INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
IFPRI

IFPRI Discussion Paper 02031

June 2021

Mismatch between Soil Nutrient Requirements and Fertilizer Applications

Implications for Yield Responses in Ethiopia

Kibrom A. Abay

Mehari H. Abay

Mulubrhan Amare

Guush Berhane

Ermias Aynekulu

Development Strategy and Governance Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Kibrom A. Abay (k.abay@cgiar.org) is a Research Fellow in the Development Strategy and Governance Division of the International Food Policy Research Institute (IFPRI), Cairo, Egypt.

Mehari H. Abay (hilufabay@gmail.com) is Associate Researcher, Tigray Institute of Policy Studies (TIPS), Mekelle, Ethiopia

Mulubrhan Amare, (m.amare@cgiar.org) is a Research Fellow in IFPRI's Development Strategy and Governance Division, Washington, DC.

Guush Berhane (g.berhane@cgiar.org) is a Senior Research Fellow in IFPRI's Development Strategy and Governance Division, Washington, DC.

Ermias Aynekulu (e.betemariam@cgiar.org) is a Land health scientist at World Agroforestry (ICRAF), Nairobi, Kenya.

Abstract

Lack of accurate information about soil nutrient requirements coupled with limited access to appropriate fertilizers could lead to mismatch between soil nutrient requirements and fertilizer applications. Such anomalies and mismatches are likely to have important implications for agricultural productivity. In this paper we use experimental (spectral soil analysis) data from Ethiopia to examine farmers' response to soil nutrient deficiencies and its implications for yield responses. We find that farmers' response to macronutrient (nitrogen and phosphorus) deficiencies is not always consistent with agronomic recommendations. For instance, we find that farmers in our sample are applying nitrogen fertilizers to soils lacking phosphorus, potentially due to lack of information on soil nutrient deficiencies or lack of access to appropriate fertilizers in rural markets. On the other hand, farmers respond to perceivably poor-quality soils and acidic soils by applying higher amount of nitrogen and phosphorus fertilizers per unit of land. We further show that such mismatches between fertilizer applications and soil macronutrient requirements are potentially yield-reducing. Those farmers matching their soil nutrient requirements and fertilizer application are likely to enjoy additional yield gains and the vice versa. Marginal yield responses associated with nitrogen (phosphorus) application increases with soil nitrogen (phosphorus) deficiency. Similarly, we find that farmers' response to acidic soils is not yield-enhancing. These findings suggest that such mismatches may explain heterogeneities in marginal returns to chemical fertilizers and the observed low adoption rates of chemical fertilizers in sub-Saharan Africa. As such, these findings have important implications for improving input management practices and fertilizer diffusion strategies.

Keywords: Mismatch, nutrient deficiency, fertilizer applications, spectral soil analysis, Ethiopia.

Acknowledgement

This study was supported by funding from the CGIAR Research Program on Policies, Institutions, and Markets (PIM), which is led by IFPRI.

1. Introduction

It is widely believed that agricultural productivity growth in Africa, among others, requires higher application of improved inputs (Evenson and Gollin, 2003; Johnson et al., 2003). This argument is built on the presumption that increased use of improved agricultural inputs, including chemical fertilizers and improved seeds can be profitable in African agriculture when applied in appropriate mixes. However, fertilizer adoption rates and intensity in many sub-Saharan African (SSA) countries still remain low, especially given ongoing efforts to increase agricultural yield in SSA (Minot and Benson, 2009; Amare et al., 2012; Rashid et al., 2013; Abay et al, 2017; Sheahan and Barrett, 2017; Binswanger-Mkhize and Savastano, 2017). Furthermore, the uptake of modern technologies in African agriculture is not uniformly low across countries, households and plots. Recent studies document substantial heterogeneities among countries and households (Sheahan and Barrett, 2017; Binswanger-Mkhize and Savastano, 2017; Abay et al., 2018; Kurdi et al., 2020; Abate et al., 2020).

There are several strands of economic and agronomic literature that attempt to explain these low and heterogeneous technology adoption rates in sub-Saharan Africa. One strand of economics literature acknowledges the role of market imperfections and frictions related to the distribution and access to these technologies (e.g., Moser and Barrett, 2006; Giné and Yang, 2009; Duflo et al., 2008; Davis et al., 2010; Spielman et al., 2010; Minten et al., 2013; Benson et al., 2020). Another strand of economics literature revisits the profitability of these modern agricultural inputs in African agriculture. Several studies show that marginal returns to inorganic fertilizers can be low and heterogenous across contexts (Duflo et al., 2008; Xu et al., 2009; Marenya and Barrett, 2009; Suri, 2011; Minten et al., 2013; Sheahan et al., 2013; Burke et al., 2017; Harou et al., 2017; Liverpool-Tasie et al., 2017).[1] For instance, some studies show that the profitability of chemical fertilizers and improved seeds depend on soil quality and soil characteristics (Marenya and Barrett, 2009; Amare et al., 2012; Burke et al., 2017).

An important underlying assumption in these discussions is that to the extent that soil quality is known to farmers, removing informational and access constraints can lead to better use of improved inputs and hence productivity increases. However, farmers lack accurate information

[1]Some studies argue that technology adoption decisions of rural farmers in Africa are consistent with their comparative advantage and expected profitability of these technologies (e.g., Sheahan et al., 2013; Suri, 2011; Liverpool-Tasie, 2017).

about their soil quality and its nutrient requirements. For example, Gourlay et al. (2017) show that farmers' subjective assessment of soil quality is only weakly correlated with objective measures of soil quality. This is not surprising given that conventional soil tests are usually expensive and inaccessible to smallholders in most of Africa. Lack of access to objectively measured soil information along with appropriate fertilizer recommendations imply that farmers are left to guessing when applying fertilizers, which could lead to mismatch between soil nutrient requirements and fertilizer applications. In the absence of objective measures of soil properties and associated nutrient requirements, farmers are forced to form some perceptions about their soil qualities or use some inaccurate soil quality proxies.[2] For instance, Berazneva et al. (2018) show that farmers' perception of soil quality and type is driven by actual crop yield. These misperceptions or proxies may lead to sub-optimal application of modern agricultural inputs.[3]

In this paper we explore another empirical pattern, mismatch between soil nutrient requirements and actual fertilizer applications, for explaining the low and heterogenous returns to chemical fertilizers in SSA. We hypothesize that farmers lack accurate information about their soil nutrient requirements, and hence may not appropriately respond to recommended agronomic nutrient requirements, which may lead to lower fertilizer yield responses. A long-existed agronomic literature shows that yield responses to fertilizers heavily depend on soil nutrient requirements and farmers' response to these nutrient requirements (Tittonell et al., 2008; Kihara et al., 2016). Furthermore, soil nutrient requirements significantly vary across plots and across communities in many African countries, proving farmers' learning about nutrient use from experience difficult (Otsuka and Larson, 2013; Tjernstrom et al., 2018). As such, these spatial variabilities in soil nutrient requirements render the usual blanket fertilizer recommendations ineffective and less relevant to many farmers (e.g., Harou et al., 2018).

Our study makes two important contributions to the literature on fertilizer applications and yield responses. First, we examine farmers' response (in terms of chemical fertilizer use) to soil fertility as measured by both objective and subjective metrics of soil properties. In Ethiopia, DAP (Diammonium phosphate) and urea are the two dominant chemical fertilizers that are meant to

[2] Learning from these imprecise proxies and experiments may discourage (risk-averse) farmers adopt yield-enhancing technologies and inputs.
[3] For instance, Abay et al. (2021) show that misperceptions associated with land area measurement drive input allocations, while Wossen et al. (2021) show similar response driven by misperceptions associated with crop variety.

address macronutrient deficiencies. We thus focus on examining farmers' response in terms of actual application of these chemical fertilizers. Second, we explicitly study the implication of these responses to soil fertility on agricultural yield. We investigate whether farmers' response to soil fertility and nutrient requirements are yield-enhancing. We use data that come from a large-scale methodological experiment involving spectral soil analysis of plot-level soil samples implemented as part of the Living Standards Measurement Survey-Integrated Surveys on Agriculture (LSMS-ISA) by the World Bank. These spectral soil analysis data provide objective plot-level measures of soil properties, which allow us examine farmers' response to soil (macro) nutrient requirements and associated yield implications. These data provide large set of information on soil health and soil quality, including availability of macronutrients (nitrogen and phosphorus) in soil samples.

Using these objectively measured soil nutrient content and self-reported input use decisions of farmers, we estimate both input demand and yield response elasticities. We find that farmers' fertilizer applications are not always consistent with (objectively measured) levels of soil macronutrients, but instead appear to be consistent with perceived soil quality indicators. Particularly, we find that nitrogen fertilizer application rates are not statistically associated with measured nitrogen nutrient levels in soils. However, the results show that phosphorus fertilizer applications are consistent with measured phosphorus nutrient requirements in soils. For instance, one percent reduction in soil phosphorus content is associated with about 0.3 percent increase in phosphorus application. Contrary to this, although input demand functions suggest farmers respond to low measured phosphorus nutrient levels, in doing so, they also respond by applying more nitrogen fertilizer levels. These responses may be driven by lack of access to appropriate fertilizer mixes as well as farmers' limited knowledge of soil nutrient requirements. For instance, in the context of Ethiopia DAP (Diammonium phosphate) fertilizer, which contains both phosphorus and nitrogen, is relatively more accessible than urea, which mainly contains nitrogen. On the other hand, farmers respond to perceived poor-quality soils and acidic soils by applying higher levels of nitrogen and phosphorus fertilizers. We further show that such mismatch between fertilizer applications and macronutrients requirements is yield-reducing. Those farmers mismatching their soil nutrient requirements and fertilizer application rates lose significant yield responses. Similarly, farmers' response to acidic soils is not productivity-enhancing, rather adversely affects marginal yield responses associated with chemical fertilizers.

The evidence we document in this paper can help improve our understanding of the relationship between objective and subjective measures of soil fertility and their implications for fertilizer use and yields, contributing to the literature in at least two important ways. First, our findings add nuanced evidence to the literature explaining the low level of fertilizer adoption and associated low marginal returns to fertilizers in SSA. The mismatch between measured soil nutrient levels and farmers' fertilizer application documented in our analysis can be one important explanation why yield responses and marginal returns to fertilizers in these contexts can be low. Second, our findings also reinforce existing evidence on the extent to which availing plot-specific soil nutrient information can be important to improve farm management practices and yield (Fishman et al., 2016; Fabregas et al., 2019; Harou et al., 2018; Tjernström et al., 2018; Murphy et al., 2020; Ayalew et al., 2020).

The rest of this paper is organized as follows. Section 2 reviews the literature on the interaction among soil properties, fertilizer applications and associated marginal yield responses. Section 3 describes the data and sampling design. Section 4 outlines our empirical approach while Section 5 presents the main results. Section 6 concludes.

2. Soil Properties, Yield Responses and Marginal Returns to Fertilizers

African agriculture faces a twin challenge of satisfying increased food demands of the ever-growing population and judicious use of soils to ensure sustainable increase in productivity (Collier and Dercon, 2014; Gollin et al., 2014; Amare et al., 2017). Currently, the low level of agricultural productivity in many SSA countries do not meet the growing demand for food from the growing population and urbanization, often pushing food prices upwards (e.g., Swinnen et al., 2015; Christiaensen and Demery, 2017; Barrett et al., 2020). Such low agricultural productivity in the region is often attributed to lack of innovation and low adoption of improved agricultural technologies, including chemical fertilizers (Sheahan and Barrett, 2017; Amare et al., 2017; Binswanger-Mkhize and Savastano, 2017).This is despite several efforts and investments to increase technology adoption and agricultural yields (Minot and Benson, 2009; Amare et al., 2012; Rashid et al., 2013; Binswanger-Mkhize and Savastano, 2017; Abay et al., 2018; Abate et al., 2020). The low adoption of agricultural technologies in many SSA countries also contradicts with the long-held view that chemical fertilizers are profitable in African agriculture and farmers should apply them in appropriate mix (e.g., Conley and Udry, 2010; Duflo et al., 2011; Liverpool-Tasie, 2017; Liverpool-Tasie et al., 2017; Jayne et al., 2018).

Other studies show that fertilizer usage in Africa has grown during the last two decades and is not as low as conventional wisdom suggests (e.g., Marenya and Barrett, 2009; Peñuelas et al., 2013; Van Der Velde et al., 2014; Liverpool-Tasie et al., 2015; Liverpool-Tasie et al., 2017; Sheahan and Barrett, 2017). However, there exist substantial heterogeneities among countries, households, and plots (e.g., Sheahan and Barrett, 2017; Binswanger-Mkhize and Savastano, 2017; Abay et al., 2018; Abate et al., 2020). Furthermore, whether such increases and heterogeneities in fertilizer applications are consistent with soil nutrient requirements remain unknown, mainly because objective measures of soil properties are not widely available. Most importantly, fertilizer management and application in several African countries are guided by blanket recommendations, which may not be relevant to several farmers and contexts (e.g., Harou et al., 2018). On the other hand, the substantial heterogeneities in soil nutrient requirement across farms and plots also impede learning from experiences of fertilizer applications based on blanket recommendations as different locations or plots respond differently to specific nutrient applications (e.g., Otsuka and Larson, 2013; Tjernstrom, 2017).

One important explanation for the existing low and heterogenous fertilizer application rates in many SSA has been heterogeneity in returns to fertilizer applications (Duflo et al., 2008; Marenya and Barrett, 2009; Suri, 2011; Sheahan et al., 2013; Burke et al., 2017; Harou et al., 2017; Liverpool-Tasie et al., 2017). Heterogeneities in marginal returns to chemical fertilizers are particularly linked with variations in soil quality and soil characteristics (e.g., Marenya and Barrett, 2009; Burke et al., 2017). For instance, Marenya and Barrett (2009) find that chemical fertilizers can be unprofitable in soils with low Soil Organic Content (SOC).[4] Similarly, Burke et al. (2017) show that chemical fertilizers are unprofitable when applied on acidic soils. Furthermore, adding some type of fertilizers to acidic soils may reduce yield while also adversely affecting overall soil and environmental health.

Marginal returns to fertilizer applications are also likely to vary across soils with varying macronutrient availability. For instance, agronomic studies show that marginal yield responses

[4] SOC is the core of soil fertility that ensures crop production and food security (Blanchet et al., 2016; Lützow et al., 2006; Marenya and Barrett, 2009). Maintaining or enhancing SOC is important for improving soil quality and mitigating carbon dioxide (CO_2) emissions.

heavily depend on soil nutrient requirements (e.g., Tittonell et al., 2008; Kihara et al., 2016). Similarly, some type of fertilizers can be more appropriate and impactful for some crops than others. For example, Van der Velde et al. (2013) show that the maize yield responses to phosphorus fertilizers are much higher than nitrogen fertilizer applications.

Despite its importance, plot-level soil nutrient information remains to be invariably missing in Africa, leaving farmers to rely on their subjective assessments when applying fertilizers. However, recent studies indicate that farmers' subjective assessments of soil properties are not strongly correlated with objective measures of soil quality (Gourlay et al., 2017). Gourlay et al. (2017) show that farmers' subjective assessments of soil quality poorly explain objective laboratory results and lack intra-household variations, while objective measures show significant variations across plots and communities. This opens doors for potential mismatch between soil nutrient requirements and fertilizer applications, with important implications to yield responses associated with chemical fertilizers. In this paper, we examine to what extent farmers' actual fertilizer applications relate to objectively measured soil nutrient levels and its implications for yield responses using objectively measured plot-level data on soil properties.

3. Data and Sample Description

3.1 Sample description and study area

We use data collected by the World Bank and partners through the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) program and under the Land and Soil Experimental Research (LASER) project. The LASER experiment, which aimed at understanding and improving soil fertility measurements, was implemented in partnership with the World Agroforestry Center (ICRAF) and the Central Statistical Agency (CSA) of Ethiopia. The LASER project is a methodological experiment originally designed to evaluate the feasibility of integrating objective soil fertility measures into household socioeconomic data collection operations. The experiment also aims to assess local knowledge of farmers in assessing their soil quality. The national LSMS-ISA surveys commonly collect household socioeconomic information including subjective plot-level information on soil quality, often asked to the head of household or plot-manager. Data collection for the LASER study was conducted in 3 zones (Borena, East Wellega, and West Arsi) of the Oromia region in Ethiopia (see Figure 1).[5] Oromia region was selected because it represents a large area of Ethiopia and encompasses areas with great variation in rainfall, elevation, and agroecological zones. The region is suitable and known for cultivating several cereal and cash crops. The most dominant cereals include maize, barley, wheat and *teff*. Macronutrients (nitrogen and phosphorus) deficiencies are one of the limiting factors for increasing productivity in Ethiopia and Oromia region, for which DAP and urea are widely recommended to address these deficiencies. In total, 85 enumeration areas (EAs) were randomly selected using the Central Statistical Agency of Ethiopia's Agricultural Sample Survey (AgSS) as a sampling frame. Within each EA, 12 households were randomly selected from the AgSS household listing completed in September 2013.[6] The field data collection was then conducted in multiple waves, which covered post-planting activities (September to December 2013) and post-harvest activities (January to March 2014).[7]

Prior to the collection of physical soil samples, a series of subjective plot-level questions were administered to the best-informed household member or plot-manager for each plot. These questions ranged from categorically coded responses on soil quality of plots to questions on soil color, texture, and type. It is worth noting that the subjective questions were administered at the dwelling, not upon direct respondent observation of the soils, as the study aimed at assessing farmers' knowledge of soil properties. Our analysis integrates these self-reported information with objectively measured plot-level soil nutrient information to understand how farmers respond (in terms of fertilizer applications) to various actual soil nutrient availabilities in these study areas.

[5] We note that smallholder agriculture in Ethiopia, including our study area, is predominantly rainfed. Agricultural production is thus limited to the main rainy season known as *Meher* ranges between June to September and a second rainy season covering some areas known as *Belg* spans from February to May. With limited access to water and irrigation structures, the rest of the year remains mostly dry in most part of Ethiopia, with no possibility to grow crops.
[6] Additional details about the sampling design are available at Gourlay et al. (2017).
[7] These household- and plot-level questionnaires were administered using computer-assisted personal (face-to-face) interviews.

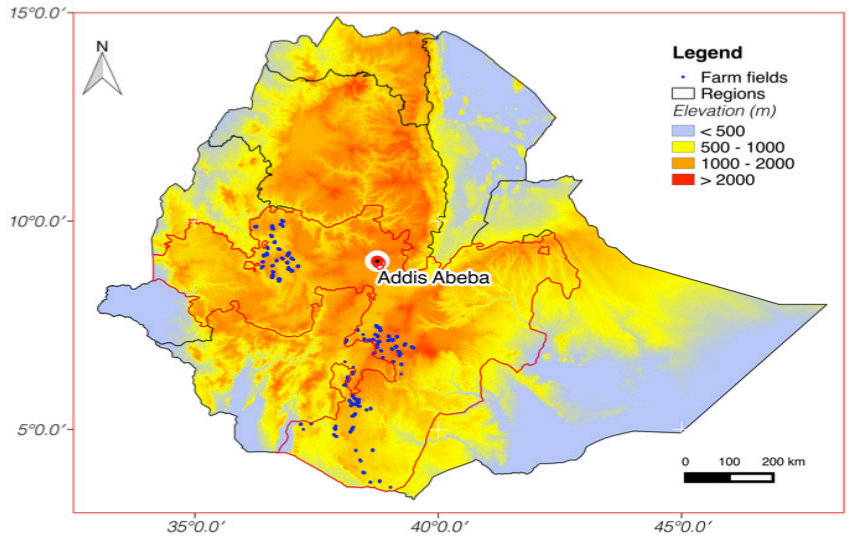

Figure 1*. Location of the study area: markers indicate fields where soil samples are collected from households in Borena, East Wellega, and West Arsi zones of the Oromia region, Ethiopia.*

3.2 Soil data collection and analyses

The collection of soil samples was made considering the nature of crops planted in soils, seasons and the timing since last fertilizer applications. The timing of soil sampling can influence the nature of some transient soil properties while stable soil properties are less likely to be affected by the time of sample collection. For these reasons, the soil samples for the LASER project were collected during dry season, September to December 2013, depending on the nature of crops. Some crops, such as *teff*, can be damaged during soil sampling and hence this requires waiting until these crops are harvested. Allowing for some time lag between planting and soil sampling reduces the effects of recent fertilizer applications on some transient soil properties (e.g., nitrogen contents in soils).

Soil samples were collected from up to two randomly selected plots per household. The in-field sampling protocol was designed by ICRAF, adapting the Land Degradation Surveillance Framework of the African Soil Information Service (Shepherd et al., 2015). Two soil samples (topsoil and subsoil) from each selected plot were collected for laboratory test.[8] Composite soil samples were collected from topsoil (0-20 cm depth) and subsoil (20-50 cm depth (Aynekulu et

[8] A thorough explanation of the soil collection, processing, and analysis protocols followed in the LASER study are found in Aynekulu et al. (2016).

al., 2016; Gourlay et al., 2017). Thereafter, the samples were air dried and sieved for laboratory analysis of soil properties, which were conducted at ICRAF laboratories. The LASER study produced objective soil property measures using spectral soil analysis technique on the soil samples taken from topsoil and subsoil.[9] The suite of spectral analyses includes the following tests: mid-infrared diffuse reflectance spectroscopy (MIR), laser diffraction particle size distribution analysis (LDPSA), x-ray methods for soil mineralogy (XRD), and total element analysis (TXRF).[10] Ultimately, approximately 50 variables were predicted for each top and subsoil sample, containing both chemical and physical soil properties (Aynekulu et al., 2016; Gourlay et al., 2017). The LASER dataset is the first large scale data of its kind that include pertinent household- and plot-level information along with subjective and objective information on soil quality and health.

Overall, the LASER survey resulted in an unprecedented dataset encompassing a series of subjective indicators of soil quality obtained from the farmers' assessment, as well as objective spectral soil analysis results on about 1677 plot-specific soil samples from 1,007 households. The main variables of interest from the spectral soil analysis include information on macronutrient (nitrogen and phosphorus) availability in soils and soil acidity (pH levels). As topsoil properties are likely to be better known (perceived) by farmers than subsoil soil properties, we mainly focus on topsoil properties (Gourlay et al., 2017). DAP and urea are the two dominant chemical fertilizers that are meant to address macronutrient deficiencies in Ethiopia. DAP fertilizers are mostly meant to supplement phosphate deficiencies while urea fertilizers mainly contain nitrogen. DAP contains 18% nitrogen and 46% phosphate while urea contains 46% nitrogen. We convert farmers' fertilizer applications into nitrogen and phosphorus equivalent per hectare using these ingredient compositions. Table 1 presents descriptive statistics of all the variables used in our estimation and analysis. Average yield in our sample amounts 1448 kilograms per hectare.[11] Average fertilizer application rates are generally low, 7 kg/ha of nitrogen fertilizers and 9 kg/ha of phosphorus

[9] Conventional soil analysis (CSA), which includes traditional wet chemistry methods for soil nutrient extraction and some basic soil spectral analyses, were conducted on 10% of samples (n = 361). Conventional analysis, while often regarded as the gold standard in soil analysis, is expensive and destructive in nature. Spectral soil analysis (SSA), or soil infrared spectroscopy, the second set of tests conducted under the LASER study, is significantly less expensive and non-destructive, allowing for multiple tests over time (Shepherd and Walsh, 2007).

[10] MIR and LDPSA spectral tests were conducted on all top- and sub-soil samples, while the x-ray tests, XRD and TXRF, were conducted on the same 10% on which conventional testing was executed. Following the methods designed by Shepherd and Markus (2002) the results of the CSA were used to predict soil properties onto the full sample based on the spectral signatures.

[11] As expected, the average yield for cereal crops appears to be slightly higher.

fertilizers. We note these are the two dominant fertilizer types (sources of macro nutrients) in Ethiopia and in our sample.

In relation to the soil properties, the mean nitrogen content was 0.27 percent, and the mean phosphorus availability was 402 mg/kg. Macronutrients such as nitrogen and phosphorus are critical for plant development, and a higher quantity is usually needed, despite significant variations across crops. Compared to some existing nutrient sufficiency ranges, the average nitrogen nutrient availability in Table 1 is expected to be low, especially for cereal crops such as maize that require higher level of nitrogen nutrients (e.g., Naidu et al., 2006; Schulte and Kelling, 2017).[12] Based on these nutrient availability indicators we generate some indicators of relative soil nutrient (nitrogen and phosphorus) deficiencies. We generate indicators of relative nutrient deficiency (requirement) by comparing maximum nutrient content in our sample and plot-specific nutrient of soils. For instance, relative nitrogen deficiency is computed as the difference between the maximum value of nitrogen content in our sample and plot-specific nitrogen availability. About 15 percent of the plots had acidic soils, while the majority 83 percent had neutral soil properties. Based on the self-reported soil quality information, 44 percent of the plots are reported to have good soil quality, 51 percent fair soil quality, and only 1 percent poor soil quality. These self-reported indicators are only weakly correlated with soil organic carbon (SOC) content, the most common objective measure of soil quality (Gourlay et al., 2017).

We note that some of the soil properties described above are strongly correlated among each other (see Table A1 in the Appendix; see also Gourlay et al., 2017). For instance, soil organic carbon content in soils is strongly correlated with nitrogen content (with a pairwise correlation of 0.95). This implies that we cannot control both in our regressions because of multicollinearity problems. Similarly, nitrogen and phosphorus availability in soils are significantly correlated. On the other hand, objective measures of soil quality (e.g., SOC content) are not strongly correlated with self-reported indicators of soil fertility. For instance, the pairwise correlation between self-reported indicator for "good" soils and SOC is very small and statistically insignificant (Table A1).

[12] Naidu et al. (2006) classify soils with nitrogen nutrient availability of 0.1-0.3 percent as "marginally suitable" for maize production, while those above 0.5 percent are classified as "highly suitable".

Table 1: Sample Descriptive Statistics

Variable	No. observations	Mean	Std. Dev.
Dependent variables			
Yield (output per hectare, kg)	2,142	1446.43	3908.67
Yield of cereal crops	879	1612.72	2864.15
Nitrogen/ha application (kg)	2,142	7.21	23.40
Phosphorus/ ha application (kg)	2,142	8.98	27.44
Fertilizer applied (0/1)	2,142	0.37	0.48
Improved seed applied (0/1)	2,140	0.14	0.34
Explanatory variables			
Objective soil indicators			
Nitrogen content (%)-topsoil	2,142	0.27	0.11
Phosphorus content (mg/kg)-topsoil	1,996	403.47	322.10
Soil organic carbon content (%)-topsoil	2,142	3.17	1.15
Relative nitrogen deficiency- topsoil	2,142	0.69	0.11
Relative phosphorus deficiency- topsoil	1,996	1731.52	322.10
Acidic (soil pH<5.5)- topsoil	2,142	0.15	0.36
Neutral (5.5<=soil pH<=8)- topsoil	2,142	0.83	0.37
Alkaline (soil pH>8)- topsoil	2,142	0.02	0.14
Subjective soil indicators			
Self-reported soil quality: good (0/1)	2,141	0.44	0.50
Self-reported soil quality: fair (0/1)	2,141	0.51	0.50
Self-reported soil quality: poor (0/1)	2,141	0.05	0.22
Self-reported soil color: black (0/1)	2,141	0.37	0.48
Self-reported soil color: red (0/1)	2,141	0.46	0.50
Self-reported soil color: white/light (0/1)	2,141	0.16	0.36
Self-reported soil color: yellow (0/1)	2,141	0.01	0.10
Household and plot characteristics			
Gender of household head (0/1)	2,142	0.82	0.38
Age of household head (years)	2,142	43.54	15.52
Household head literate (0/1)	2,142	0.40	0.49
Household size (number)	2,142	5.79	2.28
Value of assets (ETB)[13]	2,142	2376.03	5318.05
Plot is owned by household (0/1)	2,142	0.76	0.43
Distance from home (km)	2,142	0.75	2.87
Plot size (hectare)	2,142	0.27	0.29
Plot's slope is flat (0/1)	2,142	0.49	0.50
Plot is intensively cultivated (for the last 10 years)	2,142	0.46	0.50
Plot left fallow last season (0/1)	2,142	0.07	0.25

Source: Authors' calculation based on LASER data. We note that our unit of analysis is at plot-crop-level because some input management practices vary across crops planted in the same plot. Furthermore, some of the information (e.g., production) are collected for each crop in each plot.

[13] ETB stands for Ethiopian Birr. At the time of survey, 1 USD=19 ETB.

4. Empirical Estimation Strategy

To understand farmers' fertilizer use in response to soil properties and nutrient requirements, we estimate the following input demand function that quantifies the elasticity of fertilizer use to soil properties and nutrient requirements.

$$D_{hpc} = \beta_1 Soil_{hp} + \beta_2 X_{hpc} + \alpha_h + \alpha_c + \varepsilon_{hpc} \qquad (1)$$

where D_{hpc} stands for households (h) demand for specific type of fertilizer (nitrogen and phosphorus in our case) for each plot (p) and crop (c). D_{hpc} assumes both binary indicator variables for fertilizer use (DAP and urea) and continuous measures of fertilizer application per hectare. For continuous measures of fertilizer application rate, we took inverse hyperbolic sine (IHS) transformation to keep zero values. α_h stands for farmer-specific effects. $Soil_{hp}$ captures a vector of objectively measured and self-reported soil characteristics. These include objectively measured information on soil health, including macronutrients (nitrogen and phosphorus) deficiencies as well as overall soil quality indicators, including soil pH. In the interest of uncovering responses to perceived soil-qualities, this vector ($Soil_{hp}$) also includes self-reported soil-quality indicators. The vector of parameters captured by β_1 quantifies farmers' response to soil properties and requirements. These coefficients can be interpreted as fertilizer demand responses with respect to a marginal change in soil property or soil nutrient requirement. For instance, we quantify fertilizer demand elasticities associated with a unit reduction in soil nutrients (nitrogen or phosphorus).[14] X_{hpc} captures household, plot and crop-level characteristics that may affect demand for chemical fertilizers. α_c stands for crop fixed effects, which can capture differences in fertilizer and associated nutrient requirements as well as associated responses by farmers. ε_{hpc} absorbs other unobserved factors that may generate variations in demand for fertilizers.

One practical limitation in implementing the empirical specification in equation (1) relates to: (i) lack of variation in some soil properties across plots managed by the same farmer, and (ii) the fact that substantial share of the farmers in our sample have a single plot. We have a total of 1007 unique households in our data and 1677 unique plots, implying that a good number of households have single plots. These imply that potential impacts based on fixed effect specifications are likely to come from a small share of our sample. Because of these two

[14] We note that IHS transformation of small values (e.g., fertilizer use rates) require further adjustments to be interpreted as elasticities (Bellemare and Wichman, 2020), an adjustment we apply when interpreting coefficients.

limitations, we employ the Mundlak-Chamberlain correlated random effect (CRE) approach (Mundlak, 1978; Chamberlain, 1984) instead of the traditional fixed effects model. Following this approach, one can decompose α_h into mean value of plot-varying characteristics ($\bar{X}_{hp}$) and the usual random effect (ϵ_{hpc}) uncorrelated with the explanatory variables as follows: $\alpha_h = \bar{X}_{hpc} + \epsilon_{hpc}$. We thus implement correlated random effect model by controlling for average plot-varying components of the model to capture unobserved plot-invariant heterogeneity, under the assumption that such heterogeneity is correlated with farmer-specific effects (see, Wooldridge, 2010).

The vector of parameters of interest captured by β_1 in equation (1), could also be biased because of reverse causality as soil properties, including macronutrient content in soils, can be affected by recent fertilizer applications. Recent nitrogen and phosphorus applications are likely to accumulate in soils, which may generate positive correlation between soil properties and fertilizer applications, and hence an upward bias in the vector of parameters (β_1) in equation (1). For instance, phosphorous applications are likely to carry over to the next season as plant growth and crops generally use only a portion of applied phosphorous in the first year of application. Similarly, fertilizer applications may also facilitate soil acidification. For these reasons, we are cautious in interpreting our results and refrain from claiming clean causality. That said, we believe some of these biases may be captured by the average plot-varying characteristics we control for, especially if farmers' fertilizer applications and farm management practices are similar across plots. Furthermore, we also control for farming practices and plot-use in the last season, including whether the plot has been left fallow and whether the plot has been consecutively under cultivation for the last ten years. Any left-over reverse causality effects are likely to cause biases that we can anticipate. For instance, if recent nitrogen and phosphorus applications are driving macronutrient content in soils, we expect positive correlations between macronutrient content and fertilizer applications. On the other hand, if farmers respond to macronutrient requirements appropriately, we expect negative association between soil nutrient availability and fertilizer applications.

We estimate the following empirical specification to assess the implications of fertilizer use and the role of soil properties to yield responses:

$$y_{hpc} = \alpha_1 Soil\_def_{hp} + \alpha_2 D_{hpc} + \alpha_3 Soil\_def_{hp} * D_{hpc} + \alpha_4 X_{hpc} + \alpha_c + \varepsilon_{hp} \qquad (2)$$

where y_{hpc} now stands for yield (output per hectare) and all remaining terms except the interaction terms are as described in equation (1). $Soil\_def_{hp}$ stands for a vector of soli properties, including relative macronutrient deficiencies and soil acidity. The interaction terms between soil macronutrient deficiencies and fertilizer application are the new terms and main variables of interest in equation (2). The vector of parameters captured by α_3 quantifies the role of soil properties, including macronutrient deficiencies (or requirements) and soil acidity, in mediating the marginal impacts of fertilizers. These are important parameters that can inform us about the implication of mismatch or matching between soil nutrient requirements and farmers' fertilizer applications. For instance, these parameters can detect potential yield gains (losses) associated with applying nitrogen or phosphorus fertilizers on soils that are deficient (abundant) of these macronutrients. Similarly, these parameters can help to quantify potential yield gains (losses) when chemical fertilizers are applied on acidic or alkaline soils. Overall, the parameters captured in α_2 and α_3 can inform us whether farmers' chemical fertilizer applications are productivity-enhancing or not. Following the Mundlak-Chamberlain approach and to capture plot-invariant farmer-specific unobserved heterogeneity, we control for average plot-varying characteristics and hence implement a correlated random effect model. These additional controls as well as the long list of observable characteristics and crop fixed effects help to minimize potential unobserved heterogeneity that may confound our estimations. However, even the simple associational evidence between soil nutrient requirements and fertilizer application rates as well as their implications to yield responses can explain why marginal returns to fertilizers can be low and hence inform fertilizer policies.

For simplicity, we estimate linear models. For those sufficiently continuous outcomes and soil property indicators we take inverse hyperbolic sine (IHS) transformations. For these cases, the estimates in equation (1)-(2) represent elasticities, with slight adjustments when these transformations are applied to small values (Bellemare and Wichman, 2020). Households and plots in the same community are expected to share some unobserved effects, arising from similar farm management skills. We thus cluster standard errors at village level.

5. Estimation Results and Discussion

In this section we report the main estimation results based on equation (1) and (2). Although some of the relationships we report may carry causal interpretations, we refrain from claiming clean causality throughout our discussions. However, the associational relationship between soil nutrient requirements and fertilizer applications as well as potential yield implications are useful and informative. We first present estimation results based on equation (1) in Section 5.1 and we look at the potential implications of farmers' responses to soil properties and nutrient deficiencies in Section 5.2.

5.1 Soil properties and farmers' fertilizer application

As a first stage of our analysis, we examine how farmers' demand for fertilizers respond to specific soil properties, including objective and self-reported measures of soil quality and nutrient deficiencies. We emphasize that some of the objective measures of soil health and nutrient content, including macronutrient (nitrogen and phosphorus) availability and soil pH are not available to farmers. However, the LASER survey elicits farmers' perceived soil quality and soil color, which are commonly considered as indicators of soil properties. We also note that these objective and perceived indicators are expected to be correlated with other soil properties and self-reported soil quality indicators. However, as Gourlay et al. (2017) show the correlation between objective and self-reported measures of soil quality maybe weak. If so, this suggests farmers lack accurate knowledge about their soil quality and nutrient requirements. In particular, Gourlay et al. (2017) show that subsoil properties are not meaningfully correlated with farmers' assessment of soil properties and input applications. We expect that topsoil properties are relatively easier to know and characterize than subsoil properties.[15] Thus, in our estimations we focus on topsoil properties.

In Table 2 we report input demand function estimates associated with farmers' fertilizer application decisions. DAP and urea are the two dominant chemical fertilizers that are meant to address macronutrient (nitrogen and phosphorus) deficiencies in Ethiopia. Using the information on DAP and urea ingredient compositions, we convert farmers' fertilizer applications into nitrogen and phosphorus equivalent per hectare. If farmers are responding to soil nutrient deficiencies, we expect a strong inverse relationship between soil nutrient content and fertilizer applications. The specifications in the first and third columns of Table 2 characterize input demand responses as a function of objective and self-reported indicators of soil properties and crop dummies. To probe such responses further, we expand these parsimonious specifications by including additional household and plot-level characteristics in the second and fourth column of Table 2. Thus, our preferred specifications are those in column 2 and 4.

[15] Gourlay et al. (2017) show that subjective indicators of soil quality relatively better predict topsoil properties than subsoil soil health measures.

The results in Table 2 show fertilizer demand elasticities associated with soil macronutrient contents. The outcome variables in this table are inverse hyperbolic sine (IHS) transformations of nitrogen and phosphorus applied per hectare. The first two rows of Table 2 show farmers' response to soil macronutrient (nitrogen and phosphorus) availability (deficiencies). For instance, the first row shows that soil nitrogen content is not statistically correlated with nitrogen and phosphorus application rates. This suggests that farmers are not appropriately responding to soil nitrogen deficiencies. The second row in Table 2 indicate that phosphorus application rates are responsive to soil macronutrients deficiencies as shown by the statistically significant negative coefficients. For instance, one percent reduction in soil phosphorus content is associated with about 0.3 percent increase in nitrogen fertilizer applications. Thus, while phosphorus fertilizer responses are consistent with nutrient requirements nitrogen fertilizer application rates are not consistent with nutrient deficiencies (agronomic recommendations). Farmers are applying nitrogen fertilizers to soils lacking phosphorus. This may be driven by lack of knowledge on macronutrient requirements or lack of appropriate chemical fertilizers in rural markets. In the context of Ethiopia DAP fertilizer, which contains both phosphorus and nitrogen, is relatively more accessible than urea, which mainly contains nitrogen.

The next rows in Table 2 suggest that farmers respond to soil acidity, by applying higher nitrogen and phosphorus fertilizers on acidic soils and reducing fertilizer application on alkaline soils, relative to soils with normal pH (pH: 5.5-8). These responses are consistently observed for both nitrogen and phosphorus fertilizers. These interesting patterns are noteworthy as such responses may affect marginal yield response associated with fertilizer applications and hence may not be yield-enhancing (e.g., Burke et al., 2017). We note that farmers are less likely to know their soil pH. However, farmers may learn about other observable soil attributes associated with soil acidity, to which they tend to respond. Thus, these responses are probably driven by learned experiences than through objective knowledge and measure of soil acidity.

Interestingly, farmers appear to respond to subjective (perceived) indicators of soil quality, including self-reported ranking of soil quality and soil color. Farmers are likely to apply slightly higher fertilizer per unit of land on (perceived) poor and fair quality soils, relative to those soils perceived as good quality. Similarly, farmers adjust fertilizer use depending on soil colors: red and white/light colored soils receive lower amounts of fertilizers per unit of land than black colored soils. The response to soil colors is particularly strong. For instance, relative to black soils white/light colored soils receive 35-38 percent higher nitrogen and phosphorus fertilizers per hectare.[16] This is intuitive as farmers are shown to use soil colors as strong indicator of overall soil quality (Gourlay et al., 2017). As red and white/light colored soils are shown to be of poor quality and negatively correlated with objective measures of soil quality (Gourlay et al., 2017), our findings suggest that farmers are likely to apply higher amounts of chemical fertilizers on (perceivably) poor soils. This evidence is consistent with evolving pieces of evidence showing that farmers are more likely to respond to perceived input qualities than objectively measured attributes, which are not readily available to farmers (Abay et al., 2021; Wossen et al., 2021). For instance, Abay et al. (2021) show that farmers' input applications respond to self-reported plot size than to objectively measured plot size. Similarly, Wossen et al. (2021) find that input application rates respond more to perceived crop variety than to DNA-fingerprinted crop varieties.

We run two additional estimations to probe the robustness of the results in Table 3. First, to assess if the transformation and conversion of variables is driving our results, we simply use binary indicators of fertilizer use as well as only intensive margin of fertilizer application. In the first four columns in Table A2, we characterize adoption of DAP and urea fertilizers as a function of soil nutrient availability and other plot-level characteristics. We know that DAP mostly contains phosphorus while urea contains nitrogen nutrients. Thus, if farmers are responding to soil nutrient requirements strongly, we expect statistically significant and strong negative association between phosphorus availability in soils and DAP application as well as between nitrogen availability in soils and urea application. The last two columns in Table A2 estimate similar input demand functions focusing on the intensive margin of fertilizer application. The results in Table A2 show statistically insignificant associations between urea application and nitrogen availability, and significant associations between DAP application and phosphorus availability in soils. Second, we restrict the sample to cereal crops (e.g., maize, wheat, teff, barley, sorghum), which usually receive higher rate of fertilizer applications. The results based on this restricted sample show similar evidence (see Table A3).

[16] This is computed using $\exp(\beta) - 1$.

Table 2: Farmers' response to soil nutrient requirement

Explanatory variables	(1) IHS(nitrogen/ ha)	(2) IHS(nitro gen/ha)	(3) IHS(phosp horus/ ha)	(4) IHS(phosphorus/ ha)
Log (Nitrogen content (%) topsoil)	0.510	0.080	0.959	0.554
	(0.899)	(0.865)	(0.884)	(0.834)
Log (Phosphorus content (mg/kg) topsoil)	-0.292***	-0.272***	-0.335***	-0.316***
	(0.074)	(0.070)	(0.074)	(0.071)
Acidic topsoil (soil pH<5.5)	0.460**	0.439**	0.424**	0.394*
	(0.202)	(0.197)	(0.216)	(0.220)
Alkaline topsoil (soil pH>8)	-0.891***	-0.662**	-0.819***	-0.621*
	(0.317)	(0.323)	(0.311)	(0.336)
Self-reported soil quality: fair	0.104	0.108	0.145	0.144
	(0.131)	(0.138)	(0.132)	(0.137)
Self-reported soil quality: poor	0.403	0.405	0.573*	0.565*
	(0.272)	(0.279)	(0.309)	(0.305)
Self-reported soil color: red	-0.257	-0.174	-0.327*	-0.237
	(0.172)	(0.164)	(0.180)	(0.166)
Self-reported soil color: white/light	-0.543***	-0.420**	-0.600***	-0.473**
	(0.180)	(0.175)	(0.201)	(0.192)
Self-reported soil color: yellow	-0.120	-0.261	-0.213	-0.347
	(0.390)	(0.413)	(0.370)	(0.431)
Gender of household head male		-0.136		-0.175
		(0.186)		(0.188)
Age of household head		-0.006*		-0.006
		(0.004)		(0.004)
Household head literate		0.293*		0.304**
		(0.150)		(0.152)
Household size		-0.046		-0.043
		(0.028)		(0.028)
Log (value of assets)		0.238***		0.247***
		(0.067)		(0.065)
Plot is owned by household		0.454		0.648
		(0.483)		(0.459)
Distance from home (km)		-0.021		-0.021
		(0.045)		(0.041)
Log (plot size)		0.289***		0.244***
		(0.082)		(0.087)
Slope of plot is flat		-0.323		-0.361
		(0.209)		(0.233)
Plot is intensively cultivated (in the last 10 years)		-0.142		-0.228
		(0.205)		(0.239)
Plot left fallow last season		-0.613		-0.455
		(0.385)		(0.392)
Crop fixed effects	Yes	Yes	Yes	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	1978	1958	1978	1958

Source: Authors' calculation based on LASER data.
Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Soil nutrient requirement, farmers’ fertilizer application and yield response

In this section, we explore the implications of farmers’ response to soil nutrient requirement in terms of fertilizer application on yield responses. Table 3 presents results based on estimation of equation (2) using correlated random effects. The columns provide yield responses to different types of fertilizers, mainly nitrogen and phosphorous fertilizers, as well as their interactions with soil nutrient deficiencies. The main parameters of interest are therefore those estimates associated with the interaction terms between soil nutrient deficiency (or requirement) and application of fertilizers in the third and sixth rows of Table 3. These estimates inform us whether and to what extent mismatch between soil nutrient requirements and their actual applications can result in potential yield losses.

The results in column (1) and (2) indicate that generally nitrogen fertilizer applications significantly increase yield. For instance, the first column shows that a 1 percent increase in nitrogen fertilizer application is associated with about 0.1 percent yield increase. However, the marginal yield response is much higher when applied on nitrogen deficient soils. The interaction term between nitrogen fertilizer application and soil nitrogen deficiency is large and statistically significant. The results in column (3) and (4) provide results associated with yield responses associated with phosphorus applications. The fourth column shows more interesting results: phosphorus applications are yield-enhancing when applied on phosphorus deficient soils but can be yield-reducing when applied on phosphorus abundant or other soils. While the interaction term between phosphorus fertilizer application and soil phosphorus deficiency appears to be positive and statistically significant the main effect associated with phosphorus fertilizer application is negative. In other words, these results suggest that use of nitrogen and phosphorous are yield-increasing when applied to their respective nutrient deficient soils than otherwise. We run additional robustness exercises focusing on cereal crops, which usually receive higher application of chemical fertilizers in Ethiopia. These results show similar evidence (see Table A4 in the Appendix)

To facilitate interpretation, we compute marginal yield responses (elasticities) associated with chemical fertilizer application on soils with varying nitrogen and phosphorus deficiency. The marginal plots in Figure 1 show yield responses (elasticities) associated with nitrogen and phosphorus applications. The first graph shows that elasticities associated with nitrogen fertilizer applications increase with nitrogen deficiency in soils. Nitrogen applications on relatively nitrogen abundant soils does not generate statistically significant yield response. The second graph in Figure 1 shows that marginal yield responses associated with phosphorus application increases with soil phosphorus requirement. Indeed, elasticities associated phosphorus applications are negative and statistically insignificant for those farmers applying phosphorus fertilizers on phosphorus abundant soils. This implies that yield responses are positive and increasing with appropriate fertilizer applications on nutrient deficient soils. On the other hand, these results suggest that those farmers applying inappropriate chemical fertilizers are incurring substantial costs with little or no yield gains.

These results are not surprising given that farmers have almost no access to soil tests and hence information on soil nutrient requirement. Furthermore, substantial soil heterogeneity across farms and villages can impede learning and nutrient use efficiencies (Tittonell et al., 2008; Otsuka and Larson, 2013; Tjernstrom, 2017). Furthermore, farmers have varying cropping plans and crop choices, that existing recommendations and information may not be relevant to farmer specific context. These contexts and conditions can render the usual blanket recommendations by governments and extension services ineffective (Tittonell et al., 2008; Kihara et al., 2016; Harou et al., 2018; Gourlay et al., 2017; Ayalew et al., 2020). Ensuring efficient use of fertilizers as in the context of this study thus require site-specific and targeted use of fertilizers within heterogenous farms guided by agronomic measures to improve nutrient capture and utilization (Tittonell et al., 2008; Tjernstrom et al., 2018). However, extension services in Ethiopia mostly focus on expanding and improving adoption of improved inputs than appropriate management of these agricultural inputs (Berhane et al., 2018). Poor matching of fertilizers applications with actual soil nutrient deficiency can hamper both adoption of fertilizers (Tjernstrom et al., 2018) and reduce marginal yield responses associated with fertilizer applications. Overall, our findings suggest that sustainable increases in crop productivity in SSA require tailoring of soil fertility management practices to site-specific conditions (Kihara et al., 2016; Giller et al., 2009; Vanlauwe et al., 2015).

The significant variability in marginal yield responses associated with fertilizer applications across varying soil nutrient requirement provide an additional explanation for existing heterogenous marginal returns to chemical fertilizers. Thus, mismatch between fertilizer applications and soil nutrient requirements may explain the low and heterogeneous marginal returns associated with chemical fertilizers in SSA. For instance, our results show that nitrogen and phosphorus fertilizers do not enhance yield when applied on soils with abundant nitrogen and phosphorus. These findings may help to explain the empirical puzzle associated with low adoption of modern agricultural inputs in SSA.

In terms of improving measurement of agricultural metrics and alleviating asymmetric information in input quality, our findings suggest that improving agricultural statistics by reducing the uncertainties in soil quality assessment can improve decision-making and farm management practices. The availability of objective measures of soil properties can allow farmers experiment and share their knowledge consistently through targeted learning approaches. Accurate measures of agricultural metrics, including soil properties, can inform policy makers about the potential and marginal returns to improved agricultural inputs, which in turn, can inform conventional technology diffusion strategies.

Table 3: Yield response to soil nutrient requirement and fertilizer applications

	(1)	(2)	(3)	(4)
	Log(yield)	Log (yield)	Log(yield)	Log(yield)
IHS (Nitrogen application per ha)	0.133^{***}	0.189^{***}	0.134^{***}	0.138^{***}
	(0.045)	(0.061)	(0.048)	(0.051)
IHS (phosphorus application per ha)	-0.005	0.017	-0.011	-2.092^{**}
	(0.038)	(0.039)	(0.041)	(0.999)
Improved seed	0.030	-0.035	0.019	-0.067
	(0.090)	(0.098)	(0.093)	(0.107)
Acidic topsoil (soil pH<5.5)	-0.108	0.094	-0.207	-0.028
	(0.338)	(0.316)	(0.375)	(0.344)
Alkaline topsoil (soil pH>8)	0.079	0.292^{**}	0.113	0.354^{**}
	(0.154)	(0.135)	(0.161)	(0.147)
Log (relative nitrogen deficiency)	-0.577^{*}	-0.437		
	(0.337)	(0.280)		
Nitrogen application #relative nitrogen deficiency		0.222^{*}		
		(0.135)		
Log (relative phosphorus deficiency)			-0.211	-0.062
			(0.233)	(0.243)
Phosphorus application #relative phosphorus deficiency				0.275^{**}
				(0.131)
Gender of household head		-0.076		-0.082
		(0.122)		(0.131)
Age of household head		-0.001		-0.001
		(0.003)		(0.003)
Household head literate		-0.022		-0.038
		(0.096)		(0.100)
Household size		0.019		0.018
		(0.018)		(0.019)
Log (value of assets)		0.186^{***}		0.197^{***}
		(0.037)		(0.037)
Plot is owned by household		-0.199		-0.130
		(0.224)		(0.220)
Distance from home		0.007		0.021
		(0.015)		(0.029)
Log (plot size)		-0.528^{***}		-0.535^{***}
		(0.075)		(0.078)
Slope of plot is flat		-0.029		-0.029
		(0.150)		(0.148)
Plot is intensively cultivated		0.183		0.165
		(0.218)		(0.226)
Plot left fallow last season		-0.098		-0.118
		(0.313)		(0.285)
Crop fixed effects	Yes	Yes	Yes	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	1821	1807	1688	1674

Source: Authors' calculation based on LASER data.

Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. Standard errors, clustered at village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

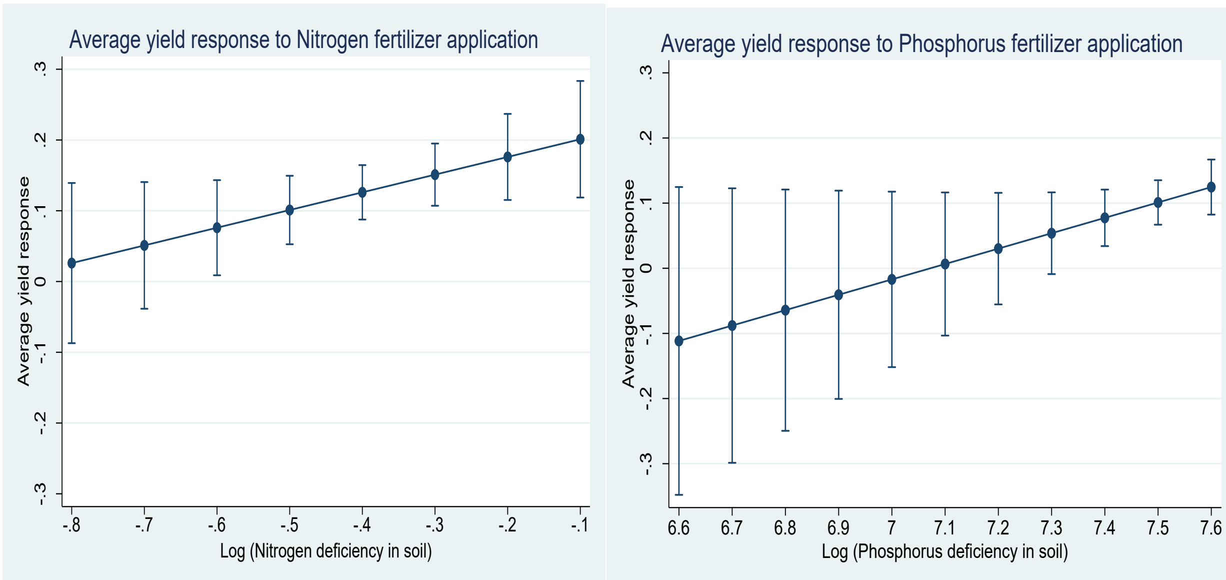

Figure 1. Average yield response to fertilizer applications on nitrogen and phosphorous deficient soils

5.3 Soil Acidity, farmers' fertilizer application and yield response

Other properties such as soil pH are also important determinants of yield and associated fertilizer responses. This section presents results associated with yield responses associated with fertilizer applications across plots with varying soil pH. Estimation results are based on equation (2) and estimated using the correlated random effects model discussed earlier. Table 4 reports the key estimation results for yield response to fertilizer application under acidic and alkaline soil conditions. The first two columns report yield responses (elasticities) for nitrogen application on both acidic and alkaline soils and the last two columns report corresponding results for phosphorous applications.

The key finding from Table 4 is that application of both nitrogen and phosphorous fertilizers on acidic soils reduces yield gains whereas application of the same nutrients on alkaline soils results in additional yield gains. This is reflected by the strongly significant and negative coefficients associated with the interaction terms between fertilizer applications and indicator variables for soil acidity. Clearly, use of fertilizers is yield increasing when applied on plots with high soil pH. Restricting the sample to cereal crops yields similar results (Table A5). Figure 2 shows that average yield response to fertilizer application linearly increases with increases in soil pH levels. This holds for both types of fertilizers, nitrogen and phosphorus. These results are consistent with findings from previous studies (e.g., Kihara et al. 2016; Burke et al., 2017).

Despite these striking results, we know from Table 2 that on average farmers apply more fertilizers on acidic soils than on alkaline soils – losing additional yield gains because of reduced fertilizer applications on alkaline soils and at the same time losing yield by wrongly applying them on acidic soils. We suspect that farmers are applying fertilizers on acidic soils thinking that this way they can fix soil health problems caused by acidity itself. Clearly, in the absence of well-established plot level soil information, fertilizer application can not only lead to lower yield gains but also result in yield losses. This may also lead to the unintended consequences that farmers totally abandoning fertilizer adoption after experiencing yield losses due to inappropriate use of it. This may be one explanation behind the low adoption of fertilizers in SSA in the face of increased fertilizer supplies in recent years and the yield gaps observed in many contexts.

Table 4: Yield response to soil nutrient requirement, soil acidity and fertilizer applications

	(1) Log (yield)	(2) Log (yield)	(3) Log (yield)	(4) Log (yield)
IHS(Nitrogen application)	0.162***	0.141***	0.128***	0.113**
	(0.041)	(0.043)	(0.046)	(0.047)
IHS(Phosphorus application)	-0.006	0.007	0.021	0.029
	(0.033)	(0.035)	(0.039)	(0.041)
Improved seed	0.065	0.295**	0.072	0.302**
	(0.148)	(0.134)	(0.149)	(0.135)
Acidic topsoil (soil pH<5.5)	0.253**	0.137	0.214*	0.105
	(0.123)	(0.137)	(0.122)	(0.135)
Alkaline topsoil (soil pH>8)	-0.214	0.052	-0.214	0.054
	(0.361)	(0.338)	(0.362)	(0.338)
IHS(nitrogen application) # Acidic topsoil (soil pH<5.5)	-0.120***	-0.096***		
	(0.033)	(0.037)		
IHS(nitrogen application) # Alkaline topsoil (soil pH>8)	0.139*	-0.034		
	(0.079)	(0.081)		
IHS(Phosphorus application) # Acidic topsoil (soil pH<5.5)			-0.097***	-0.077**
			(0.030)	(0.035)
IHS(Phosphorus application) # Alkaline topsoil (soil pH>8)			0.116*	-0.030
			(0.067)	(0.068)
Crop fixed effects	Yes	Yes	Yes	Yes
Household and plot-level characteristics	No	Yes	No	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	1822	1808	1822	1808

Source: Authors' calculation based on LASER data.
Notes: IHS stands for inverse hyperbolic sine transformation of input values. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

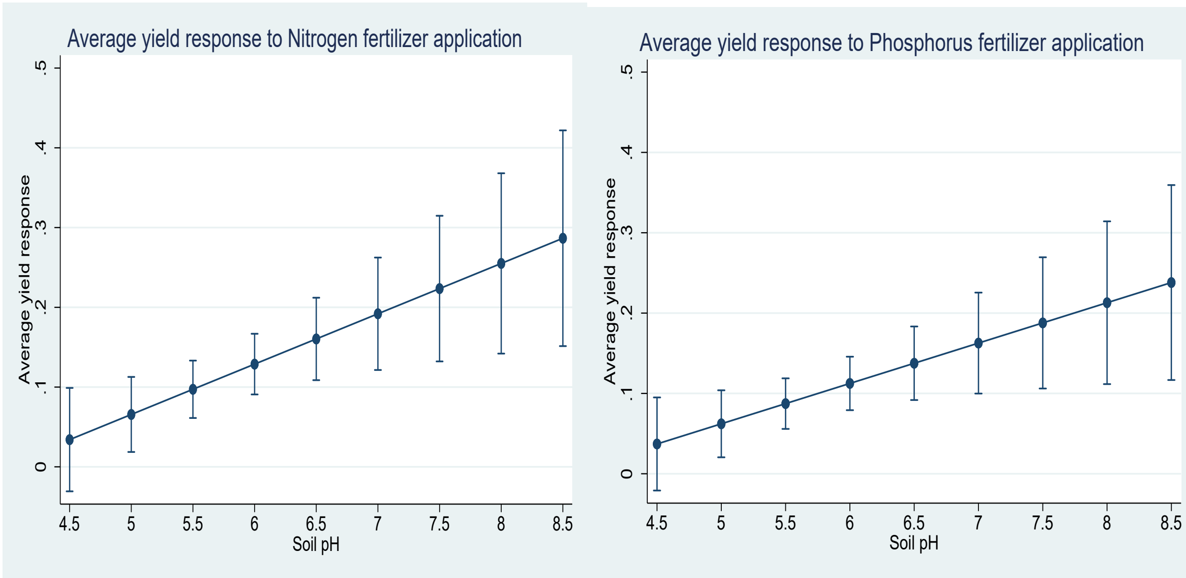

Figure 2. Average yield response to fertilizer application across plots with varying soil pH.

6. Concluding Remarks

In this paper we first examine farmers' fertilizer application responses to soil nutrient deficiencies (requirements) based on their objective measures and subjective perceptions of soil quality. We also explore associated yield responses to fertilizer applications given actual soil nutrient requirements. We hypothesize that lack of access to objectively measured soil nutrient requirements and appropriate fertilizer recommendations may lead to mismatch between fertilizer applications and nutrient requirements. Such mismatch between soil nutrient requirements and fertilizer applications could lower yield responses. We argue that such mismatch between soil nutrient requirements and fertilizer applications can explain the low and heterogenous returns to chemical fertilizers use in SSA. To test these hypotheses, we use experimental (spectral soil analysis) data that provide both objective measures of soil properties, including macronutrient deficiencies, and self-reported indicators of soil properties. These data come from a methodological experiment involving spectral soil analysis of relatively large-scale plot-level soil samples in Ethiopia.

We find that farmers do not appropriately respond to soil macronutrient (nitrogen and phosphorus) deficiencies. For instance, we find that farmers are not responding to soil nitrogen deficiencies. Similarly, although input demand functions respond to phosphorus deficiencies, farmers respond to phosphorus deficiencies by applying nitrogen fertilizers. On the other hand, farmers respond to perceived poor-quality soils and acidic soils by applying higher nitrogen and phosphorus fertilizers. We further show that such mismatches between fertilizer applications and soil macronutrient requirements are potentially yield-reducing. Those farmers mismatching their fertilizer application and actual soil nutrient requirements are likely to forgo additional yield gains. Marginal yield responses associated with nitrogen (phosphorus) application increases with soil nitrogen (phosphorus) deficiencies. Nitrogen (phosphorus) applications on relatively nitrogen (phosphorus) abundant soils does not generate statistically significant yield response. This implies that yield responses are positive and increasing with appropriate fertilizer applications on nutrient deficient soils. On the other hand, these pieces of evidence suggest that those farmers applying inappropriate chemical fertilizers are incurring substantial costs with little or no yield gains. Similarly, farmers' response to acidic soils is not productivity-enhancing, rather adversely affects marginal yield responses associated with inorganic fertilizers. Application of both nitrogen and phosphorous fertilizers on acidic soils reduce yield gains whereas application of the same nutrients on alkaline soils results in additional yield gains. Such disappointing experiences with fertilizer applications may encourage farmers totally abandon fertilizer adoption after experiencing yield losses due inappropriate use of it.

These results are not surprising given that farmers have almost no access to soil tests and hence information on soil nutrient requirements and soil properties. The lack of such objective measures along with significant soil heterogeneity across farms and villages can impede learning and nutrient use efficiencies. This, in turn, can lead to poor matching of fertilizers applications with actual soil nutrient deficiencies. Our findings suggest that such mismatches can create significant variability in marginal yield responses associated with fertilizer applications across varying soil nutrient requirements, which may explain potential heterogeneities in adoption rates and associated marginal returns to chemical fertilizers.

Besides explaining potential heterogeneities in adoption and marginal returns to chemical fertilizers, our findings have important implications for improving input management practices and fertilizer diffusion strategies. Our findings suggest that sustainable increases in crop productivity in SSA requires tailoring soil fertility management practices to site-specific conditions. This reinforces evolving pieces of evidence on the potential of plot-specific fertilizer and related input recommendations to improve farm management practices and yield (Kihara et al. 2016; Giller et al., 2011; Vanlauwe et al., 2015; Fishman et al., 2016; Fabregas et al., 2018; Harou et al., 2018; Tjernstrom et al., 2018; Murphy et al., 2019; Ayalew et al., 2020). Strengthening existing extension systems in Ethiopia may help address these mismatches to ensure appropriate adoption of modern agricultural inputs (e.g., Berhane et al., 2018; Ragasa and Mazunda, 2018). Further investments in R&D that can avail soil information and agronomic recommendations can minimize potential inefficiencies due to information asymmetries associated with soil information. Finally, our findings suggest that improving agricultural statistics by reducing the uncertainties in soil quality assessment can improve decision-making and farm management practices. Accurate measures of agricultural metrics, including soil characteristics, can address farmers' asymmetric information and misperceptions (Abay et al., 2021; Wossen et al., 2021). Such improvements in agricultural metrics can also inform policy makers about the potential and marginal returns to improved agricultural inputs, which in turn, can inform conventional technology diffusion strategies.

Despite our attempt to shed light on farmers' response to soil fertility as captured by both objective and subjective metrics, this study is not without limitations. First, measurement of some of our outcomes of interest (e.g., yield) may suffer from some inaccuracies, with important implications for computing marginal yield gains and responses (e.g., Abay et al., 2019). Second, our inference relies on observational data and variation and hence further studies based on randomized variations in access to soil nutrient information may provide additional insights on the inferential and behavioral implication of information asymmetry in soil nutrients.

References

Abay, K. A., Abate, G. A., Barrett, C.B., Bernard, T., 2019. Correlated Non-Classical Measurement Errors and 'Second Best' Policy Inference: The Case of The Inverse Size-Productivity Relationship in Agriculture. *Journal of Development Economics* 139, 171-184.

Abay, K.A., Berhane, G., Taffesse, A.S., Abay, K., Koru, B., 2018. Estimating Input Complementarities with Unobserved Heterogeneity: Evidence from Ethiopia. *Journal of Agricultural Economics*, 69(2): 495–517.

Abay, K.A., Bevis, L., Barrett, C. B., 2021. Measurement Error Mechanisms Matter: Agricultural Intensification with Farmer Misperceptions and Misreporting. *American Journal of Agricultural Economics*, 103(2): 498–522.

Abay, K.A., Blalock, G., Berhane, G., 2017. Locus of Control and Technology Adoption in Developing Country Agriculture: Evidence from Ethiopia. *Journal of Economic Behavior and Organization*, 143: 98-115.

Abate, G.T., Abay, K.A., Spielman, D., 2020. Fertilizer Policies and Implications for African Agriculture. In Resnick, D., Diao, X., and Tadesse, G. (Eds.). *Sustaining Africa's Agrifood System Transformation: The Role of Public Policies*. ReSAKSS 2020 Annual Trends and Outlook Report. Washington, DC, and Kigali.

Amare, M., Asfaw, S., Shiferaw, B., 2012. Welfare impacts of maize-pigeonpea intensification in Tanzania. *Agricultural Economics*, 43(1), 27–43.

Amare, M., Shiferaw, B., 2017. Nonfarm employment, agricultural intensification, and productivity change: empirical findings from Uganda. *Agricultural Economics* 48 (S1), 59–72.

Ayalew, H., Chamberlin, J., Newman, C., 2020. Site-Specific Agronomic Information and Technology Adoption: A Field Experiment from Ethiopia. TEP Working Paper No. 0620, Trinity College Dublin, The University of Dublin.

Aynekulu, E., Carletto, C., Gourlay, S., Shepherd, K., 2016. Soil Sampling in Household Surveys: Experience from Ethiopia. The World Bank, Washington, D.C., and World Agroforestry Centre, Nairobi.

Barrett, C.B., Reardon T., Swinnen, J., Zilberman D., 2021. Agri-food Value Chain Revolutions in Low- and Middle-Income Countries. Forthcoming, *Journal of Economic Literature*.

Bellemare, M. F., Wichman, C. J., 2020. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1), 50-61.

Benson, T., Amare, M., and Ogunniyi, A. 2020. The relative commercial orientation of smallholder farmers in Nigeria: Household and crop value-chain analyses. NSSP Working Paper 66. Washington, DC: International Food Policy Research Institute (IFPRI).

Berazneva, J., McBride, L., Sheahan, M., Guerena, D., 2018. Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers. *World Development*, 105: 367-382.

Berhane, G., Ragasa, C., Abate, G.T., Assefa, T., 2018. The state of agricultural extension services in Ethiopia and their contribution to agricultural productivity. ESSP-IFPRI Working Paper 118.

Binswanger-Mkhize, H.P., Savastano, S., 2017. Agricultural intensification: The status in six African countries. *Food Policy,* 67: 26–40.

Blanchet, G., Gavazov, K., Bragazza, L. Sinaj, S., 2016. Responses of soil properties and crop yields to different inorganic and organic amendments in a Swiss conventional farming system. *Agriculture, Ecosystems and Environment*, 230: 116–126.

Burke, W.J., Jayne, T., Black, J.R., 2017. Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics*, 48: 115–126.

Chamberlain, G., 1984. Panel Data. In Handbook of Econometrics, Volume 2, ed. Z., Grilliches, and M.D. Intriligator, 1248–318. Amsterdam: North-Holland Press.

Christiaensen, L., Demery, L., 2017. Agriculture in Africa – Telling myths from facts: A synthesis. *Food Policy,* 67: 1–11.

Collier, P., Dercon, S., 2014. African Agriculture in 50Years: Smallholders in a Rapidly Changing World? *World Development,* 63(C): 92-101.

Conley, T.G., Udry, C., 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100 (1): 35–69.

Davis, K., Swanson, B., Amudavi, D., Mekonnen, D.A., Flohrs, A., Riese, J., Lamb, C., Zerfu, E., 2010. In-depth assessment of the public agricultural extension system of Ethiopia and recommendations for improvement. IFPRI Discussion Paper, 1041.

Duflo, E., Kremer, M., Robinson, J., 2008. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *American Economic Review*, 98: 482–488.

Duflo, E., Kremer, M., Robinson, J., 2011. Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review*, Vol. 101(6), 2350–90.

Evenson, R.E., Gollin, D., 2003. Assessing the impact of the Green Revolution, 1960 to 2000. Science 300, 758–762.

Fabregas, R., Kremer, M., Lowes, M., On, R., Zaney, G., 2019. SMS-extension and Farmer Behavior: Lessons from Six RCTs in East Africa. Working paper.

Fishman, R., Kishore, A., Rothler, Y., Ward, P.S., Jha, S., Singh, R.K.P., 2016. Can Information Help Reduce Imbalanced Application of Fertilizers in India? Experimental Evidence from Bihar. Working Paper, IFPRI.

Giller, K., Witter, E. Corbeels, M., Tittonell, P.A., 2009. Conservation Agriculture and Smallholder Farming in Africa: The Heretics' View. *Field Crops Research*, 114: 23-34.

Giné, X., Yang, D., 2009. Insurance, credit, and technology adoption: Field experimental evidence from Malawi. *Journal of Development Economics*, 89(1): 1-11.

Gollin, D., Lagakos, D., Waugh, M.E., 2014. The agricultural productivity gap. *Quarterly Journal of Economics, 129(2): 939–993.*

Gourlay, S., Aynekulu, E., Shepherd, K., Carletto, C., 2017. Collecting the Dirt on Soils: Advancements in Plot-Level Soil Testing and Implications for Agricultural Statistics. Policy Research Working Paper 8057, World Bank, Washington, DC.

Harou, A., 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 Economies*, 26(3), 342–371.

Harou, A.P., Madajewicz, M. Magomba, C., Michelson, H., Tschirhart, K., Amuri, N., and Palme, C., 2018. Can information improve investment? Effects of site-specific soil recommendations on fertilizer demand. Working paper.

Jayne, S. T., Mason, N. M., Burke, W. J., Ariga, J., 2018. Review: Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy,* 75: 1-14.

Johnson, M., Hazell, P., Gulati, A., 2003. The role of intermediate factor markets in Asia's Green Revolution: lessons for Africa? *American Journal of Agricultural Economics* 85 (5), 1211–1216.

Kihara J., Huising J., Nziguheba G., Waswa B.S., Njorogeg S., Kabambe V., Iwuafor E., Kibunja C., Esilaba A.O., Coulibaly A., 2016. Maize response to macronutrients and potential for profitability in sub-Saharan Africa. *Nutrient Cycling in Agroecosystem* 105**,** 171–181.

Kurdi, S., Mai, M., Abay, K., Breisinger, C., 2020. Too much of a good thing? Evidence that fertilizer subsidies lead to overapplication in Egypt. IFPRI-MENA RP working paper 27.

Liverpool-Tasie, L.S. 2017. Is fertilizer use inconsistent with expected profit maximization in sub-Saharan Africa? Evidence from Nigeria. *Journal of Agricultural Economics,* 68(1): 22–44.

Liverpool-Tasie, L.S., 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: 41–51.

Liverpool-Tasie, L.S.O., Adjognon, S., Kuku-Shittu, O., 2015. Productivity effects of sustainable intensification: the case of Urea deep placement for rice production in Niger State, Nigeria. *Afr. J. Agric. Resour. Econ.* 10 (1): 51–63.

Lützow, M., Kögel-Knabner, I., Ekschmitt, K., Matzner, E., Guggenberger, G., Marschner, B., Flessa, H., 2006. Stabilization of Organic Matter in Temperate Soils: Mechanisms and Their Relevance under Different Soil Conditions – a Review. *European Journal of Soil Science,* 57: 426 - 445.

Marenya, P.P., Barrett, C.B., 2009. State-Conditional Fertilizer Yield Response on Western Kenyan Farms. *American Journal of Agricultural Economics*, 91(4): 991–1006.

Minot, N. W., Benson, T. D., 2009. Fertilizer Subsidies in Africa: Are Vouchers the Answer? Issue briefs No. 60 (International Food Policy Research Institute: Washington, DC, 2009.

Minten, B., Koru, B., Stifel, D., 2013. The last mile(s) in modern input distribution: Pricing, profitability, and adoption. *Agricultural Economics* 44(6), 629–646.

Moser, C.M., Barrett, C.B., 2006. The complex dynamics of smallholder technology adoption: the case of SRI in Madagascar. *Agricultural Economics* 35(3), 373–388.

Mundlak, Y., 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica* 46 (1): 69–85.

Murphy, D.M., Roobroeck, D.,Lee, D.R., Thies, J., 2019. Underground Knowledge: Estimating the Impacts of Soil Information Transfers through Experimental Auctions. *American Journal of Agricultural Economics.* 102(5): 1468-1493.

Naidu, L. G. K., Ramamurthy, V., Challa, O., Hegde, R., Krishnan, P., 2006. Manual Soil-Site Suitability Criteria for Major Crops. National Bureau of oil Survey and Land Use Planning. Publication Number 129.

Otsuka, K., Larson, D. 2013. An African green revolution: Finding ways to boost productivity on small farms. Springer. 10.1007/978-94-007-5760-8.

Peñuelas, J., Poulter, B., Sardans, J. et al. 2013. Human-induced nitrogen–phosphorus imbalances alter natural and managed ecosystems across the globe. *Nature Communications,* 4: 2934.

Ragasa, C., Mazunda, J., 2018. The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Development*, 105: 25–47.

Rashid, S., Tefera, N., Minot, N., Ayele, G., 2013. Can modern input use be promoted without subsidies? An analysis of fertilizer in Ethiopia. *Agricultural Economics*, 44: 595–611.

Schulte, E. E., Kelling, K. A., 2017. Plant analysis: a diagnostic tool. National Corn Handbook No. 46. Purdue University. https://www.extension.purdue.edu/extmedia/NCH/NCH-46.html

Sheahan, M., Barrett, C.B., 2017. Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy* 67, 12–25.

Sheahan, M., Black, R., Jayne, T.S., 2013. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy,* 41: 39–52.

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.

Shepherd, K.D., Walsh, M.G., 2007. Infrared spectroscopy-enabling an evidence-based diagnostic surveillance approach to agricultural and environmental management in developing countries. *Journal of Near Infrared Spectroscopy*, 15: 1-19.

Spielman, D. J., Kelemework, D., Alemu, D., 2011. Seed, Fertilizer, and Agricultural Extension in Ethiopia. IFPRI-ESSP Working Paper No. 20.

Spielman, D.J., Byerlee, D., Alemu, D., Kelemework, D., 2010. Policies to promote cereal intensification in Ethiopia: the search for appropriate public and private roles. *Food Policy* 35, 185–194.

Suri, T., 2011. Selection and comparative advantage in technology adoption. *Econometrica*, 79, 159–209.

Swinnen, J., Deconinck, K., Vandemoortele, T., Vandeplas A., 2015. Quality Standards, Value Chains and International Development. *Economic and Political Theory*. New York: Cambridge University Press.

Tittonell, P., B. Vanlauwe, M. Corbeels, Giller, K. E., 2008: Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous small- holder farms of western Kenya. *Plant and Soil*, 313, 19–37.

Tjernström, E., 2017. Learning from Others in Heterogeneous Environments. Working Paper, University of Wisconsin, Madison.

Tjernström, E., Lybbertz, T.J., Hernánde, R.F., Correaz, J.S. 2018. Learning by (virtually) doing: experimentation and belief updating in smallholder agriculture. Working Paper, University of Wisconsin - Madison.

van der Velde M, Folberth C, Balkovič J, Ciais P, Fritz S, Janssens I, Obersteiner M, See L, Skalský R, Xiong W, Peñuelas J., 2014. African crop yield reductions due to increasingly unbalanced Nitrogen and Phosphorus consumption. *Global Change Biology* 20(4):1278–1288.

Van der Velde M, See L, You L, Balkovič J, Fritz S, Khabarov N, Obersteiner M, Wood S., 2013. Affordable nutrient solutions for improved food security as evidenced by crop trial. *PLoS One* 8(4): e60075.

Vanlauwe B, Descheemaeker K, Giller KE, Huising J, Merckx R, Nziguheba G, Wendt J, Zingore S., 2015. Integrated soil fertility management in sub-Saharan Africa: unravelling local adaptation. *Soil* 1:491–508.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, 2nd Edition. Cambridge, MA: MIT Press.

Wossen, T., Abay, K., Abdoulaye, T., 2021. Misperceiving and Misreporting Input Quality: Implications for Input Use and Productivity. Forthcoming, *Journal of Development Economics*.

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.

APPENDIX

Table A1: Pairwise correlations between objective and self-reported measures of soil properties.

	Soil organic carbon content	Nitrogen content (%)	Phosphorus content (mg/kg)	Soil pH	Soil quality good (self-reported)	Soil color black (self-reported)
Soil organic carbon content (%)-topsoil	1.00					
Nitrogen content (%) topsoil	0.95***	1.00				
Phosphorus content (mg/kg) topsoil	0.55***	0.52***	1.00			
Soil pH-topsoil	-0.17***	-0.12***	-0.04	1.00		
Soil quality good (self-reported)	0.01	0.01	0.03	-0.11**	1.00	
Soil color black (self-reported)	0.21***	0.16***	-0.14***	0.01	0.24***	1.00

Source: Authors' calculation based on LASER data.
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Farmers' response to soil nutrient requirement (DAP and urea application)

	(1) DAP (dummy variable)	(2) DAP (dummy variable)	(3) Urea (dummy variable)	(4) Urea (dummy variable)	(5) Log(nitrogen/ ha)	(6) Log(nitrogen/ ha)
Log (Nitrogen content (%) topsoil)	0.143	0.093	-0.134	-0.175	-2.389	-0.878
	(0.155)	(0.146)	(0.124)	(0.107)	(1.896)	(1.664)
Log (Phosphorus content (mg/kg) topsoil)	-0.060***	-0.054***	-0.011	-0.003	-0.219**	-0.318***
	(0.013)	(0.012)	(0.010)	(0.010)	(0.107)	(0.104)
Acidic topsoil (soil pH<5.5)	0.069*	0.066*	0.052**	0.059**	0.443*	0.373
	(0.036)	(0.036)	(0.026)	(0.025)	(0.255)	(0.322)
Alkaline topsoil (soil pH>8)	-0.161***	-0.124*	-0.104***	-0.079**	-0.702	-0.428
	(0.060)	(0.065)	(0.035)	(0.037)	(0.524)	(0.563)
Self-reported soil quality: fair	0.031	0.039*	0.006	0.019	-0.054	-0.003
	(0.022)	(0.023)	(0.020)	(0.018)	(0.232)	(0.265)
Self-reported soil quality: poor	0.080*	0.094**	-0.008	0.016	0.256	0.510
	(0.047)	(0.048)	(0.028)	(0.028)	(0.499)	(0.551)
Self-reported soil color: red	-0.059*	-0.040	-0.008	-0.004	-0.346	-0.497*
	(0.033)	(0.031)	(0.022)	(0.024)	(0.307)	(0.285)
Self-reported soil color: white/light	-0.107***	-0.087**	-0.059**	-0.057**	-0.418	-0.497
	(0.035)	(0.034)	(0.024)	(0.025)	(0.385)	(0.449)
Self-reported soil color: yellow	-0.045	-0.062	0.028	-0.011	-1.092*	-1.249*
	(0.060)	(0.069)	(0.066)	(0.047)	(0.638)	(0.719)
Crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household and plot-level characteristics	No	Yes	No	Yes	Yes	Yes
Plot-varying averages	No	Yes	No	Yes	Yes	Yes
No. observations	1977	1957	1977	1957	714	714

Source: Authors' calculation based on LASER data.
Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. The results in the last two columns are based on the intensive margin of fertilizer use, by restricting sample to those plots receiving some fertilizer. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Farmers' response to soil nutrient requirement (focusing on cereals)

	(1) IHS(nitrogen/ ha)	(2) IHS(nitrogen/ha)	(3) IHS(phosphorus/ ha)	(4) IHS(phosphorus/ ha)
Log (Nitrogen content (%) topsoil)	1.606	0.925	2.315	1.554
	(1.668)	(1.514)	(1.727)	(1.516)
Log (Phosphorus content (mg/kg) topsoil)	-0.388***	-0.359***	-0.449***	-0.413***
	(0.100)	(0.098)	(0.102)	(0.100)
Acidic topsoil (soil pH<5.5)	0.695**	0.623**	0.539*	0.452
	(0.292)	(0.273)	(0.304)	(0.307)
Alkaline topsoil (soil pH>8)	-1.151***	-0.687*	-1.073**	-0.642
	(0.414)	(0.410)	(0.431)	(0.413)
Self-reported soil quality: fair	0.371	0.293	0.386	0.290
	(0.238)	(0.261)	(0.240)	(0.260)
Self-reported soil quality: poor	0.664*	0.763*	0.827*	0.899*
	(0.386)	(0.441)	(0.431)	(0.478)
Self-reported soil color: red	-0.503*	-0.284	-0.601**	-0.366
	(0.284)	(0.271)	(0.300)	(0.278)
Self-reported soil color: white/light	-1.020***	-0.727**	-1.027***	-0.729**
	(0.293)	(0.291)	(0.333)	(0.324)
Self-reported soil color: yellow	-0.311	-1.124	-0.455	-1.324*
	(0.936)	(0.808)	(0.873)	(0.748)
Crop fixed effects	Yes	Yes	Yes	Yes
Household and plot-level characteristics	No	Yes	No	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	796	791	796	791

Source: Authors' calculation based on LASER data.
Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. Standard errors, clustered at household level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Yield response to soil nutrient requirement and fertilizer applications (focusing on cereals)

	(1) Log(yield)	(2) Log (yield)	(3) Log(yield)	(4) Log(yield)
IHS (Nitrogen application per ha)	0.133***	0.207***	0.133***	0.141***
	(0.048)	(0.062)	(0.048)	(0.053)
IHS (phosphorus application per ha)	0.050	0.054	0.050	-1.351
	(0.041)	(0.041)	(0.041)	(0.939)
Improved seed	0.230	0.380***	0.230	0.459***
	(0.146)	(0.122)	(0.146)	(0.133)
Acidic topsoil (soil pH<5.5)	0.015	-0.050	0.015	-0.119
	(0.109)	(0.099)	(0.109)	(0.106)
Alkaline topsoil (soil pH>8)	-0.799***	-0.362	-0.799***	-0.435
	(0.309)	(0.334)	(0.309)	(0.314)
Log (relative nitrogen deficiency)		-0.626		
		(0.611)		
Nitrogen application #relative nitrogen deficiency		0.291**		
		(0.144)		
Log (relative phosphorus deficiency)				0.113
				(0.339)
Phosphorus application #relative phosphorus deficiency				0.181
				(0.123)
Crop fixed effects	Yes	Yes	Yes	Yes
Household and plot-level characteristics	No	Yes	No	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	806	802	806	730

Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. Standard errors, clustered at village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Yield response to soil nutrient requirement, soil acidity and fertilizer applications (focusing on cereals)

	(1) Log (yield)	(2) Log (yield)	(3) Log (yield)	(4) Log (yield)
IHS(Nitrogen application)	0.174***	0.142***	0.128**	0.102**
	(0.040)	(0.041)	(0.053)	(0.050)
IHS(Phosphorus application)	0.037	0.040	0.074	0.072
	(0.033)	(0.036)	(0.046)	(0.046)
Improved seed	0.225	0.393***	0.232	0.400***
	(0.144)	(0.123)	(0.147)	(0.126)
Acidic topsoil (soil pH<5.5)	0.348**	0.229*	0.269*	0.159
	(0.159)	(0.139)	(0.160)	(0.139)
Alkaline topsoil (soil pH>8)	-0.835**	-0.369	-0.848**	-0.376
	(0.345)	(0.359)	(0.345)	(0.358)
IHS(nitrogen application) # Acidic topsoil (soil pH<5.5)	-0.126***	-0.106***		
	(0.036)	(0.034)		
IHS(nitrogen application) # Alkaline topsoil (soil pH>8)	0.240***	-0.028		
	(0.072)	(0.093)		
IHS(Phosphorus application) # Acidic topsoil (soil pH<5.5)			-0.093***	-0.078***
			(0.032)	(0.030)
IHS(Phosphorus application) # Alkaline topsoil (soil pH>8)			0.202***	-0.026
			(0.061)	(0.078)
Crop fixed effects	Yes	Yes	Yes	Yes
Household and plot-level characteristics	No	Yes	No	Yes
Plot-varying averages	No	Yes	No	Yes
No. observations	806	802	806	802

Source: Authors' calculation based on LASER data.
Notes: IHS stands for inverse hyperbolic sine transformation of input values. The base outcome for soil acidity level is neutral soils (with 5.5≤pH≤8). The base (self-reported) soil quality indicator is "good" while black colored soils are the base outcomes for soil color. Moderate and steep sloped plots serve as base outcomes for comparing the role of slope of plots on fertilizer application rates. Standard errors, clustered at village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org