and content are novel contributions to the literature.

ACRONYMS

Aps	average products
AVCR	average value cost ratios
CEC	cation exchange capacity
cm	centimeter
CSO	Central Statistics Office
GPS	global positioning system
IAPRI	Indaba Agricultural Policy Research Institute
kg/ha	kilogram/hectare
LMF	largest maize field
MAL	Zambian Ministry of Agriculture and Livestock
meq	milliequivalents
OLS	ordinary least squares
pH	potential hydrogen
RALS	Rural Agricultural Livelihoods Survey
SEAs	Standard enumeration areas
SOM	soil organic matter
USDA	United States Department of Agriculture
ZARI	Zambia Agricultural Research Institute
ZMK	Zambia Kwacha

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"Supporting broadly based income growth … will require in the first instance an increase in the productivity of small farmers. So long as agricultural labor earns only $1 a day, the vast majority of rural citizens who work as farmers will remain poor…"

-Robert Paarlberg, 2013, in the second edition of "Food Politics"

"There isn't the land out there. Despite what everybody says, you don't see expansion of land … we've got to produce more on the existing land … but we've got to do it in such a way that we are prudent in our use of … pesticides, herbicides and fertilizer."

-Sir Gordon Conway, author of "One Billion Hungry" speaking at Stanford in 2015

As it now stands, Africans would benefit greatly if farmers (and particularly small-scale farmers) were more productive agriculturally per unit of land. Regardless of how we define *poor, hungry* or *malnourished*, a vast number of the world's worst off live in Africa (Paarlberg 2013). The majority of that group are agrarian, but net buyers of even staple grains (Barrett 2011; Jayne et al. 2003), so it is the poorest who stand to gain the most from increased land productivity.

While the importance of increased production per unit of available cropland is more urgent than ever now, the need is constantly growing (Conway and Wilson 2012). Both rural and urban population densities are rising rapidly (Masters et al. 2013). Paradoxically, population growth both demands and threatens agricultural productivity growth. On one hand, higher rural population on finite land resources combines with rising urban demand for grain intensive (meaty) diets to put upward pressure on land productivity. On the other hand, if agricultural intensification is not done sustainably in the short-run, soils will be depleted of nutrients and soil properties will change so that production per unit of land and other inputs will decrease in the medium-to-long-run.

Fertilizer use will be crucial for raising farm productivity in Africa (Jayne and Rashid 2013). When virgin land is converted to agriculture the natural *nutrient cycle*, which keeps soils fertile and plants growing, is broken.; sustainable production requires that removed nutrients be returned to the soil (Jones et al. 2013; Vitousek et al. 2009).

That said, soil characteristics affect crop response to fertilizer and hence the profitability of and demand for fertilizer. (Burke, Jayne, and Black forthcoming; Marenya and Barrett 2009a; Matsumoto and Yamano 2009). Specifically, the physical, biological and chemical characteristics of soils strongly influence the amounts of nutrients that can be stored and released, water storage, and the ability of plants to take-up nutrients (Jones et al. 2013).

The importance of the relationship between soil characteristics and fertilizer effectiveness has received too little attention in the agricultural economic literature, particularly as related to fertilizer promotion policies. Hence, the objective of this article is to quantify the impacts of soil characteristics on yields and yield response to fertilizer by looking at the case of maize in Zambia (maize is by far the most commonly grown and consumed staple food in the country).

In 2012, a sample of the largest maize fields cultivated by 1,653 rural households was designed using a nationally representative framework. In addition to an economic survey, farmers were asked details of their farm management practices and field sizes were measured using global positioning system (GPS) trackers. Finally, from each field a composite sample of the first 20 cm of the soil profile were collected and analyzed for several soil characteristics by the Zambia

Agricultural Research Institute (ZARI). To the best of our knowledge, no data with this combined scope of geography and content has ever been available.

This article makes important contributions to the small agricultural economics literature that quantifies yield response to fertilizer applications in Africa. The most thorough similar study to date is arguably Marenya and Barrett (2009b), who focus on the effects of soil organic matter in western Kenya. By contrast, our article examines a broader range of important soil characteristics, so our insights into the relationship between soil and productivity and possible interventions is more complete. Our analysis is also more geographically expansive, based on a nationally representative sample of farm households in Zambia. We integrate agronomic principles into econometric models of crop response to fertilizer and discuss the kinds of *soil data* that may be more (or less) useful in combination with household survey data.

Also, our respondents were chosen at random, meaning we estimate realized response rates, rather than the potential responses found using field trials or lead farmers that are often referenced in policy analyses. Such trials may overestimate response rates for many reasons (Snapp et al. 2014), while we believe our approach more accurately describes crop response rates to fertilizer application that smallholder farmers actually obtain. Finally, we look beyond the past and present to consider the importance of our findings in the context of larger, denser populations moving forward. We do this by statistically investigating the relationship between population density and the intensity of land use across Zambian districts and then the evidence in our data as to whether intensification affects soil characteristics. This article thus provides useful insights for policy makers in the design of comprehensive strategies for increasing productivity and intensification while maintaining soil fertility.

2. SOIL DATA AND THE CHARACTERISTICS DETERMINING PLANT GROWTH

This section discusses the nutrients plants need to grow, selected soil properties that determine nutrient storage and release and other determinants of plant growth and response to fertilizers. Broadly speaking, the measurable soil-based determinants of plant growth, or soil data, can be categorized as either available nutrients or general characteristics.

2.1. Nutrients

Plant growth requires 17 nutrients. Fourteen of these are taken up in an ionic form from the soil solution. These can be sub-categorized as either micronutrients or macronutrients depending on the nutrient concentration in the plant.[1] The macronutrients hydrogen, carbon, and oxygen come from the air and water and makeup the bulk of plant biomass. Nitrogen (N), phosphorus (P) and potassium (K) are taken up in the largest quantity from the soil and are most likely deficiencies on low productivity soils. These elements are also the primary ingredients in most fertilizers used throughout the world.[2] Besides the presence of nutrients, their relative importance to each plant also determines yield. Plants need nutrients in certain proportions; if one is taken up in excess or in too small amount yield will be limited by the nutrient imbalance.

This rule for plant growth, named the *law of the minimum*, was first posited by Carl Sprengel (1837), and later inaccurately credited to Justus von Liebig (1840). A popular analogy is *Liebig's Barrel*, where the amount of water held by a wooden barrel represents realized yield. Each plank of the barrel represents a required nutrient, and the length of the plank the availability of the same. Obviously, whichever plank is shortest determines the amount of water the barrel can hold. Economists might refer to this as the plant's Leontief production function.

The levels of available nutrients are the direct determinants of plant growth, and though technically measureable, specific nutrient data are not ideal when carrying out large-scale survey analysis. Firstly, the timing of soil collection (and nutrient availability) relative to a plant's growth stage is very important, particularly for nitrogen. N is a very mobile element and does not stay in the soil solution long before either being taken up by a plant, washing away, escaping as a gas or leaching deep into the soil (Jones et al. 2013; Vitousek et al. 2009). Since the relevant timing is going to be specific to the plant, it is effectively impossible for any broadly representative household survey to measure relevant nitrogen consistently across observations.

Rather than measuring available nutrients directly, a more common and reliable practice is to measure the general soil characteristics that partially determine, and are highly correlated with availability of nutrients.

2.2. Soil Characteristics and Nutrient Availability

General characteristics can be sub-categorized as indicators of soil chemistry, soil physics, or soil biology. There are numerous ways to measure each, but this section focuses on the characteristics used for this article and how they relate to productivity and expected yield response to fertilizers.

Soil chemistry can be quantified using cation exchange capacity (CEC), measured in milliequivalents (meq) per 100 grams of soil. Whether they come from inorganic fertilizer application or any other source, plants do not usually take up nutrients immediately after they are

[1] The macronutrients not discussed in the text are calcium, magnesium and sulfur; the micronutrients are boron, chlorine, copper, iron, manganese, molybdenum, nickel and zinc.

[2] *Fertilizer* means water-soluble inorganic fertilizers. We use *element* and *nutrient* interchangeably.

applied to soil. Rather, they must be held in the soil solution by bonding with other elements. Eventually enzymes released either from microbial activity or plant roots break these bonds and release nutrients to become available for plants. The CEC is the number of negative charges displayed by a soil and is a measure of soil's ability to hold cations (positively charged nutrient particles). Soils with higher CEC have a greater capacity to store cations, and are therefore likely to be more fertile (Jones et al. 2013). The CEC is also correlated with soil organic matter and clay content.

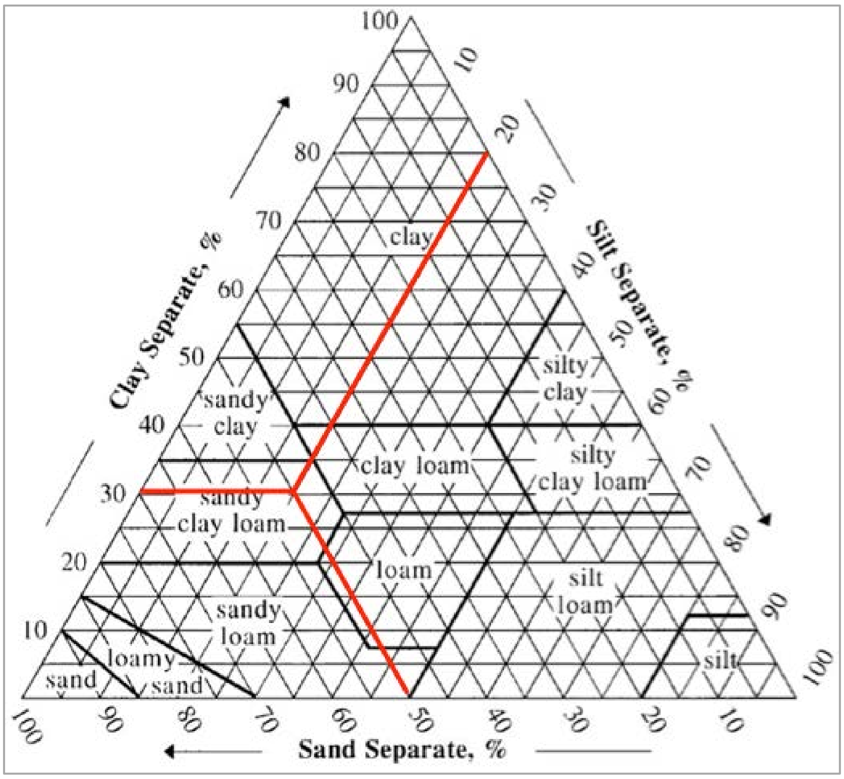
A second measure of soil chemistry is pH (potential hydrogen), which measures soil acidity. pH values range from 0 to 14, with 7 being neutral and lower (higher) values being more acidic (alkaline). At low pH, hydrogen protons (H^+) and ionic aluminum forms (Al^{3+}) saturate the cation exchange capacity hindering the retention of K, Ca, Mg, and other essential elements. Also at low pH values, specific nutrients like P can be strongly sorbed on positively charged soil particles limiting the availability of P derived from both the soil and fertilizers. Soil microbial activities and root growth are also negatively influenced at low pH values, particularly at high levels of Al^{3+}. On the contrary, soils with high pH values can store K, Ca, and Mg that can then be released to the solution and taken up by the roots. Also phosphate species formed under neutral conditions remain much more available than those formed under highly acidic conditions (Jones et al. 2013).

A common soil biology measure is soil organic matter (SOM).[3] Marenya and Barrett (2009a; 2009b) and subsequent agricultural economics literature refer to SOM as the best measure of soil quality, and indeed SOM is an indicator for several important factors. First, higher SOM suggests higher levels of nutrient stocks (especially nitrogen, phosphorus, and sulfur), a high CEC (see above), and a high capacity to hold water. Higher SOM also suggests soils that are higher in microbial activity, and thus higher levels of the enzymes needed to free up nutrients stored in organic forms so that they may be taken up by plants. High SOM also suggests soil structures that ensure good growth conditions for roots. In short, for many reasons higher SOM is expected to be associated with higher yields and yield response to fertilizer (as found in Kenya by Marenya and Barrett (2009b) and Uganda and Kenya by Matsumoto and Yamano (2009)).

We measure soil physics using texture classification, or the tangible makeup of the soil. All soil is made up of particulates and every particulate is classified as either clay, silt or sand according to its size. The smallest, clay, are less than 0.002 millimeters (mm), followed by silt (0.002-0.05 mm) and sand (larger than 0.05 mm). We use the United States Department of Agriculture (USDA) soil texture classifications as identified by the *texture triangle* (Figure 1). Along each axis of the triangle, one can locate the share of soil particulates in each classification and trace a straight line towards the triangle's interior. Texture is defined according to where these lines intersect. For example (Figure 1), if a soil is 30% clay, 20% silt and 50% sand, the texture is called *sandy clay loam*. All possible combinations can be found on the triangle, and are sorted into 12 categories.

[3] Related measurements are organic carbon content or soil carbon content. These measures are highly correlated, and can effectively be thought of as rebased measures of each other.

Figure 1. USDA Soil Texture Triangle (e.g., Sandy, Clay, Loam)



Source: Adapted from USDA, online at:
http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_054167

While texture classification may seem to rely on tediously precise particulate and percentage measurements, it is actually one of the simplest and most dependable characteristic tests available. This is because a *hand texture* process allows a properly trained person to classify soils with a high degree of accuracy without the use of laboratory equipment (Thien 1979). Among other sources, most land grant university extension services in the U.S. provide tutorials for this process. Presley and Thien (2008), for one example, describe the process in a Kansas State University extension service (also see: http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/edu/?cid=nrcs142p2_054311).

For our purposes, the key issue related to texture is that higher clay content soils tend to be more productive. This is for several reasons. First, clayish soils tend to hold moisture longer, making plant growth less vulnerable to weather fluctuations and drought. Higher clay content is also positively correlated with higher CECs and higher levels of SOM (and all the beneficial characteristics that go with them).

2.3. Fertilizer and Other Determinants of Yield and Response Rates

In addition to soil characteristics, we model yield as a function of management practices and other control variables. First, Zambian farmers apply either *basal* fertilizer, which is 10% nitrogen, 20% phosphates and 10% potash (potassium) or NPK=10-20-10, or *top dress* fertilizer, more commonly known as Urea (NPK=46-0-0). Of course, any fertilizer could be applied, but virtually all fertilizer used on maize in Zambia (>99%) is one of these blends.

The timing of fertilizer application is another factor that affects yield response on farmer-managed fields in our model, particularly for phosphorus. Phosphorus availability is especially important at early stages of maize growth. Used as a building block of DNA, RNA, ATP (for photosynthesis) and phospholipids, phosphorus regulates cell division during early growth, and is key for the development of roots and protein formation (Jones et al. 2013). Late application (i.e., after planting time), which is common in Zambia, is thus expected to have a negative effect on yield response.

Other control variables include the plant variety (sowing *improved* hybrid and OPV seeds or not) and seed application rate (kg/ha). The timing of planting with respect to the beginning of the rainy season is also relevant. Planting before or near the beginning of the first rains is beneficial since plants can then take advantage of moisture and the annual nutrient flush (the release of nutrients from organic material that has decomposed since the previous rainy season) (Haggblade, Kabwe, and Plerhoples 2011). Finally, a series of indicator variables control for yield differences related to tillage methods (ripping, ridging, bunding, plowing, basin, or zero tillage, each as compared to traditional hand hoeing).

In addition to all of the above mentioned determinants, a wide range of data were collected regarding field management, including rates for liming, irrigation, agroforestry tree use, crop mixing, insecticide, herbicide, manure and compost, flooding and flood prevention. Unfortunately, there are too few observations (not enough variation) in our data to identify the effects of employing these techniques (from 5% to less than 1% of households employed each of these practices). We also cannot control for the effects of weeding due to lack of variation, but for the opposite reason—99% of the fields in the sample were weeded.[4]

Having only cross-sectional data available, our model controls for unobserved factors related to farmer ability and labor availability to the extent possible using proxy variables. Specifically, we include the education level of the household head, the family land to labor ratio as well as an indicator for whether the family hired labor in our model.

2.4. Empirical Model

The above discussion leads to estimating a model of yield with conditional response to fertilizer where:

(1) E(yield | <u>soilchar2</u>)=f(basal, topdress, <u>fert^2</u>, (<u>soilchar1*fert</u>), <u>basal*weeks</u>, soilchar2, seedrate, seedrate^2, hybrid, early, late, **tillage**, educ, landlabratio, hirelab)

Where: yield = maize harvested (kg/ha)

basal = basal fertilizer (kg/ha) – “Compound D” (NPK=10-20-10)

topdress = top dressing (kg/ha) – Urea (NPK=46-0-0)

fert = basal + topdress

weeks = number of weeks after planting for basal application

seedrate = seeding rate (kg/ha)

hybrid = was hybrid or open pollinated seed variety planted (1=yes)

early = did planting occur before ZARI recommendation (1=yes)

late = did planting occur after ZARI recommendation (1=yes)

tillage = vector of binary indicators for tillage method

[4] Weeding was quantified simply as *number of weedings*. A more detailed enumeration of this management practice would improve future analyses.

educ = years of education for the household head

landlabratio = land to household labor ratio

hirelab = did household hire additional labor (1=yes)

The variables soilchar1 and soilchar2 represent two of the soil characteristics used in this analysis. The yield function is quasi-linear conditional on one soil characteristic, and within each linear component, yield response is conditional on one other soil characteristic. Notice in addition to soil characteristics, yield response to basal fertilizer is conditional on the timing of application in relation to planting date, and yield response to total fertilizer is a quadratic function of application rates.

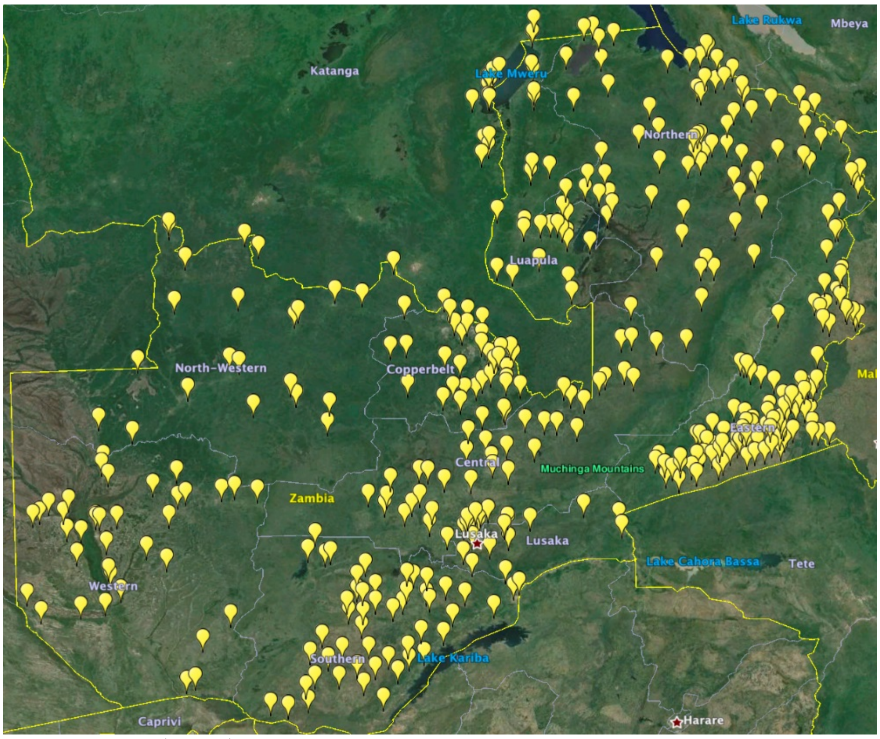
Since we estimate unique yield responses to fertilizer for each observation, much discussion focuses on the mean of the average products (APs) of fertilizer across observations. The AP is the additional kilograms of maize attributable to each kilogram of fertilizer applied (kg/kg), the means of which can be disaggregated according to soil characteristics (or any other categorization). We also discuss cumulative distributions of the APs across the country.

3. DATA

The sample for this survey is a sub-set of the observations interviewed during the Rural Agricultural Livelihoods Survey (RALS) carried out in May and June 2012 as a collaborative effort among the Indaba Agricultural Policy Research Institute (IAPRI), the Central Statistics Office (CSO), and the Zambian Ministry of Agriculture and Livestock (MAL). The standard enumeration areas (SEAs), as designated by CSO for census purposes, were selected using probability proportional to size, and a constant sample size of 20 households was surveyed in each SEA. Within selected observations in each SEA, 4 households were chosen at random to be included in the sub-sample used for this analysis. The RALS survey instrument covered a broad range of household economic data covering the 2011 harvest and 2012 marketing season.[5] Among the households selected for soil sampling, an additional small survey collected information related to the 2012 harvest for the largest maize field and farm management and input use for that maize field in 2011.[6] Each maize field in our sample was measured using a GPS device. For a full description of sampling methods, see IAPRI/CSO/MAL (2012). The sample village locations are illustrated in Figure 2.

1,714 soil samples and largest maize field (LMF) surveys were collected from 1,680 households. Soil samples outnumber households because fields with noticeable differences in slope or soil (e.g. color or texture) were sampled more than once (26 households provided two samples each and four households provided three samples). Data are aggregated to the field level as un-weighted means across soil samples. Of these 1,680 households, 12 are excluded because they lack all corresponding farm management data due to either enumerator or data entry errors that are treated as random occurrences.

Figure 2. Village Locations Where Soil Samples Were Collected (Four Samples Each)



Source: IAPRI/CSO/MAL. 2012; Google Earth.

[5] The full questionnaire is available on-line at http://fsg.afre.msu.edu/zambia/2012_Rural_Agricultural_Livelihoods_Survey%28RALS%29.pdf

[6] The smaller questionnaire has not been posted on-line, but can be made available.

Of the 1,668 remaining, two observations used fertilizer without reporting quantities used and are, thus, dropped from econometric analysis. Ten replacement households in the LMF survey sample were not included in the RALS sample because respondents were unavailable.

Twenty-three observations experienced total crop loss and harvested no area, thus having undefined yields. Of the remaining (N=1,633), 157 fields were in a wetland area, and are excluded from our analysis. A Chow test confirms the structural difference in the relationships between production factors and yields for this group and the remainder of the sample. Finally, 23 remaining observations report harvests on small fields that would correspond to yields greater than 14.5 mt/ha (about three standard deviations above the mean), which are excluded as outliers. As such, the final data we work with is from 1,453 field-level observations.

Enumerators and their supervisors were trained by ZARI to collected soil samples. Each sample analyzed was a composite of 10-20 sub-samples of soil collected throughout each field. The protocol for the number of sub-samples and the collection pattern throughout the field followed by enumerators was specified according to field size. Each sub-sample was a composite of equal parts soil in the 0-10 cm and 10-20 cm depth horizons, where the highest maize root density (cm root/cm3 soil) is found. For fields planted using ridge tillage, samples were taken directly from the ridges. A full description of the methods used to collect samples is described in IAPRI/CSO/MAL (2012).

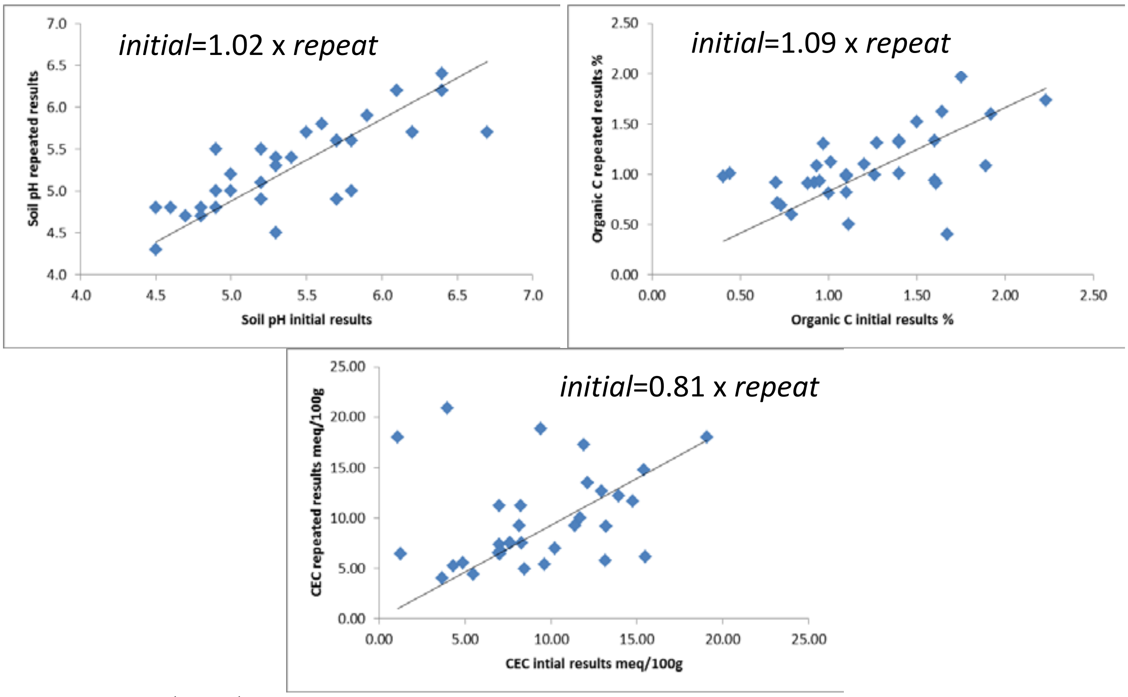
Soil texture was assessed manually following methods discussed above. Soil pH was analyzed in 0.01 M $CaCl_2$ (calcium chloride) solution. Soil organic matter was following the Walkley and Black method (Walkley and Black 1934). CEC was analyzed using the ammonium acetate method at pH 7.0 and measurement of the sorbed ammonium (NH_4) by titration following the exchange of sorbed NH_4 with excess sodium chloride (NaCl). ZARI laboratory operators were trained by a team of soil scientists from the University of Wageningen and follow established protocols that can be implemented with the locally available equipment.

Employing ZARI's laboratory for soil analysis has obvious advantages, not least of which are their presence in Zambia, willingness to train soil sampling teams and a collegial relationship with the policy makers that stand to benefit from this study. One important caveat is that the ZARI laboratory is not formally accredited, meaning no recent, independently evaluated data are available to determine the reliability of our results. Specifically, it is useful to scrutinize the accuracy and precision (or respectively the external and internal validity) of test results. Accuracy, or closeness of test results to actual values, is typically evaluated by comparing blind test results to known parameters from fabricated samples. Unfortunately, this was not possible for our study (and should be a priority moving forward).

Precision refers to the repeatability of test results; less variation within multiple tests of the same sample indicates greater precision. While we cannot demonstrate the accuracy of the ZARI results, confidence in the lab's precision provides assurances that results are valid for comparing across samples. For example, a pH result measured as 7 may or may not be truly neutral, but if the lab has a high measureable degree of precision, we can be confident that the sample is less acidic (alkaline) than another sample with lower (higher) pH results.

To evaluate ZARI's precision, 2% of our observations were randomly selected for a second round of testing and comparison to initial measurements. Precision-check results are illustrated in Figure 3.

Figure 3. Assessment of the Precision of ZARI Laboratory Results



Sources: IAPRI/CSO/MAL 2012.
Note: Soil analysis conducted at the Zambia Agricultural Research Institute laboratories, Mt. Makulu, Zambia.

Clockwise, starting from the top left, each panel is a scatter plot of initial results on the horizontal axis and re-testing results on the vertical axis for pH, organic carbon, and CEC. Observations on the 45^{o} line (shown) demonstrate exact precision.

To formalize the comparison we report results from regressing the initial results on the re-test results without an intercept (thus, a coefficient estimate of “1” would suggest exact precision, on average). In each case, our estimate is substantively close to 1 and we fail to reject the hypothesis that each coefficient is one ($p < 0.05$). The R-squared comparing initial to re-test results for pH, organic carbon, and CEC are 0.996, 0.91, and 0.75 respectively.

Texture is a categorization rather than a continuous variable, and so it doesn’t lend itself to this type of evaluation. That said, this is one of the simplest tests to carry out, and such analyses are seldom questioned. In addition, we include texture in our model as more general categories according to clay content (see below), so the effects of potential measurement error are likely to be low.

Soil analysis is summarized in Table 1. According to ZARI, the large variability observed for organic C, CEC and soil pH is credible. Variability in CEC and soil pH, for example, could be driven by strong differences in soil weathering observed across the country which includes strongly weathered soils (e.g., ferralsols and podzols), soils that are little weathered (cambisols and luvisols) and saline soils (Mambo and Phiri 2003). Similarly, high organic matter could be explained by excessive soil moisture as in histosols.

Overall, we conclude the sum of evidence suggests ZARI test results have an acceptable level of precision for the present analysis, but we are not able to attest to the laboratory’s accuracy. The implications of these conclusions vis-à-vis our estimation approach is discussed in the next section.

Table 1. Summary of Zambian Field-Level Soil Analysis Results

Soil characteristic	Mean	Std. dev.	-------------------Percentile-------------------				
			1	25	50	75	99
Soil pH (Acidity)	5.38	0.62	4.00	5.00	5.30	5.80	6.80
Organic Matter (%)	1.85	0.70	0.34	1.37	1.80	2.28	3.39
Cation Exchange Capacity (meq)	9.77	5.62	1.52	6.04	8.37	12.3	26.8

Source: IAPRI/CSO/MAL 2012 and ZARI soil analysis (N= 1,453).

4. ESTIMATING YIELD RESPONSE TO FERTILIZER

Soil characteristics enter the yield function as interaction terms and by specifying a quasi-linear functional form. That is, the effects of fertilizer and other determinants are allowed to differ systemically depending on whether soil characteristic measurements are above or below estimated threshold levels. The concept of thresholds in the process of plant growth is well established in the agronomic literature; a nice illustration of this is the law of the minimum mentioned earlier.

Marenya and Barrett (2009a; 2009b) use this principal to motivate a quasi-linear yield model using data from Western Kenya and soil organic matter as the threshold variable. Matsumoto and Yamano (2013) used a similar model and procedure to study fertilizer effects in parts of Uganda and Kenya. Each concluded that below a critical level of SOM, yield response significantly decreases. Burke, Jayne, and Black (forthcoming) apply the threshold principle to yield response to fertilizer with respect to soil pH levels. In that case, however, thresholds were imposed ex ante (not estimated) based on levels published by ZARI (2002) and elsewhere in agronomic literature.

4.1. Model Specification With Respect to Soil Characteristics

Unlike previous studies, a key to this analysis is that we do not rely on just one measure of soil quality. Specifically, we use data for four different measures (pH, CEC, SOM, and texture). It is infeasible to use all of these in the same model with our data because some characteristics are highly correlated. For example, as measures of soil chemistry, pH and CEC are often correlated with each other. Soil clay content and soil organic matter are also correlated with each other, so our models include either texture or SOM, and either pH or CEC.

For our primary analysis, we estimate two models: 1) allowing yield and response to fertilizer to be conditional on pH and SOM, and 2) replacing SOM in the model with soil texture. In two alternative models, we could replace pH with CEC. For now we focus on pH because of the relative measurement precision (Figure 3). Results from models including CEC are also available (Figure 6) and briefly discussed below.

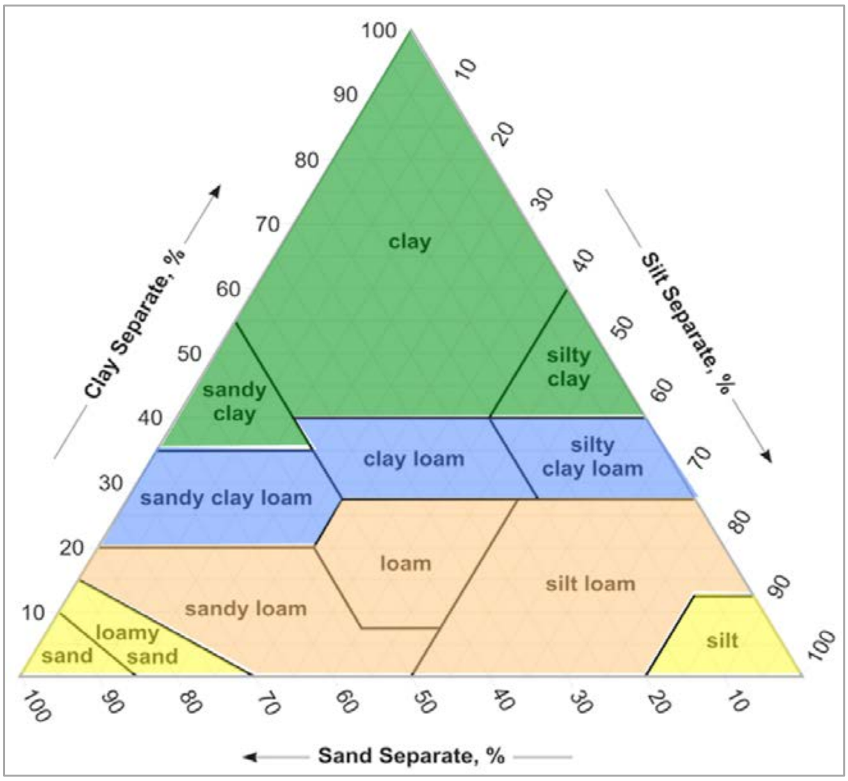
Since texture is a categorical variable, we do not formally search for thresholds, per se. Rather, we group textures into four meta-categories according to clay content. As illustrated in Figure 4, soils in group 1 (sand, loamy sand and silt) have virtually no clay, those in group 2 (sandy loam, loam and silt loam) are roughly between 5-25% clay, group 3 (sandy clay loam, clay loam and silty clay loam) is about 25-40% clay, and group 4 (sandy clay, silty clay and clay) is 40-100% clay. These categories represent 17%, 25%, 51% and 7% of our sample respectively. For all other soil characteristics, we estimate thresholds as described presently.

4.2. Estimating Thresholds

Knowledge regarding the approximate values at which we might expect to find threshold effects can be found in the literature. George, Horst, and Neumann (2012),[7] for example, suggest a critical value for pH is 5.5, which is consistent with the ZARI maize production guidelines. Interviews with ZARI crop and soil scientists indicated we might expect to find a SOM threshold between 1% and 2%.

[7] It is important to note George, Horst, and Neumann (2012) do not specify whether they measured pH in Cacl2 (as we have) or in water. This would affect the comparability of results.

Figure 4. Soil Category Groups According to Clay Content



Source: Adapted from USDA, online at:
http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/edu/?cid=nrcs142p2_054311

Despite extant knowledge, however, we maintain it is best practice to estimate (rather than impose) thresholds; recall our independent assessment of the lab tells us nothing about the accuracy of our data but gives us confidence in its precision (i.e., we would rather rely on the evidence-supported internal validity of our data than the unknown degree of external validity).

We allow for two types of threshold effects ("type 1" and "type 2"). A type 1 threshold variable (T1) acts to shift expected yield and it's response to fertilizer depending on whether T1 is above or below a threshold to be estimated, (θ_1). Mathematically, this can be written as:

(2)
$$yield = \beta_1 F + \beta_2 d + \beta_3 (F \cdot d) + \boldsymbol{X\gamma}$$

$$\text{where } d = \begin{matrix} 0 \text{ if } T1 \leq \theta_1 \\ 1 \text{ if } T1 > \theta_1 \end{matrix}$$

Where F is the level of fertilizer application and **X** is the vector of other control variables previously described. β and $\boldsymbol{\gamma}$ are coefficients and θ_1 is the threshold parameter, all to be estimated.

A type 2 threshold variable (T2) affects the entire production function depending on whether T2 is above or below a (different) threshold to be estimated (θ_2), as in:

(3)
$$yield = \begin{matrix} \beta_{11} F + \beta_{21} d + \beta_{31} (F \cdot d) + \boldsymbol{X\gamma_1} & \text{if } T2 \leq \theta_2 \\ \beta_{12} F + \beta_{22} d + \beta_{32} (F \cdot d) + \boldsymbol{X\gamma_2} & \text{if } T2 > \theta_2 \end{matrix}$$

At this point, two questions emerge: 1) Why have two types of thresholds, and 2) how should they be estimated? The answer to the first question is a simple matter of balancing flexibility with feasibility. The most flexible way to allow soil characteristics into the model would be to treat them all as type 2 threshold variables, but in the present application, this would require more data than are available. So, to allow for the flexibility of having more than one measure of soil quality, we impose the restriction that one measure affects only response to fertilizer (and the intercept).

Regarding the second question, we use a grid search approach similar to that used by Marenya and Barrett (2009a) to estimate the threshold values θ_1 and θ_2, which is common, for example, in threshold cointegration literature (Balke and Fomby 1997). That is, we estimate the model under all feasible assumptions regarding the values of θ_1 and θ_2 and select that which best fits the data.

Since we have two threshold values to estimate, an iterative process is employed. First, we estimate $\hat{\theta}_1$ using an ordinary least squares (OLS)-based grid search and the full sample (assuming $(\theta_2 = 0)$). Second, we estimate $\hat{\theta}_2$ assuming $\theta_1 = \hat{\theta}_1$ is the same in both T2 regimes. Third, we update our prior, now assuming $(\theta_2 = \hat{\theta}_2)$ and re-estimate the T1 threshold value within each T2-based regime. Call these new estimates $\hat{\theta}_{11}$ and $\hat{\theta}_{12}$ for the low T2 and high T2 regimes respectively. A specified convergence rule could be applied and this process could go on until it is satisfied, but in each of our cases, this proves unnecessary.

To justify splitting the sample into two T2-based regimes we conduct a Chow test. If we reject the null hypothesis that the yield function is no different between regimes, OLS within each regime (holding standard assumptions) provides unbiased estimates, and the usual t-statistics can be used for inference. Since the estimates $\hat{\theta}_2$, $\hat{\theta}_{11}$ and $\hat{\theta}_{12}$ do not have a known distribution (standard errors are "nuisance parameters"), we conduct hypothesis testing on them using bootstrapped standard errors, as described in Hansen (1996) and used by Marenya and Barrett (2009a).

5. RESULTS

We report the results one model specification at a time, as described in the sub-headings according to which soil characteristic is used as each threshold type.

5.1. Model 1: SOM=Type 1 and pH=Type 2

Select estimate results from the model including SOM and pH are shown in Table 2 (several controls are included in regressions as described but not shown. Full results are available). To estimate this model, we first search for a SOM threshold-affecting yield and fertilizer response (only), which is initially identified at 1.2%. Then, assuming this threshold holds throughout the model, we search for a pH threshold to identify two regimes for the entire production function. The total sum of squared residuals for the model is minimized at the pH threshold level of 5.4. A Chow test rejects the hypothesis that these regimes are no different (p=0.00) and the bootstrapped standard error suggests the threshold value itself is statistically significantly different from zero at the 1% level. Finally, within each pH regime, we re-evaluate the potential SOM thresholds and estimate little or no change at 1.2% and 1.4% for the low and high pH regimes respectively. Note that pH and SOM thresholds are close to ex ante expectations.

Table 2. Select Results with SOM as Type 1 and pH as Type 2 Threshold Variables

	pH level	
pH threshold	5.4***	
Bootstrap SE	(0.24)	
Chow p-value	(0.00)	
Regression results	Low	High
Fertilizer rate	3.647*** (0.72)	2.089+ (1.30)
Fertilizer rate squared	-0.001*** (0.00)	0.001 (0.00)
High SOM	-308.13* (159.9)	-488.51* (287.2)
High SOM*Fertilizer rate	2.157*** (0.61)	3.434*** (0.86)
SOM Threshold	1.2%	1.4%
Weeks delay*Basal fertilizer rate	-0.278 (0.26)	-0.593+ (0.36)
N	831	622
R^2	0.51	0.44
Weighted R^2	0.48	

*, **, *** Indicate significance at the 10%, 5% and 1% levels respectively, + indicates significance at the 11% level.

Table 3a. Matrix of Maize Average Product (kg/kg) of Basal Fertilizer

		pH level	
		Low <=5.4	High >5.4
Soil Organic Matter	High	4.47*** (0.56) [n=91]	3.90*** (0.84) [n=294]
	Threshold	*1.2%*	*1.4%*
	Low	2.22*** (0.68) [n=107]	0.37 (0.92) [n=495]

Source: IAPRI/CSO/MAL 2012. Delta-method standard errors in parentheses, sub-sample sizes in brackets. Note – APs include fertilizer users only.

Table 3b. Matrix of Maize Average Product (kg/kg) of Top Dress Fertilizer

		pH level	
		Low <=5.4	High >5.4
Soil Organic Matter	High	4.91*** (0.85) [n=91]	5.72*** (0.83) [n=294]
	Threshold	*1.2%*	*1.4%*
	Low	3.16*** (0.70) [n=107]	2.28* (1.18) [n=495]

Source: IAPRI/CSO/MAL 2012. Delta-method standard errors in parentheses, sub-sample sizes in brackets. Note – APs include fertilizer users only.

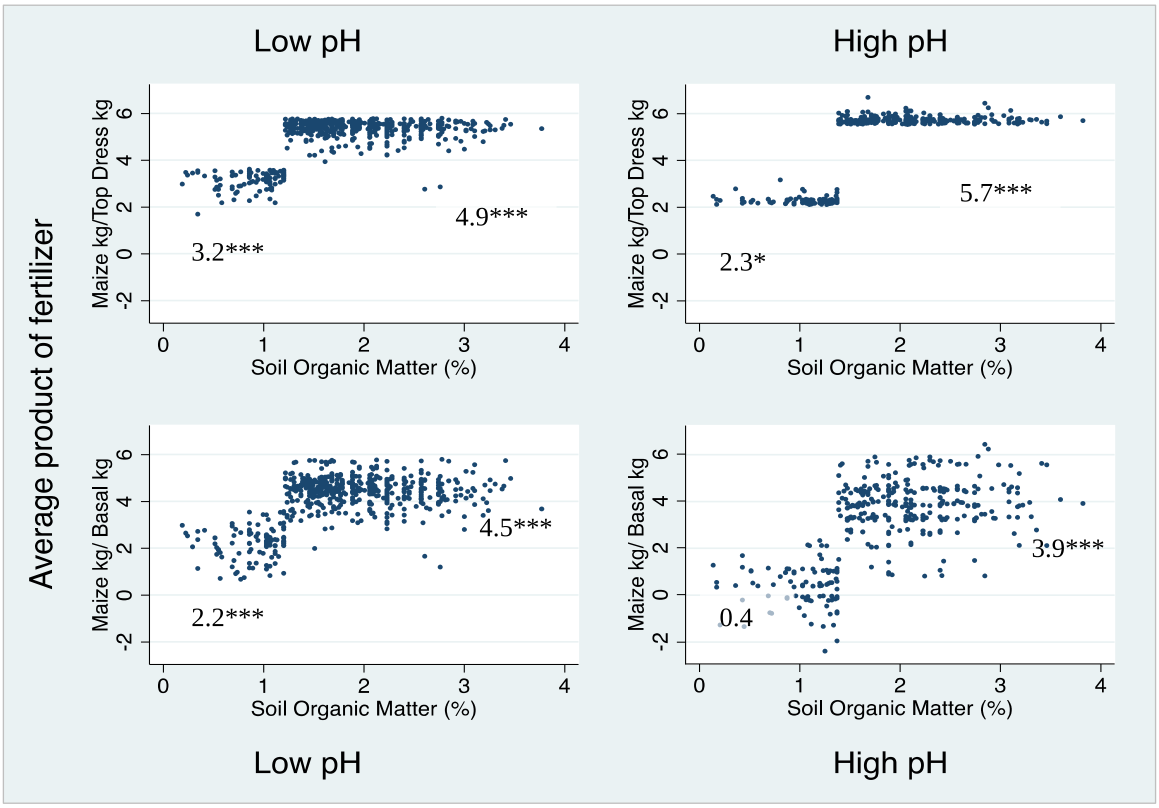
To better understand these results, the mean APs (amongst fertilizer users) of the two types of fertilizer used in Zambia are presented in Tables 3a and 3b by pH and SOM regimes. The first (3a) shows the AP for basal and the second (3b) shows the AP for top dressing. Again, a key difference between the two is that the AP of basal is modeled as a function of application delays while the AP for urea is not.

For both types of fertilizer, results with respect to the effect of SOM regimes are consistent with expectation and in line with earlier results reported in Marenya and Barrett (2009a) and elsewhere. Specifically, for a given type of fertilizer and pH regime, the mean AP of fertilizer is between 1.75 and 3.5 kg/kg higher on soils with higher SOM levels. This amounts to a difference between 55% to well over than 100%.

For urea, where SOM is above the critical threshold, the average product of fertilizer is greater on higher pH soils, as expected (5.7 kg/kg versus 4.9 kg/kg). On lower SOM soils, on the other hand, the estimated AP of urea is greater on acidic soils, which is counterintuitive. Similarly, the estimated AP for basal fertilizer is higher on more acidic soils regardless of SOM regimes (Figure 5).

In the three latter cases (low SOM for urea, and high and low SOM for basal) these results are less confounding when we examine results beyond the mean effects. Figure 5 shows scatter plots of the estimated average product of fertilizers for each observation by fertilizer type and soil quality regimes. Notice the variability of estimated effects of urea (top panels) when SOM is below its critical thresholds is greater on lower pH soils.

Figure 5. Scatter Plots of Estimated Average Product of Fertilizers by Type and Soil Regimes for Model 1: SOM=Type 1 Threshold and Ph=Type 2 Threshold



Source: IAPRI/CSO/MAL 2012 and authors' calculations.

Notes: Each dot indicates an individual observation's estimated AP. Numbers within the plots indicate the mean AP amongst observations in each regime. *, ** and *** respectively indicate statistical significantly different from zero at the 10, 5 and 1% level (e.g., the mean AP of basal fertilizer amongst those in the high pH and high SOM regimes is 3.9 kg/kg, significant at the 1% level)

In other words, while the mean estimated AP of urea is somewhat lower on less acidic soils, the risk of lower response rates is greater on more acidic soils, which is consistent with known agronomic principles.

Figure 5 also underscores the importance of controlling for delayed application when examining the APs of basal. So again, the unexpected difference in mean AP across pH regimes becomes more sensible when the distribution of estimates is examined more generally (bottom panels of Figure 5). Recall from Table 2, for every week after planting basal fertilizer application is delayed on acidic soils, the expected AP decreases by about 0.3 kg/kg. Figure 5 illustrates the potential yield effects of basal fertilization are greater on less acidic soils, where on-time application has an estimated AP greater than 6 kg/kg. However, that potential decreases roughly twice as much for each week after planting a farmer applies basal as compared to delays on more acidic soils. Moreover, while neither two-sided tests reject the hypothesis that the effect of delayed application is statistically significantly different from zero, one sided tests in the high pH regimes fail to reject the hypothesis that delays have a strictly negative effect and reject the hypothesis that the effect is non-negative (p=0.06)

Table 4. Select Results with Texture as Type 1 and pH as Type 2 Threshold Variables

pH threshold	5.6***	
Bootstrap SE	(0.26)	
Chow p-value	(0.00)	
	pH regime	
Regression results	Low	High
Fertilizer rate	3.664***	3.30+
	(0.67)	(2.06)
Rate squared	-0.001***	-0.44 e-3
	(0.3e-3)	(0.7e-3)
Clay group		
1 - very low	Subsumed	Subsumed
	-	-
2	116.85	219.25
	(176.6)	(412.3)
3	333.72 *	-262.57
	(187.6)	(371.7)
4 - more than about 40%	135.27	88.37
	(247.8)	(394.0)
Fertilizer rate x Clay group		
1 - very low	Subsumed	Subsumed
	-	-
2	1.528**	1.677
	(0.70)	(2.42)
3	1.074+	3.886*
	(0.72)	(2.26)
4 - more than about 40%	1.274+	2.966
	(0.90)	(2.61)
Weeks delay*Fert rate	-0.364	-0.826+
	(0.25)	(0.56)
N	1002	451
R^2	0.47	0.47
Weighted R^2	0.47	

*, **, *** Indicate significance at the 10%, 5% and 1% levels respectively, + indicates significance at the 15% level. The delta-method was used to estimate SEs of the AFE.

5.2. Model 2: Clay Content=Type 1 and pH=Type 2

Table 4 shows select results from the alternative model where soil texture categories replace SOM as the type 1 threshold variable. In this model, soil texture categories are established prior to estimation and a grid search is employed to identify the pH regimes that minimize the sum of squared errors. Here the estimated pH threshold is found at 5.6, which is also close to ex ante expectations (ZARI 2002).

Tables 5a and 5b present mean AP estimates by texture and pH regimes analogously to Tables 3a and 3b as described for model 1. For a given pH regime and fertilizer type, these results are again consistent with ex ante expectations. The mean AP of fertilizers is lowest on the lowest clay content soils. Again, though, understanding the impacts of soil acidity requires more than a cursory examination of mean effects. The counterintuitive results (suggesting fertilizers are more effective on more acidic soils) are again explained by the importance of timely application. Here too, the estimated cost of delayed application is roughly twice as great on higher pH soils, and again the estimated effect has a higher variance on more acidic (lower pH) soils.

Table 5a. Matrix of Maize Average Product (kg/kg) of Basal Fertilizer

		pH level	
		Low <=5.6	High >5.6
Soil texture group	Less clay - 1	2.27*** (0.70) [n=84]	0.34 (2.61) [n=33]
	2	3.79*** (0.75) [n=205]	2.17** (1.07) [n=61]
	3	3.40*** (0.77) [n=367]	4.47*** (1.21) [n=145]
	More clay - 4	3.75*** (0.91) [n=39]	3.60* (1.95) [n=23]

Source: IAPRI/CSO/MAL 2012. Delta-method standard errors in parentheses, sub-sample sizes in brackets. Note – APEs include fertilizer users only.

Table 5b. Matrix of Maize Average Product (kg/kg) of Top Dressing Fertilizer

		pH level	
		Low <=5.6	High >5.6
Soil texture group	Less clay - 1	3.54*** (0.65) [n=85]	3.22 (2.04) [n=32]
	2	5.06*** (0.75) [n=208]	4.89*** (1.71) [n=64]
	3	4.61*** (0.85) [n=376]	7.11*** (1.34) [n=150]
	More clay - 4	4.81*** (0.92) [n=40]	6.19*** (1.95) [n=25]

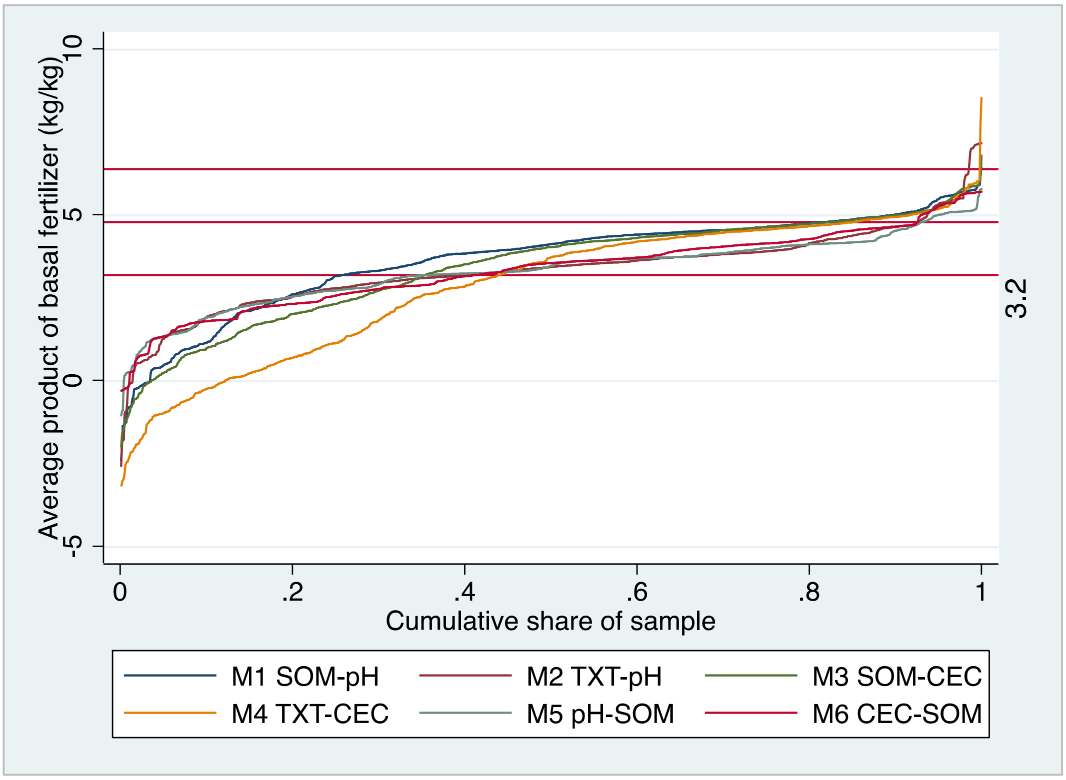
Source: IAPRI/CSO/MAL 2012. Delta-method standard errors in parentheses, sub-sample sizes in brackets. Note – APEs include fertilizer users only.

5.3. Profitability and the Robustness of Findings to Model Specification

So far, we have only discussed results of two models out of several possible specifications. Moreover, for better or worse, no theory is readily available to base a decision regarding which specification is *best*. To address this, Figure 6 illustrates results from models 1 and 2 as well as several additional specifications in the form of the cumulative distributions of estimated average product of (basal) fertilizer (a similar figure for top dressing shows similar results). Each of six models (M1 to M6) are described in the legend with the type 1 threshold variable listed first, followed by the type 2 threshold variable (M1 and M2 are the models discussed above). This clearly illustrates that our results describing the distribution of APs for the overall population are robust to model specification.

Reference lines on Figure 6 are at 3.2, 4.8, and 6.4 kg of maize per kg of fertilizer applied. These respectively indicate average value cost ratios (AVCR) of 1, 1.5 and 2 for fertilizer applications based on mean commercial prices paid for fertilizer (ZMK 3,723/kg) and harvest time (May-July) commercial maize prices (ZMK 1,177/kg) reported by farmers in the RALS 2012 data. An AVCR equal to 1 indicates the fiscal *break even* point, irrespective of transfer costs. In this case, the various models predict between roughly 25-45% of fertilizer users operate at a fiscal loss. Kelly (2005) suggests an AVCR of at least 2 is required for smallholder farmers to adopt a technology because of transfer costs and risk aversion. Using Kelly's suggestion, we would conclude virtually no farmers break even using basal fertilizer regardless of model specification.

Figure 6. Cumulative Distribution of Average Product of Fertilizer Estimates (amongst Fertilizer Users) under Various Model Specifications



Source: IAPRI/CSO/MAL 2012 and authors' calculations.
Notes: Model 1 (M1)-SOM=Type 1 (T1) threshold and pH=Type 2 (T2) threshold; M2-Texture=T1 and pH=T2; M3-SOM=T1 and CEC=T2; M4-texture=T1 and CEC=T2; M5-pH=T1 and SOM=T2; M6-CEC=T1 and SOM=T2.
Reference lines are at 3.2, 4.8 and 6.4 marginal kg of maize per kg of fertilizer applied.

6. POPULATION IMPACT ON INTENSIFICATION AND SOIL CHARACTERISTICS

Our analysis so far has examined how degraded soil may affect yields both independent of fertilizer use and by rendering plants less responsive to fertilizers. The current situation is alarming, but improved productivity will be of greater importance in the future as rural and urban population densities increase. Looking forward, this section examines how rising population may affect productivity. We investigate: a) whether fallow periods can be expected to decrease (farmland use intensity can be expected to increase) as population density increases, and if so, b) whether increased intensity will lead to further land degradation given current soil management practices.

6.1. Population Effects on Land Use Intensity

We examine the implications of population pressure by combining our sample with data on land use from annual crop forecast surveys and the 2010 population census. A common measure of land-use intensity is the ratio of fallow-land to total-farmland (fallow plus cultivated, or fallow, cultivated and virgin farmland) (Boserup 1965). Table 6 shows several simple regression estimates of 2012 fallow ratios on 2010 district population densities. Variables on both left and right hand sides of these regressions are at the district level, however we have assigned them to our household-level sample to maintain national representativeness (i.e., to account for variance in district size). Also, note the *full sample* regressions only include the 1390 households in districts where the administrative boundaries did not change between 2010 and 2012 (several boundaries were revised after the 2011 presidential election).

The first four columns of Table 6 exclude virgin land from the fallow ratio calculations while results in columns (v) through (viii) include virgin land. Each equation is estimated four times, using: 1) the full sample; 2) only those observations where population density is less than 1,000 persons per square kilometer (persons/km^2) (excluding 8 observations); 3) only those observations where population density is less than 500 persons/km^2 (excluding eight more observations); and 4) only those observations where population density is less than 200 persons/km^2 (excluding 23 more observations). These various levels of density truncation are chosen subjectively to demonstrate how the relationship meaningfully (and statistically significantly, not shown) changes.

Regression results consistently show areas with higher population density demonstrably use land more intensively. Moreover, the effect is more dramatic when we exclude already densely populated areas. Column (iv), for example, excludes observations in districts with more than 200 persons/km^2 (e.g., Ndola, Lusaka, etc.) Results indicate the mean fallow ratio is about 25% of non-virgin farmland when population density is very low, however, an increase in population density to about 180 persons/km^2 can be expected to effectively reduce that fallow ratio to zero.

Figure 7 further illustrates the relationship between population density and fallow ratios using the results (not shown) from quantile regression. The vertical axis indicates the fallow ratio (excluding virgin land) and the horizontal axis indicates population percentiles. Each line in Figure 7 represents predicted percentiles for various given population densities from sparse (effectively 0 persons/km^2) to 100 persons/km^2. In this example, we include observations in districts with fewer than 100 persons/km^2 (n=1320).

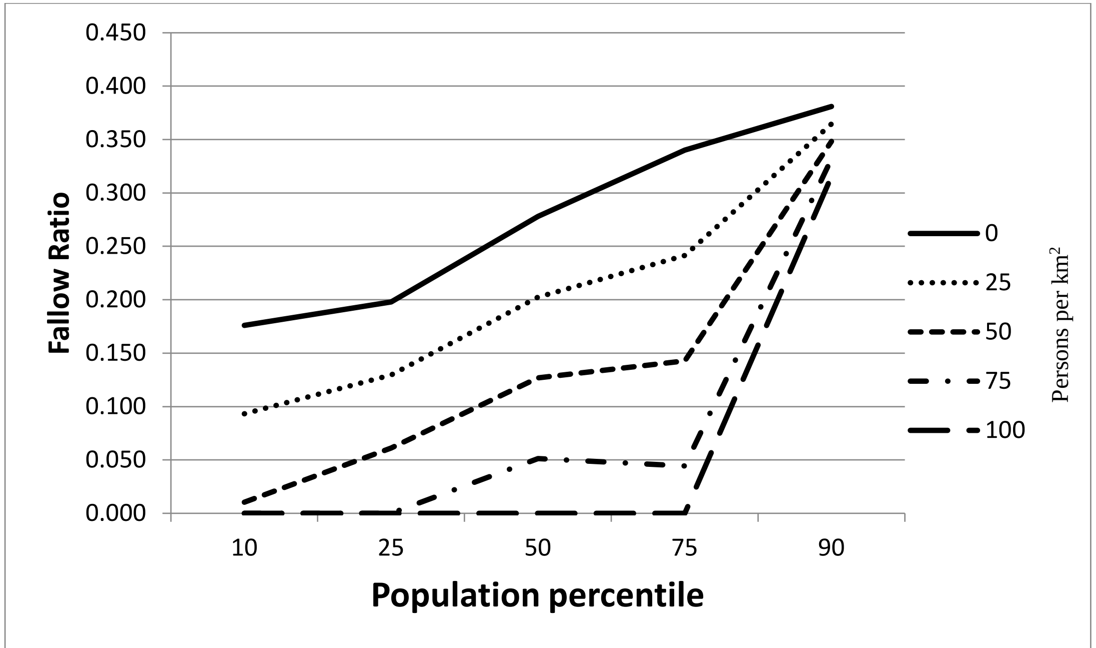
Table 6. Land Use Intensity (Ratio of Fallow to Farm Land) as a Function of Population Density

	Dependent variable							
	F/(F+C)				F/(F+C+V)			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vi)	(vii)
Pop density[a]	-0.110***	-0.295***	-0.477***	-1.393***	-0.070***	-0.184***	-0.322***	-0.821***
Constant	0.221***	0.226***	0.231***	0.251***	0.160***	0.163***	0.167***	0.178***
Model	All obs	PD<1	PD<0.5	PD<0.2	All obs	PD<1	PD<0.5	PD<0.2
N	1390	1382	1374	1351	1390	1382	1374	1351
R^2	0.011	0.022	0.024	0.097	0.010	0.019	0.024	0.075

F – Fallow; C – Cultivated; V – Virgin

Notes – a) Population density measured in thousands of people per square kilometer according to 2010 census data.

Figure 7. Predicted Quantiles of Fallow Ratio as Population Density Increases



Sources: IAPRI/CSO/MAL 2012 Crop forecast surveys and authors' calculations.

Each line in Figure 7 can be thought of as an estimated cumulative population density for fallow ratios. Consider, for example, a fallow ratio of 0.1. These results suggest that in sparsely populated areas (solid line) essentially every farmer fallows at least this much land. At a population density of 25 persons/km^2 (small-dotted line), a little more than 10% of the population is expected to have a fallow ratio of 0.1 or lower. Where there are 50 persons/km^2, 40% have an expected fallow ratio below 0.1, and for the two simulations with population densities greater than 50 persons/km^2, we estimate three-quarters or more of the population fallow just a tenth of their land or less.

In short, these results are consistent with the Boserup's principle that areas with higher population density tend to use their farmland more intensively, and so as population density increases over time we can expect more intensive farming.

6.2. Decreased Fallow Effects on Soil

The final question is whether we should expect future intensification to be sustainable based on observed management practices. We begin to inform this discussion by examining how fallow ratios relate to SOM and pH, controlling for farm management practices insofar as our data allows. Table 7 presents results from several instrumental variables estimations for the determinants of pH and SOM. We suspect the fallow ratio is endogenous in these equations because there may be two-way causality between population density and soil quality. We control for endogeneity using population density and distance to the nearest town as instruments.[8]

Table 7. Population and Management Factors Affecting Soil Organic Matter and pH

	Soil measurement	
Control variables	pH	SOM
District fallow/cultivable ratio[a]	8.05**	2.29
	(3.42)	(3.04)
Maize last year (1=yes)	0.04	-0.10*
	(0.06)	(0.05)
Fallow last year (1=yes)	-0.16	-0.12
	(0.19)	(0.16)
Planted with N-fixing legume (1=yes)	0.35**	0.21*
	(0.17)	(0.11)
"Agro-forestry" trees in field (1=yes)	0.31**	0.24**
	(0.15)	(0.10)
Fertilizer application rate (100 kg/ha)	-0.01	-0.01
	(0.01)	(0.01)
Provincial Fixed Effects (not shown)	*Yes*	*Yes*
Constant	3.62***	1.52**
	(0.74)	(0.66)
N	1390	1389
R^2	0.05	0.12

Notes: *, **, *** indicate statistical significance at the 10%, 5% and 1% levels respectively. a) Regressor treated as endogenous using District population density and village distance to nearest town as additional instruments.

In addition to the fallow ratio, indicator variables are included for: 1) whether the field was planted with maize in the previous year as well; 2) whether the field was fallowed in the previous

[8] These results are again restricted to the 1,390 observations in districts with consistent administrative boundaries from 2010 to 2012. One additional outlier is excluded from the SOM regression. This outlier is not influential in the previous analyses since the value is reduced to a binary threshold/regime indicator.

year; 3) whether the current harvest was planted along with nitrogen fixing legumes; and 4) whether the field contains agro-forestry trees. Finally, the contemporaneous fertilizer application rate is included as are Provincial fixed effects.

All else equal, expected soil pH increases significantly (becomes/remains less acidic) as fallow ratios increase. For example, the data-mean fallow ratio is about 0.20. Compared to no fallow, this suggests a difference of 1.6 on the pH scale, which could have a profound impact on yields and response to fertilizer. The effect of fallow is similarly positive in the SOM model, however not statistically significantly different than zero. We do find that SOM is expected to be lower on fields where maize has been farmed for at least the prior two years, as expected. We see no effect from previous year fallow, though with fewer than 3.5% of our observations having fallowed previously, this is neither surprising nor indicative of the benefits of fallow.

In the models for both SOM and pH, we find positive and significant improvements in soil conditions associated with the practices of agro-forestry and legume intercropping. While this result is consistent with expectations, it is worth noting that the estimated effects are statistically significant despite very low adoption rates (i.e., very little variation in the data).

To summarize this discussion, we argue that the big-picture perspective further emphasizes the urgency of the analysis in prior sections. It is underappreciated that soils with unfavorable physical, chemical, and biological properties host crops that are less responsive to fertilizers, but threats to productivity run even deeper. Imminent population growth is not in doubt. We have endeavored to show empirically that we can expect further farmland intensification to accompany population growth; when land is carrying as few as 100 persons per square kilometer, we may see as much as 75% of farmland under continuous use (Figure 7). Moreover, barring the adoption of (currently rare) management practices, we expect intensification to negatively affect soil quality and input productivity. In short, while it is important to recognize that status-quo input use is not particularly productive, it is perhaps more important to acknowledge the indicators on the horizon that the trajectory of productivity may turn down if more appropriate practices are not adopted.

7. CONCLUSION

In this article, we incorporate farm management and household data with soil analysis to understand and quantify the variable and low response rates to inorganic fertilizer applications. Unlike earlier work, we develop a model that simultaneously allows for the effects of multiple soil characteristics and critical thresholds. We estimate critical threshold effects on yield response to fertilizer between pH levels of 5.4 and 5.6, soil organic matter levels 1.2-1.4%, and we find significant texture-related effects. Alternative models incorporate these characteristics and cation exchange capacity to demonstrate robustness to model specification. Several average yield response estimates range from not significant to 5.7 maize kg/fertilizer kg depending on soil characteristics. We find fertilizer use unprofitable at commercial prices for the majority of Zambian fields (under current practices). Even if transfer costs are ignored, up to 45% of fertilized fields have an estimated average value-cost ratio for fertilizer less than one at commercial prices.

Several key implications emerge from this study. First, it is well known that soil characteristics vary widely across Africa and even within countries. Nevertheless, far more policy focus is given to encouraging inputs use than to the appropriateness of the technologies being promoted. Our article contributes to a growing literature that consistently suggests inputs' yield effects can be dramatically limited (or enhanced) depending on prevailing conditions. We believe it is important to continue pursuing this vein of literature so as to build knowledge regarding the actual effectiveness of the inputs being used and promoted, the determinants of that effectiveness on farms (as opposed to field trials) and to identify possible complementary (or substitutive) practices that could sustainably increase farm yields.

Second, promoting timely fertilizer application could be a potentially powerful lever to increase the productivity of blended fertilizers. Farmers often delay applications to avoid risk, fearing that applications to soil before germination may go to waste. Another cause for delay, at least in Zambia, is frequently a lack of availability as government acquired fertilizers are delayed due to payment or customs issues. Addressing farmer risk aversion is potentially a very powerful policy lever, but a difficult one to pull. Avoiding delays due to administrative issues is more likely to be a tenable option.

Third, another policy lever that appears to be underutilized is research and extension. Developing and sharing knowledge regarding efficient input use, by nearly all accounts, will more effectively lead towards sustainable intensification than the naïve and generalized promotion of fertilizer types and application rates. In Zambia and other African countries, agricultural research institutions are underfunded and extension agencies are essentially defunct, largely because the bulk of financial and human resources are dedicated to subsidy programs. Diversification of productivity enhancing strategies is another potentially very powerful policy lever.

Finally, the urgency behind addressing low and variable land productivity will only increase in the near future. Empirical evidence presented here strongly supports the hypothesis that as population increases, we can expect land use intensity to increase (or fallow periods to decrease). Furthermore, under current management practices we can expect increasing intensity to lead to further land degradation. One could view this as discouraging. On the other hand, one might consider the array of under-promoted and under-employed alternatives to naïve fertilizer applications as a readily available opportunity to affect yields in the near and long-term.

Producing more on the same land, with the same or fewer additional inputs, increasing rural farm incomes and the advantageous social outcomes that go with it are attainable goals.

Accomplishing these goals, however, is almost certainly going to require the scope of prevailing strategies to broaden. The sooner the better.

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