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Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers

Julia Berazneva [a,*], Linden McBride [b], Megan Sheahan [c], David Güereña [d]

[a] Department of Economics, Middlebury College, 305D Warner Hall, 303 College Street, Middlebury, VT 05753, USA
[b] Charles H. Dyson School of Applied Economics and Management, Cornell University, 410 Warren Hall, Ithaca, NY 14853, USA
[c] Precision Agriculture for Development, 32 Atlantic Avenue, Pilot House-Lewis Wharf, Boston, MA 02110, USA
[d] International Maize and Wheat Improvement Center (CIMMYT), CIMMYT South Asia Regional Office, NARC Botany Division, Khumaltar, P.O. Box 5186, Lalitpur, Nepal

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ABSTRACT

Bringing together emerging lessons from biophysical and social sciences as well as newly available data, we take stock of what can be learned about the relationship among subjective (reported) and objective (measured) soil fertility and farmer input use in east Africa. We identify the correlates of Kenyan and Tanzanian maize farmers' reported perceptions of soil fertility and assess the extent to which these subjective assessments reflect measured soil chemistry. Our results offer evidence that farmers base their perceptions of soil quality and soil type on crop yields. We also find that, in Kenya, farmers' reported soil type is a reasonable predictor of several objective soil fertility indicators while farmer-reported soil quality is not. In addition, in exploring the extent to which publicly available soil data are adequate to capture local soil chemistry realities, we find that the time-consuming exercise of collecting detailed objective measures of soil content is justified when biophysical analysis is warranted, because farmers' perceptions are not sufficiently strong proxies of these measures to be a reliable substitute and because currently available high-resolution geo-spatial data do not sufficiently capture local variation. In the estimation of agricultural production or profit functions, where the focus is on averages and in areas with low variability in soil properties, the addition of soil information does not considerably change the estimation results. However, having objective (measured) plot-level soil information improves the overall fit of the model and the estimation of marginal physical products of inputs. Our findings are of interest to researchers who design, field, or use data from agricultural surveys, as well as policy makers who design and implement agricultural interventions and policies.

1. Introduction

While many socio-economic factors contribute to poor crop yields across Sub-Saharan Africa (SSA), a major biophysical contributor is the depletion of soil fertility (Sanchez, 2002; Sanchez & Swaminathan, 2005; Tully, Sullivan, Weil, & Sanchez, 2015; Vanlauwe, Six, Sanginga, & Adesina, 2015). Across different agro-ecological zones in SSA, soils poor in nutrients and soil organic matter not only partially account for low yields but also limit the effectiveness of other inputs such as fertilizer and labor, and reduce farm households' resilience to external stressors and shocks (e.g., pests, crop diseases, climate change). Moreover, the direct links between soil fertility, agricultural productivity, food insecurity, and rural poverty can be self-reinforcing. Whether due to poor initial soil endowments or resource constraints that lead to low input use (fertilizers and/or organic soil amendments), the broad pattern across much of SSA is soil degradation over time (Güereña, Kimetu, Riha, Neufeldt, & Lehmann, 2016; Tittonell, Vanlauwe, Leffelaar, Rowe, and Giller, 2005). As a result, some farmers find themselves trapped in low productivity equilibria (Antle, Stoorvogel, & Valdivia, 2006; Barrett & Bevis, 2015; Shepherd & Soule, 1998; Stephens et al., 2012).

Despite the importance of soil fertility in the context of agricultural development, major barriers remain in our understanding of how farmers form perceptions about their soil fertility, and how soil fertility—subjective (reported) and objective (measured)—is related to farmers' management practices in terms of input use. Together with farmer ability, soil fertility is often unobserved by

* Corresponding author.
E-mail addresses: jberazneva@middlebury.edu (J. Berazneva), lem247@cornell.edu (L. McBride), msheahan@precisionag.org (M. Sheahan), d.guerena@cgiar.org (D. Güereña).

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the researchers (and delegated to the error term of the econometric models). Yet both natural endowments like soil and farmer managerial abilities are highly heterogeneous and have been shown to explain the low adoption rates of agricultural inputs (Suri (2011), for example, demonstrates that heterogeneity in net returns explains the adoption patterns of hybrid maize seeds in Kenya). Without having access to detailed and reliable soil information it is impossible to assess the contribution of heterogeneous soil fertility to agricultural production, both in terms of crop yields and farmer management decisions.

A confounding factor in this relationship stems from the fact that heterogeneity in soil fertility occurs both at high and low spatial scales (Hengl et al., 2015; Tittonell, Vanlauwe, Leffelaar, Shepherd, & Giller, 2005). More is known about the heterogeneity at larger (e.g., provincial and up) scales where the sources of heterogeneity include underlying geological material, agroecological zone, and biome (e.g., rainforest, savannah, desert). Modern geospatial tools coupled with historic surveys have provided this information. What is less known is how this heterogeneity changes at increased spatial resolutions as the influence of human management decisions alters the underlying biophysical soil conditions. These include land-use change (e.g., clearing of forests for agriculture) (Recha et al., 2013), historic cropping patterns and input use (Chivenge, Vanlauwe, & Six, 2011), cropping intensity (Güereña et al., 2016), and nutrient cycling (Vitousek et al., 2009). When integrated together, all of these things have unknown effects on the various soil parameters that constitute soil quality and fertility.

A paucity of research directly examines the relationship between soil fertility and existing farm management practices, especially in SSA. Agronomic studies that have precise measures of soil fertility and yields often ignore farmers' behavioral responses (see, for example, Chivenge et al. (2011)), while economic studies fail to account for soil fertility in estimation of agricultural profits and farmer welfare, at best including indicator proxy variables for soil fertility (e.g., Duflo, Kremer, and Robinson (2008), Sheahan, Black, and Jayne (2013)). Only a few studies with access to precise measures of soil fertility analyze farmers' knowledge of land quality and within-farm variability in resource allocation and yields (e.g., Tittonell, Vanlauwe, Leffelaar, Rowe, et al. (2005)). Therefore, in this paper, we attempt to bring together emerging lessons from the biophysical and social sciences as well as newly available data to take stock of what we can learn about the relationships among subjective (farmer-reported) and objective (researcher-measured or estimated) soil fertility and farmers' management practices.

Several other studies have examined these relationships, with mixed results. Cross-sectional data from the World Bank's Living Standards Measurement Study-Integrated Survey in Agriculture (LSMS-ISA) across six different countries, for example, suggest that farmers in SSA do not significantly vary input application rates according to perceived soil quality (Sheahan & Barrett, 2017). At the same time, evidence from Kenya indicates that farmers apply fewer external inputs on soils with objectively verified low soil carbon content (Marenya & Barrett, 2009a), and adjust planting timing and weeding intensity on plots with different land quality (Tittonell, Vanlauwe, Leffelaar, Shepherd, et al., 2005).

In order to better understand these empirical observations, we identify the input and output correlates of farmers' perceptions of soil fertility, and assess whether farmers' perceptions correlate with objective laboratory measurements of soil fertility characteristics. We also explore the extent to which publicly available geospatial soil data, estimated via sophisticated interpolation methods from point observations across the African continent, are adequate to capture local soil chemistry realities at the household, village, and data set levels. Such data sets are an incredible resource and their availability may obviate the need for detailed on the ground soil data collection, saving researchers, agricultural organizations, and governments both time and money. This exercise allows us to make recommendations to the broader research community about the relative trade-offs inherent in relying on one soil metric over another. Finally, we assess the role of soil information from a research standpoint by interchanging various soil metrics in a production function approach to the analysis of yields.

In particular, we address the following four research questions:

1. What can we learn from household survey data about the determinants of farmers' soil fertility perceptions? Do agricultural inputs and outputs vary with perceived soil quality and soil type?
2. To what extent do farmers' subjective perceptions of soil quality and type correlate with objective laboratory measurements of soil chemical fertility? In addition, can we identify any observable plot or household level characteristics that are correlated with farmers' soil quality perceptions?
3. Can new high-resolution and publicly available geo-spatial soil fertility data sets provide insight into the levels and variation of local (household, village, and data set level) soil fertility such as would obviate the expensive and time-consuming collection of detailed plot-level data?
4. What is the role of soil (mis)information in farmers' and researchers' estimation of yields and returns to fertilizer?

To answer these questions, we rely on three data sets that correspond with a small number of maize farming households in western Kenya and two data sets that correspond with a nationally representative sample of maize farmers in Tanzania. In both study regions, farmers' perceptions of soil quality[1] and their agricultural practices are drawn from household survey responses. Global positioning system (GPS) coordinates allow us to match these households with publicly available geo-referenced soil data at 250-meter spatial resolution from the Africa Soil Information Service (AfSIS) (Hengl et al., 2015). In western Kenya, additional laboratory measures of plot-level soil fertility are obtained from soil analyses based on the resource- and time-intensive collection of soil samples (Berazneva, Lee, Place, & Jakubson, 2017). Apart from geographic differences, both the Kenya and Tanzania data sets also offer different contexts in terms of data collection efforts: the Kenya data are from a small-scale detailed survey, while the Tanzania data are from a nationally representative large-scale project. Combining the two geographic locations allows us to compare across the contexts, provide limited external validity to our findings, and offer recommendations to researchers on soil data collection and use.

Our contributions are twofold. First, we evaluate three potential sources of soil information: farmer-reported perceptions, plot-level measurements, and geo-referenced soil data. Second, we provide some initial evidence as to whether the variation in inputs and crop yields can be explained by soil information. Our results offer evidence of correlation between farmer perceptions of soil quality and soil type with crop yields but no clear correlation with inputs. We also find that, in Kenya, farmer-reported soil type (soil texture) is a reasonable predictor of several objective soil fertility indicators drawn from plot-level measurements while farmer-reported soil quality is not. In addition, we find that the differences between the two objective soil data sets that we compare in Kenya—plot-level measured soil analysis data and geo-spatial AfSIS soil

[1] The term "soil quality" was used in the household surveys in Tanzania and Kenya and refers to general farmer perceptions of soil fertility. The term "soil fertility" is used throughout this paper to either represent the specific soil chemical and physical fertility tests measured or as a general term to describe the relationship between soil attributes and crop production.

data—are considerable, indicating that the time-consuming exercise of collecting detailed objective measures of soil content is justified when the farmer or researcher is in need of local biophysical data, despite the growing availability of high-resolution georeferenced soil data sets. In the estimation of agricultural production, cost, or profit functions, where the focus is on averages and in areas with low variability in the soil properties, the addition of different types of soil information does not considerably change the estimation results. However, having objective (measured) plot-level soil information improves the overall fit of the model and the estimation of marginal physical products of inputs. Our findings are of interest to researchers who design, field, or use data from agricultural surveys, as well as policy makers who design and implement agricultural interventions and policies.

Our paper proceeds as follows. In the next section, we briefly discuss the context from which our research questions arise. We then discuss our data sources and methods. The following section offers results for each of the four questions under investigation. The last section summarizes these findings and concludes, taking stock of what we have learned about the relationships among and role of various sources of soil information, and offering additional research directions worth pursuing, both for better comprehension of farmer behavior and for the collection of better data.

2. Soil information and its uses

The international development community has recently begun to turn its attention towards the role of soils in agricultural and human development; in fact, the Food and Agriculture Organization of the United Nations declared 2015 the International Year of Soils. Aware that soils are important, development and agricultural economists are increasingly including soil data in their analyses.

When it comes to using soil data, economists generally fall into three camps. The first takes farmers' subjective assessments of soil fertility as a sufficient measure of or proxy for soil fertility without any verification exercise or follow-up discussion about how farmers make these determinations (see, for example, Sherlund, Barrett, and Adesina (2002)). Most agricultural household surveys collect subjective information—farmers report their yields, input use, as well as environmental conditions. And apart from several exceptions (see, for example, Komba and Muchapondwa (2015) who compare farmers' perceptions of decadal precipitation and temperature mean and variance to the data from the Tanzanian Meteorological Agency), most studies do not verify reported data. The second camp assumes that farmers are too information-constrained to accurately report soil fertility measures and therefore relies on highly aggregated or estimated measures of soil quality or soil type, derived from external mapping exercises and often matched using administrative boundaries (e.g., Sheahan et al. (2013)). The third camp makes the same assumptions as the second but collects and analyzes soil samples from the actual plots or farms under study in lieu of relying on highly aggregated or predicted external data sets (e.g., Marenya and Barrett (2009a)). The costs of data collection efforts that follow from each of these assumptions differ dramatically. Each camp makes reasonable assumptions under the reality of data constraints, but little research attempts to empirically understand the uniqueness of the information embodied in each of these types of soil data. This information is valuable when choosing the most accurate soil fertility metrics for analysis and in understanding the reasons why other metrics may be insufficient.

While it is reasonable to expect that farmers in SSA are constrained in their ability to know the precise nutrient content of their soils, farmers do form assessments of their soil fertility and productivity (Niemeijer & Mazzucato, 2003). To our knowledge, only a few studies in economics have sought to aid our understanding of this process absent measurement.[2] Marenya et al. (2008), for example, study farmers' perceptions of soil fertility and the impacts of fertility on yields in western Kenya. Using objective measures of soil fertility, the authors find evidence of widespread farmer misperception of soil fertility and show that these misperceptions cannot be easily explained by observed plot or farmer characteristics such as plot size or farmer's gender or age. The Kenyan farmers in the study, similar to the farmers of the south-central highlands of Ethiopia (Karltun, Lemenih, & Tolera, 2013), use crop yields as the key soil fertility indicator. Yet if yield changes lag behind the changes in soil fertility, farmers may be unable to identify important dynamic patterns in soil fertility and may be slow to update their assessments. This delayed response can result in significant deterioration in soil fertility or render soils unresponsive. Once soil has degraded below a productivity threshold, soil restoration can become prohibitively costly and therefore "economically irreversible" (Antle et al., 2006). For example, a series of studies looked at crop yields across a time series of land-use change in western Kenya. Critical soil organic matter levels, pH, and other soil fertility metrics declined over one to two decades (Moebius-Clune et al., 2011), yet the resulting low yields remained over multi-decadal time-scales despite fertilization. Judicious application of organic resources was necessary to reverse the soil fertility decline (Kimetu et al., 2008), but these application rates (18 tons per hectare) were well above economic feasibility and, if not maintained, yield reduced to pre-application levels within a few years (Güereña et al., 2016).

Moreover, resource allocation and crop management can differ according to perceived soil fertility. Tittonell, Vanlauwe, Leffelaar, Shepherd, et al. (2005), for example, find differences in the timing and intensity of crop management according to farmers' perceptions of the quality of their land in Kenya. More fertile plots are planted earlier, with more spacing between plantings, and are weeded more often. These practices unsurprisingly lead to greater yields. Therefore, subjective soil fertility perceptions matter. However, beyond these few papers, the formation of farmers' soil fertility assessments as well as the interactions between farmers' assessments and land management practices have not been explored.

The formation of farmers' perceptions about their soil fertility and the farming practices that flow from these perceptions are important to understanding the critical linkages between resource endowments, crop and land management, and agricultural productivity. These linkages, in turn, may have major policy and programmatic implications. From a research perspective, understanding the correlates of farmers' soil assessments is a first step towards evaluating the research value of these subjective measures. And if objective measures of soil fertility are deemed preferable over subjective measures, then the next logical question is whether researchers should forsake free and publicly available data sets for the expensive and time-consuming collection of their own soil chemistry data; i.e., which of the soil-data-using-economist-camps is preferred?

Massive amounts of resources have been funneled into the creation of publicly available soil data sets with high resolution and either continental or global coverage, including but not limited to AfSIS[3] and the FAO's Harmonized World Soil Database.[4] In fact, the

[2] A review of rural development literature, as well as studies in ethnopedology that focus on how farmers understand their soils based on collective experiences, can be found in Marenya, Barrett, and Gulick (2008).

[3] Available at www.isric.org/data/afsoilgrids250m3.

[4] Available at www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

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publicly available household survey data collected by national statistics agencies throughout SSA and overseen by the LSMS-ISA initiative include files with soil data from the FAO. Researchers wanting an even fuller complement of soil variables can easily match household survey data with the AfSIS database using provided enumeration level coordinates. But, in the end, these soil data sets are the result of interpolation and are only as good as the data fed into the algorithm and the underlying model. Moreover, interpolation itself means that the areas between sampling points are estimated, which, depending on the spatial resolution of the underlying data, may have large associated error. Without a critical assessment of how well these data represent local soil chemistry realities, as derived from plot-level soil analysis, researchers cannot make good decisions about which data may be most appropriate for their work. With very few exceptions (e.g., Bui (2010)) comparative analyses of a publicly available spatial soil databases with plot-level soil data are not available, and we have found no studies that assess the performance of AfSIS at the local level beyond the model validation exercises (e.g., Hengl et al. (2015)).

With renewed international recognition of the important role soils play in agricultural production, welfare dynamics, and carbon sequestration (Barrett & Bevis, 2015; Lal, 2012; Lehmann & Kleber, 2015) as well as with major resources being devoted to the collection of a variety of subjective and objective, measured and estimated indicators of soil fertility, it is imperative to assess what these data can and cannot tell us. This paper helps to sort through the implications by bringing together and comparing some of these data sources.

3. Data and methods

Since crop choice may be both a function of and response to a farmer's perceived soil fertility, we limit our analysis to maize, the main and most important cereal in east Africa. In Kenya and Tanzania, for example, maize is cultivated on about four percent of total land area (FAOSTAT, 2017). Tittonell, Vanlauwe, Leffelaar, Rowe, et al. (2005) and Tittonell, Vanlauwe, Leffelaar, Shepherd, et al. (2005) document that farmers in Kenya plant maize across their landholdings, with the exception that famers tend not to plant maize in their most fertile plots near homesteads. In Tanzania, maize is grown by 48 percent of households. And while there is some variation in perceived soil quality of maize plots within households and maize plots vary by soil types in our data (see Tables A2 and A3 in the Appendix), we cannot rule out the possibility that farmers' crop choice may mask the true relationship between perceptions, yields, and inputs. In fact, in Tanzania, plots deemed to have good soil quality by the farmer are more likely to be planted with maize than those deemed to have average soil quality; likewise, plots with farmer-reported loamy soils are more likely to be planted with maize.

Our data come from Tanzania and western Kenya and are described in the subsections that follow; a summary of these data sources is available in Table 1. After providing details on the data, we describe the analytical methods used to answer our four research questions.

3.1. Farmer-reported soil fertility measures, yields, inputs

We use a nationally representative sample of households from the 2010–2011 wave of the publicly available Tanzania National Panel Survey, data collected as part of the World Bank's LSMS-ISA project (TZNPS, 2016). From the full sample, we restrict our analysis to the sub-sample of 2360 plots containing maize in the main growing season across 1566 households, with plot-level data on agricultural inputs and maize yield. A typical LSMS-ISA questionnaire asks respondents to specify soil quality and type for each plot under cultivation without prompting or guidance so that farmers' responses should be purely based on their perceptions. The responses are then grouped into pre-coded categories. For the Tanzania LSMS-ISA, the pre-coded categories for soil quality are good, average,[5] or bad; for soil type or texture they are sandy, loam, clay, or other. The presence of sampling weights allows us to apply household-level population weights in the statistical analysis that follows.

The standard modules of the LSMS-ISA questionnaire were adopted for a household survey effort of over 300 households collected in 2011–2012 in fifteen villages in the Nyando and Yala river basins of rural western Kenya (Berazneva et al., 2017). We use data for all maize-growing households for which soil analysis is available, for a sample size of 509 maize plots cultivated by 307 households. Identical to the LSMS-ISA survey, respondents classify their soil quality and type based on their knowledge, as well as report agricultural input and maize production levels. The near-identical questions and classifications between the LSMS-ISA survey implemented in Tanzania and that implemented in Kenya allow us to easily compare across the two regions.[6]

Agricultural input and output variables are drawn from farmer recall related to the last main season. Where applicable, we standardize input and output values by plot size. For Kenya, plot area is measured with hand-held GPS units. For Tanzania, GPS-measured plot areas are only available for a sub-set of all plots, so we rely on imputed plot sizes as described in Palacios-Lopez and Djima (2014). We also draw on a variety of plot- and household-level characteristics from the survey data, relying mainly on those variables observed consistently across the two countries.

3.2. Researcher-collected plot-level soil samples

In western Kenya, soil samples were collected from the largest maize plot of each farm household at the end of the long rains season of 2011. Topsoil (0–20 cm) was randomly sampled from four points across the plot, mixed together (homogenized), and analyzed at the World Agroforestry Center's Soil–Plant Spectral Diagnostics Laboratory in Nairobi, Kenya. The samples were analyzed using mid-infrared spectroscopy (MIR), a rapid nondestructive technique for examining the chemical composition of materials (Cozzolino & Moron, 2003; Shepherd & Walsh, 2002, 2007; Terhoeven-Urselmans, Vagen, Spaargaren, & Shepherd, 2010). The MIR analysis provided information on several key soil characteristics: soil carbon measured as percentage of total soil carbon by mass (% by weight or % w/w),[7] nitrogen content measured as percentage of total nitrogen in the soil by mass (% by weight or % w/w), soil pH (measured on 1 to 7 scale), and cation exchange capacity (CEC) measured in milliequivalent of hydrogen ions per 100 grams of dry soil (meq/100 g). While, in the case of Kenya, we refer to the MIR analyzed soil samples as objective, we acknowledge that, as with all soil measurement, MIR comes with its own measurement error.

Soil carbon and total nitrogen content have been used as proxies for soil fertility in the past (see, for example, Marenya and Barrett (2009b)). These two measures are highly collinear and correspond to soil organic matter content that can be transient and influenced by farm management practices. Soil pH and CEC, on the other hand,

[5] We use good, average, and bad soil categorizations to mirror the questions in the household surveys. Average should be understood as intermediate (not an arithmetic mean).

[6] The soil type question was identical across the two data sources. The soil quality question offered several additional pre-coded options (poor, very poor, and not productive at all) in Kenya that were later grouped into the category of bad to correspond with the Tanzania data.

[7] The soils in the research site in Kenya are acidic and do not contain carbonates so that total stocks of soil carbon are equivalent to total organic carbon content.

Table 1
Summary of data.

Dataset	In-text disambiguation	Source	Location	Years covered	Number of observations (plot level)	Number of observations (household level)	Nationally representative	Type of data	Analysis method	Sample weights
Tanzania National Panel Survey	Tanzania survey data	World Bank LSMS-ISA	Tanzania	2010–2011	2360	1566	Yes	Household & plot-level survey	NA	Yes
Economics of Biomass Management in Western Kenya	Kenya survey data	Berazneva et al. (2017)	Western Kenya	2011	509	307	No	Household & plot-level survey	NA	No
Economics of Biomass Management in Western Kenya	Soil analysis data	Berazneva et al. (2017)	Western Kenya	2011	307	NA	No	Soil chemistry from sampled soils	MIR	NA
Soil Property Maps of Africa at 250 m	AfSIS data	AfSIS, Hengl et al. (2015)	African continent		NA	NA	NA	GIS data at 250-meter resolution	Interpolated soil characteristics (obtained via MIR) from >28,000 sampling locations across the continent (see Hengl et al. (2015))	NA

relate more strongly to soil texture and mineralogy, and therefore are more stable indicators of soil fertility (Sparks, 1996). We also classify soils as "fertile," using thresholds and recommendations for soils in western Kenya from the Kenya Agricultural Research Institute (Mukhwana & Odera, 2009) and from the Cornell Soil Health Test (Moebius-Clune et al., 2011). Fertile soil is defined as soil with organic carbon content greater than or equal to 2% w/w, total nitrogen content greater than or equal to 0.2% w/w, and pH greater than or equal to 5.2. The resulting soil data offer on-the-ground insight into the plot-level soil fertility of smallholder farmers in rural western Kenya. In the discussion below, we refer to these laboratory measurements as "measured soil data" or "soil analysis data." Descriptions and interpretations of measured soil chemical fertility metrics are summarized in Table 2.

3.3. Geo-referenced and estimated soil fertility measures

We also match the household survey data with publicly available data from AfSIS. AfSIS, a collaborative soil ecosystem services project, provides data on soil characteristics at 250-meter spatial resolution (Vagen et al., 2010). The data were created by interpolating soil characteristics (obtained via MIR and Near Infrared Spectroscopy) from more than 28,000 sampling locations across Africa using techniques detailed in Hengl et al. (2015).

The AfSIS data were downloaded from the Soil Property Maps of Africa at 250 m, where tifs of a variety of soil characteristics are available at 0–5 cm, 5–15 cm, 15–30 cm, and etc. depths. So as to ensure that the AfSIS data are comparable with the laboratory measured soil data in Kenya, we selected the data representing the 0–20 cm depth where available (total soil nitrogen). Where the 0–20 cm-depth level was not available (soil organic carbon, pH, and CEC), we selected data representing the 0–5 cm and 5–15 cm depths and averaged them together.

We paired the AfSIS data with the Kenyan and Tanzanian households by extracting the gridded AfSIS data pertaining to the geo-references available in the household surveys. In Kenya, these points pertain to plots; in Tanzania, these points pertain to the average of the enumeration area (EA), as per World Bank LSMS-ISA restrictions.[8] Although we cannot guarantee an exact match up of AfSIS data with the household survey data in the case of Tanzania due to the EA offsets in the publicly available data, we note that there is low variation in the AfSIS data overall due to the way in which the AfSIS data were developed (estimation and interpolation based on available data points); by design, these data will have lower variation than the individual data points that informed them. Due to this low variation, our results are not greatly affected by the offsets, as data from different EAs differs very little. While the AfSIS data repository provides information about a large number of soil indicators, we extracted only the soil characteristics that best matched the available soil analysis data in order to make valid comparisons: soil organic carbon, total soil nitrogen, pH, and CEC.[9] While

[8] In order to pair the AfSIS data with the Kenya plot-level geo-references, we extracted the values for each soil characteristic as observed (i.e., we extracted the value for the 250-meter cell in which the geo-referenced point fell). So as to pair the AfSIS data with the Tanzania enumeration area geo-references, we extracted the values for each soil characteristic as interpolated (i.e., we extracted a value produced via interpolation from the values of the four nearest raster cells in the AfSIS data). We took these two different approaches—strict extraction versus interpolation—for the two countries due to the nature of the geo-references available to us in the household survey data for each country. However, it should be noted that there was little substantive difference between the observed and interpolated points in either country. For eight EAs in Tanzania, the included geo-reference details landed in bodies of water, meaning that we were unable to match these with AfSIS data. In these cases, we drew from the median values across EAs within a ward.

[9] Carbon: A/10; nitrogen: A/10; pH: A/10; CEC: no conversion necessary as the AfSIS data are already in the same units as the soil analysis data. A indicates AfSIS data.

Table 2
Descriptions and interpretations of measured soil chemical fertility metrics.

Soil variable	Description	Sufficient values	Deficient values
Organic carbon (% w/w)	While not a plant nutrient, organic carbon is one of the best measures of overall soil fertility and is highly influenced by management.	≥2	<2
Total nitrogen (% w/w)	Nitrogen is a major plant essential nutrient. As most nitrogen is held in the organic matter, there is high colinearity between total nitrogen and organic carbon in the soil.	≥0.2	<0.2
pH	Soil pH controls plant nutrient availability and toxicity.	5.2–7.5	<5.2, >7.5
CEC (meq/100 g)	CEC is the measure of a soil to retain and hold nutrients and is an indication of soil fertility potential.	<15	≥15

organic carbon and total nitrogen content are susceptible to change over time, soil pH and CEC are more stable and therefore potentially more appropriate measures of soil fertility to obtain through geo-spatial data.

Summary statistics for all data are included in Table A1 in the Appendix.

3.4. Analytical methods

We combine the four aforementioned data sets to address our research questions. Graphically, Fig. 1 displays the sample of Kenyan plots with the soil analysis data (in circles) overlaid on the AfSIS soil pH data. From this figure we can see the relative resolution of the two data sets. In the left panel we observe fifteen study villages as well as the general variation in soil pH across western Kenya. Zooming in on one of the villages in the Lower Nyando region in the right panel, we see that the soil pH both decreases in variation and becomes more pixelated as we approach the 250-meter resolution level.

Our statistical analysis relies mainly on difference-in-means tests. To determine whether the means of perceived soil quality and soil type differ significantly across agricultural inputs, maize yield, and the plot-level soil analysis and geo-spatial AfSIS indicators of soil fertility, we use the Tukey–Kramer test, which allows for multiple pairwise comparisons while accounting for the family-wise error rate. To control for additional variables and to explore the heterogeneity in farmers' perceptions, we also estimate an ordered probit model (Greene, 2008) with a set of variables similar to that included in the difference-in-means analysis. The dependent ordered variable is farmers' perceptions of soil quality (1 = bad, 2 = average, 3 = good), while factors hypothesized to affect farmers' classification include estimated (AfSIS) soil organic carbon and CEC, maize yield, agricultural inputs, and plot- and household-level characteristics.

In addition, we undertake several descriptive analyses to assess how well the geo-spatial AfSIS data capture the results from the plot-level soil analysis data in Kenya. We provide scatter plots to visually explore how the data differ by maize plot. We also report pairwise correlation coefficients and equivalence tests at the village and data set-level to assess whether the AfSIS data can statistically capture the village-level means.

Finally we assess the role of soil information in the estimation of production, cost, or profit functions. Environmental production conditions, which may significantly vary over time and space, necessarily influence both yields and farmers' production decisions (e.g., application of inputs). Not including conditions such as soil fertility in the estimation of production functions results in omitted variable bias (Sherlund et al., 2002). We therefore estimate a series of production functions, starting with specifications that contain no soil information then swapping in the three soil data information types available to us.

The choice of functional form has received significant attention in the literature, both in the estimation of deterministic and stochastic production models. Some recent papers that focus on maize production in developing countries use a Cobb-Douglas specification (e.g., Arslan & Taylor, 2009), a quadratic specification (e.g., Sheahan et al., 2013), or a translog specification (e.g., Abdulai & Abdulai, 2017). The point of estimating a production function here is to demonstrate whether the coefficients, fit, and predicted yields and marginal physical products of inputs change after including different soil variables. We estimate a Cobb-Douglas production function that is linear in logarithms and often used for screening and approximation purposes.[10] We note, however, that our results suggest only approximations to, for example, true response of yields to nutrient applications and therefore should not be taken literally. We report the results of the production function with two inputs (labor and fertilizer,[11] normalized by land), with and without controls, as well as the means of predicted yields (in tons per hectare) and of marginal physical products of fertilizer across all observations (in kilograms per hectare) for Kenya and Tanzania. Marginal physical product (MPP)[12] measures the additional output that results from the use of one additional unit of input. In our case, MPP of fertilizer measures the additional maize yield in kilograms from using one additional kilogram of fertilizer. By including subjective (farmers' perceptions) and objective (plot-level soil analysis and AfSIS) soil variables in separate specifications, we can assess whether the use of different types of available soil information changes estimates and the decisions/conclusions that would stem from those estimates.

4. Results and discussion

We present and discuss results for each of our four research questions below. A synthesis of the findings is then offered in the conclusion.

Before addressing our first research question, we provide three useful descriptive findings that help to shed light on our main results. First, we assess to what extent perceived soil quality measures vary within and across farms so as to understand whether farmers are ranking their fields' fertility relative to others' plots, relative to some local mean, or relative to their own plots. In a decomposition of perceived (good, average, and bad) soil quality within and between households and villages/enumeration areas (EAs) (Table A2 in the Appendix), we find that variation in farmer soil quality assessment at the plot level is largely due to differences between farms within a given village or EA as opposed to within farms.

Second, we note the correlations between farmer-perceived soil quality and type in the cross-tabulation of frequencies shown in

[10] Since Cobb-Douglas imposes constant elasticity of substitution and we are cautious to impose this assumption, we also estimate a generalized quadratic specification that is a more flexible functional form and allows for zero valued inputs and the interaction between soil fertility and different inputs. The quadratic specification shows very similar results to the Cobb-Douglas that are available from authors upon request.

[11] To address zero valued fertilizer input, we add one to all input levels before taking logs.

[12] $\mathrm{MPP} = \frac{d(yield)}{d(fertilizer)}\left(\frac{yield}{fertilizer}\right)$.

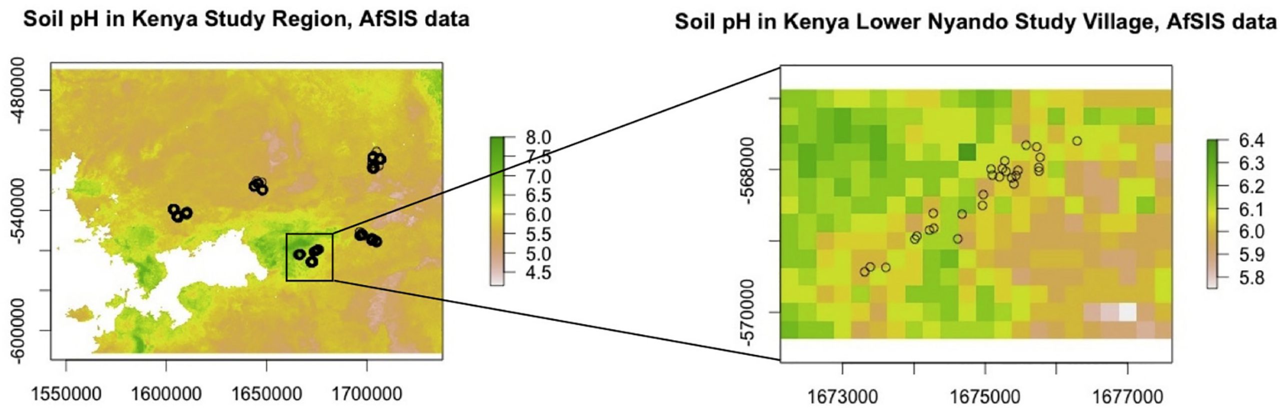

Fig. 1. AfSIS soil pH with the Kenyan soil analysis study plots represented by circles. X and Y-axes are latitude and longitude in UTM WGS84.

Table 3
Cross tabulations of subjective soil quality and type (farmer-reported).

		Soil type									
		Sandy		Loam		Clay		Other		Total	
		Number	%	Number	%	Number	%	Number	%	Number	%
Kenya, 509 plots											
Soil quality	Good	19	15	85	30	20	23	–	–	192	24
	Average	68	55	136	48	50	57	8	57	422	52
	Bad	37	30	62	22	18	20	6	43	195	24
	Total	124	100	283	100	88	100	14	100	809	100
Tanzania, 2360 plots											
Soil quality	Good	180	43	722	47	239	63	11	48	1305	49
	Average	186	44	732	48	124	33	8	35	1174	44
	Bad	56	13	82	5	16	4	4	17	181	7
	Total	422	100	1536	100	379	100	23	100	2660	100

Table 3. Farmers distinguish between good and bad soils across all soil types (sandy, loam, and clay) both in Kenya and Tanzania. For example, 15 percent of sandy soils are thought to have good soil quality as opposed to 30 percent of loam soils and 23 percent of clay soils in Kenya. In Tanzania, 43 percent of sandy soils have good soil quality as opposed to 47 percent of loam soils, and 63 percent of clay soils.

Third, we note the major difference in distribution of plots across farmer-perceived good, average, and bad classifications in western Kenya and Tanzania (Table 4). In Tanzania, only six percent of maize plots are classified by their farmers as bad relative to 24 percent in Kenya. In Kenya, over half of all maize plots are regarded as average quality, with a mostly even split of remaining plots between good and bad. In both countries, a majority of farmers classify their soil type as loam (though the percentage is higher in Tanzania), with the remaining plots split between clay and sandy soils.[13]

4.1. Question one: farmers' perceptions of soil fertility vs. inputs and yields

Table 4 displays the multiple pairwise comparisons of farmer-reported soil quality and type against agricultural inputs and maize yield levels. The mean values of maize yield are highest on good plots and lowest on bad plots in both Kenya and Tanzania. However, only in Kenya do we find that good plots produce statistically significantly higher yields and only relative to bad plots. Therefore, farmers either base their soil quality perceptions on the yield from their maize fields or report obtaining greater yields from plots they believe to have good soil quality; the causal direction of this relationship is not clear from the survey data or our analysis. Loam soils in Kenya have statistically significant higher yield values than do sandy soils.

When looking at inputs used on maize plots, we find that Tanzanian farmers are far more likely to apply some amount of chemical fertilizer (e.g., DAP, urea) on their bad plots than on their good or average ones. This may be an indication that farmers try to improve the fertility of their bad plots through chemical fertilizer supplements or that farmers believe their good or average plots are sufficiently fertile. Average fertilizer application rates (column 4) displayed are conditional on use (column 1). We find no difference in binary or continuous chemical fertilizer use decisions based on farmer-perceived soil quality in Kenya. We find, however, that loam fields are more likely to receive chemical fertilizer than are sandy fields, likely because loamy soils have higher clay and CEC contents and therefore tend to be more responsive to fertilizer use (Lal, 2006). We also note that far more farmers in Kenya use chemical fertilizer than do farmers in Tanzania and, therefore, may feel less constrained in their decision to use fertilizer on any of their plots.

With respect to other agricultural inputs, we find that in Kenya good quality plots are more likely to receive herbicide or pesticide than bad plots, but this is not the case in Tanzania. Herbicides are often used to prepare land for planting (in lieu of time-consuming human-powered tilling), which could help to explain this finding. Most strikingly, we find that farmers do not vary their organic resource application based on perceptions of soil quality in either Kenya or Tanzania. Only with respect to farmer-reported soil type in Tanzania do we find any statistically significant difference; loam soils are more likely to receive organic resources than are clay soils, perhaps because soils high in clay already have relatively high

[13] For the purposes of our work, we drop all plots classified as "other" from the farmer-perceived soil type analysis. There is only a small percentage of plots in this category in both Kenya and Tanzania.

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Table 4
Question 1: Farmer-reported soil data vs. inputs, yield.

	Chemical fertilizer		Herbicides, pesticides		Organic resources		Conditional fertilizer		Maize yield	
	1 = yes		1 = yes		1 = yes		kg/ha		t/ha	
KENYA										
Soil quality, mean (st. err.)										
Good (n = 124)	0.50 (0.04)	a	0.19 (0.03)	a	0.64 (0.04)	a	137.97 (16.47)	a	2.07 (0.14)	a
Average (n = 262)	0.56 (0.03)	a	0.14 (0.02)	ab	0.66 (0.03)	a	144.08 (10.70)	a	1.73 (0.09)	ab
Bad (n = 123)	0.55 (0.04)	a	0.08 (0.03)	b	0.67 (0.04)	a	120.37 (15.72)	a	1.38 (0.14)	b
Soil type, mean (st. err.)										
Clay (n = 88)	0.57 (0.05)	ab	0.17 (0.04)	a	0.65 (0.05)	a	149.49 (18.42)	a	1.85 (0.16)	ab
Loam (n = 283)	0.60 (0.03)	a	0.14 (0.02)	a	0.67 (0.03)	a	128.07 (10.02)	a	1.83 (0.09)	a
Sandy (n = 124)	0.42 (0.04)	b	0.10 (0.03)	a	0.64 (0.04)	a	149.45 (18.06)	a	1.44 (0.14)	b
TANZANIA										
Soil quality, mean (st. err.)										
Good (n = 1152)	0.17 (0.01)	a	0.09 (0.01)	a	0.15 (0.01)	a	146.90 (12.5)	a	1.18 (0.04)	a
Average (n = 1050)	0.18 (0.01)	a	0.09 (0.01)	a	0.14 (0.01)	a	146.29 (11.13)	a	1.11 (0.05)	a
Bad (n = 158)	0.26 (0.04)	a	0.10 (0.03)	a	0.15 (0.03)	a	97.04 (17.47)	a	0.94 (0.11)	a
Soil type, mean (st. err.)										
Clay (n = 379)	0.21 (0.02)	a	0.10 (0.02)	a	0.10 (0.02)	a	129.90 (112.93)	a	1.10 (0.07)	a
Loam (n = 1536)	0.17 (0.01)	a	0.10 (0.01)	a	0.15 (0.01)	a	147.11 (160.79)	a	1.15 (0.04)	a
Sandy (n = 422)	0.20 (0.02)	a	0.07 (0.01)	a	0.16 (0.02)	a	133.46 (15.8)	a	1.01 (0.09)	a

Note: Analysis at plot level for 2011–2012 long rains season. 'Other' soil type is excluded. For Tanzania, observations are weighted using household sampling weights and maize yield variable is winsorized at the 99th percentile of the raw distribution. Common letters indicate values are not statistically different at the 95% confidence level using a Tukey-Kramer test, e.g., values both marked with "a" are not statistically significantly different from each other at the 95% confidence level.

Table 5
Question 2: Farmer-reported vs. AfSIS soil data.

	Carbon, C (% by weight)		Nitrogen, N (% by weight)		pH 1–7		CEC (meq/100 g)		Fertile soil** =1	
KENYA										
Soil quality, mean (st. err.)										
Good (n = 67)	2.24 (0.06)	a	0.25 (0.01)	a	5.74 (0.03)	a	24.42 (0.84)	a	0.75 (0.05)	a
Average (n = 173)	2.30 (0.04)	a	0.24 (0.00)	a	5.75 (0.02)	a	24.49 (0.53)	a	0.73 (0.03)	a
Bad (n = 68)	2.27 (0.06)	a	0.24 (0.01)	a	5.78 (0.03)	a	23.35 (0.84)	a	0.66 (0.05)	a
Soil type, mean (st. err.)										
Clay (n = 57)	2.34 (0.07)	a	0.25 (0.01)	ab	5.72 (0.03)	b	25.79 (0.91)	a	0.81 (0.06)	a
Loam (n = 166)	2.33 (0.04)	a	0.25 (0.00)	b	5.73 (0.02)	b	23.63 (0.54)	a	0.79 (0.03)	a
Sandy (n = 75)	2.12 (0.06)	b	0.23 (0.01)	a	5.82 (0.03)	a	24.17 (0.80)	a	0.52 (0.05)	b
TANZANIA										
Soil quality, mean (st. err.)										
Good (n = 1152)	1.67 (0.03)	a	0.12 (0.00)	a	6.12 (0.01)	a	14.50 (0.22)	a		
Average (n = 1050)	1.57 (0.03)	a	0.12 (0.00)	a	6.12 (0.01)	a	14.32 (0.23)	a		
Bad (n = 158)	1.46 (0.07)	b	0.12 (0.01)	a	6.06 (0.03)	a	12.69 (0.51)	b		
Soil type, mean (st. err.)										
Clay (n = 379)	1.80 (0.06)	a	0.13 (0.00)	a	6.08 (0.02)	b	14.48 (0.38)	a		
Loam (n = 1536)	1.62 (0.03)	b	0.12 (0.00)	a	6.15 (0.01)	a	14.74 (0.20)	a		
Sandy (n = 422)	1.36 (0.04)	c	0.11 (0.00)	b	6.04 (0.02)	b	12.11 (0.33)	b		

Note: Analysis at plot level for 2011–2012 long rains season. 'Other' soil type is excluded. For Tanzania, observations are weighted using household sampling weights and maize yield variable is winsorized at the 99th percentile of the raw distribution. Common letters indicate values are not statistically different at the 95% confidence level using a Tukey-Kramer test, e.g., values both marked with "a" are not statistically significantly different from each other at the 95% confidence level.

nutrient contents. As organic soil amendments help to rebuild degraded soils, it is of concern that farmers do not appear to differentiate organic resource application based on perceived soil quality, especially since most organic resources are generated from on-farm sources (not market-purchased).

4.2. Question two: farmers' perceptions vs. objective measures of soil fertility

Keeping in mind the limitations of the AfSIS data detailed above, Table 5 provides results of statistical tests comparing the AfSIS data to farmers' perceptions of soil quality for both Kenya and Tanzania. We find limited correspondence between farmer-perceived soil quality and AfSIS soil data in Kenya. However, soil characteristics vary significantly across the farmer-reported soil types. Soil pH, for example, is lowest (more acidic) on plots with clay soils: 5.72 relative to 5.82 on plots with sandy soils. The pattern is similar for the measurements of soil organic carbon, total nitrogen, pH, and CEC from the soil analysis data in Kenya (Table A3 in the Appendix).

In addition, we find statistically significant relationships between our indicator for fertile[14] soils and soil type in Kenya.

[14] Fertile soil is defined as soil with organic carbon content greater than or equal to 2% w/w, total nitrogen content greater than or equal to 0.2% w/w, and pH greater than or equal to 5.2.

Eighty-one percent of plots with fertile soils correspond to plots with farmer-perceived clay soils while only 52 percent of plots with fertile soils correspond to plots with farmer-perceived sandy soils. Distinctions among soil textures, thus, appear to be the main correlates for soil fertility classification in Kenya.

The picture is somewhat different in Tanzania (Table 5), where we only have objective measurements of soil organic carbon, total nitrogen, pH, and CEC from the AfSIS data. While farmer-perceived soil type remains the main correlate for the differences in objective measurements, plots with better soil quality, as reported by farmers, also have statistically significantly higher carbon content and CEC. Average soil organic carbon content on plots with good soil quality, for example, is 1.67% w/w versus 1.57% w/w for plots with average soil quality and 1.46% w/w for plots with bad soil quality. As the variability between the means is relatively small (as it is in Kenya), the bigger sample perhaps increases statistical significance.

Moving to multivariate analysis so as to ascertain whether the above correlations hold up when controlling for plot and household characteristics, the mean marginal effects of the ordered probit estimations for Kenya and Tanzania are presented in Table 6. Farmers' perceptions in Kenya do not statistically correspond to the chemical measurements of soil fertility indicators; in Tanzania, plots perceived to be good have higher soil organic carbon, supporting Table 5. Marginal effects on maize yield are statistically significant and positive with good soils and negative with bad soils, in both countries. This offers further evidence that farmers' perceptions of soil fertility are correlated with maize yield (similar result seen in Table 4), even when controlling for plot and household characteristics; however, the magnitudes of the marginal effects

Table 6
Question 2: Factors affecting farmers' soil fertility perceptions (marginal effects).

	Kenya		Tanzania	
Variables	(1) Bad soil	(2) Good soil	(3) Bad soil	(4) Good soil
Soil organic carbon (% w/w)	0.0292	−0.0287	−0.0138***	0.0433***
	(0.0501)	(0.0493)	(0.00411)	(0.0126)
Soil CEC (meq/100 g)	−0.00260	0.00256	−0.000333	0.00105
	(0.00399)	(0.00394)	(0.000519)	(0.00163)
Maize grain yield (t/ha)	−0.0499***	0.0491***	−0.00000541**	0.0000171**
	(0.0153)	(0.0147)	(0.00000234)	(0.00727)
Chemical fertilizer: 1 = yes	0.132***	−0.130***	0.00797	−0.0251
	(0.0487)	(0.0479)	(0.00850)	(0.0267)
Herbicides, pesticides: 1 = yes	−0.0591	0.0582	−0.00596	0.0188
	(0.0613)	(0.0603)	(0.0110)	(0.0346)
Organic resources: 1 = yes	0.0438	−0.0431	−0.00722	0.0227
	(0.0408)	(0.0401)	(0.00896)	(0.0282)
Improved seeds: 1 = yes	0.0391	−0.0385	−0.0112	0.0353
	(0.0559)	(0.0551)	(0.00991)	(0.0311)
Plot size (ha)	0.00444	−0.00436	−0.00148	0.00466
	(0.0123)	(0.0122)	(0.00163)	(0.00512)
Own plot: 1 = yes	−0.161*	0.158*	0.00832	−0.0262
	(0.0895)	(0.0889)	(0.00954)	(0.0300)
Soil erosion: 1 = yes	0.0779*	−0.0767*	0.0228***	−0.0719***
	(0.0401)	(0.0395)	(0.00854)	(0.0265)
Slope: 1 = gentle	−0.0186	0.0182	−0.00648	0.0204
	(0.0395)	(0.0386)	(0.00663)	(0.0208)
Slope: 1 = steep	−0.0499	0.0533	0.0133	−0.0419
	(0.118)	(0.142)	(0.0159)	(0.0499)
Distance from home (km)	−0.0107	0.0106	−0.552	1.739
	(0.0474)	(0.0467)	(0.395)	(1.239)
Plot altitude (km)	−0.0563	0.0554	0.0365***	−0.115***
	(0.0827)	(0.0814)	(0.00712)	(0.0210)
Intercropped: 1 = yes	−0.00584	0.00575	−0.00450	0.0142
	(0.0459)	(0.0452)	(0.00623)	(0.0196)
Household head female: 1 = yes	0.0338	−0.0333	−0.0101	0.0319
	(0.0536)	(0.0527)	(0.00756)	(0.0237)
Household head age	0.000532	−0.000524	0.0000671	−0.000211
	(0.00134)	(0.00132)	(0.000225)	(0.000707)
Household head years of education	−0.00151	0.00149		
	(0.00473)	(0.00466)		
HH education: 1 = some primary or adult			0.00299	−0.00942
			(0.00905)	(0.0285)
HH education: 1 = completed primary			0.0119	−0.0374
			(0.00842)	(0.0264)
HH education: 1 = more than primary			−0.0209	0.0657
			(0.0142)	(0.0444)
Household size (adult equivalents)	−0.00621	0.00611	0.00190	−0.00599
	(0.00822)	(0.00809)	(0.00141)	(0.00442)
Herd size (TLU)	−0.00197	0.00194	−0.000861	0.00271
	(0.00756)	(0.00744)	(0.000541)	(0.00169)
Crop income (USD)			−0.0000142	0.0000447
			(0.0000104)	(0.0000326)
Observations	307	307	2360	2360

Note: Standard errors in parentheses. ***p < .01, **p < .05, *p < .1. First column for each country captures the mean marginal effect of each variable on changing farmer's perception from average to bad soil; the second column captures the mean marginal effect on changing farmer's perception from average to good soil. Soil variables are from AfSIS.

are very small. In the case of Kenya, farmers are also less likely to apply chemical fertilizer on plots perceived to have higher soil quality and more likely where soil quality is considered low and plots owned by the household are perceived to have better soils. In both countries, farmers are less likely to report good soils where they report erosion and vice versa.

Farmers' perceptions of soil quality, therefore, seem to be strongly associated with soil erosion and, as seen above, farmer-reported yields across the two samples. As indicated above, the direction of the soil quality and yield relationship cannot be determined from the data we have available. This indeterminate causal relationship may pose endogeneity concerns for the estimation of agricultural production or profit functions. Therefore, absent more information or an exogenous instrument, one must exercise caution when predicting yields based on farmers' perceptions of soil fertility.

4.3. Question three: high resolution, publicly available soil data vs. researcher-collected plot-level soil data

We find significant differences at the plot, village, and data set levels between the AfSIS data and the plot-level soil analysis data in Kenya. By construction, the AfSIS data show less variation than the soil analysis data; they also suggest different summary statistics than the soil analysis data. Table 7 displays the correlation coefficients for the two data sets. While many coefficients are statistically significant ($P < .05$), they are only high for the two stable indicators of soil fertility (0.68 for soil pH and 0.55 for soil CEC). For the two indicators that can vary over time due to both exogenous factors and endogenous management decisions, organic carbon and total nitrogen, we see much lower correlation between the two data sets. The higher correlation between the stable indicators and the lower correlation between the indicators subject to change over time is as we would expect for the full data set.

The correlation pattern is also readily observed graphically (Fig. 2). The AfSIS data track the soil analysis data, with the soil analysis data showing more variation overall. However, the differences are significant enough to reject most (52 of 64) t-tests of the equivalence of means between the two data sets at the data set and village levels (Table 8). The notable exceptions are again the more stable soil fertility indicators—soil pH and CEC—where, in each case, four of 16 t-tests show that the equivalence of means cannot be rejected. The differences observed across the two data sets in terms of average soil organic carbon and total nitrogen content at both the village and data set level may be partially explained by the differences in sampling periods, as these soil characteristics are subject to change. However, pH and CEC, more stable indicators of soil fertility, are also different for 13 and 12 (out of 15), respectively, villages in the survey and across the full sample for soil pH. The only metric not statistically distinguishable between data sets at the full sample level is CEC.

When comparing the analyses involving the Kenya data, the AfSIS and soil analysis data do exhibit similar patterns when broken down by subjective soil quality and type measures (Tables 5 and A3). We find in both the AfSIS and soil analysis data statistically significant differences in soil type (texture) by soil chemistry. However, in moving from the general pattern to the details of the analysis, we again find serious differences between the AfSIS and soil analysis data. In particular, the difference in CEC by soil texture is not observed in the AfSIS data, and the statistically significant discernments of soil texture by soil chemistry differ between the two data sets.

We conclude that these statistically significant differences at the plot, village, and data set levels justify collection of plot-level soil data for laboratory analysis despite the availability of AfSIS data when precise plot-level soil data are important for the analysis at hand (e.g., providing context-specific recommendations to farmers) and especially when the soil chemistry is subject to change over time and with farmer investment (i.e., organic carbon and nitrogen).

4.4. Question four: role of soil information

Finally, we consider the role of soil fertility information in a production function framework. Table 9 shows the results of a Cobb-Douglas production function for Kenya and Tanzania. The first and fifth columns of the table show estimated coefficients of the specification without any soil information. The subsequent columns represent the same basic model but add soil information: first farmer-reported soil data, then, in the case of Kenya only, the plot-level soil analysis data (soil organic carbon and CEC), and then AfSIS data (soil organic carbon and CEC). We examine the role of the soil information in three ways: we assess whether and to what extent inclusion/exclusion of the different types of data produce (1) changes in the magnitude and significance of coefficients when soil variables are included, (2) changes in the average of predicted maize yield, and (3) changes in the average predicted marginal physical products (MPP) of fertilizer.

The coefficients on two input variables (labor and chemical fertilizer, normalized by land area) are positive, statistically significant, and stable across all specifications. The relative magnitudes and significance levels of the control variables (not shown but available by request) are similarly unchanged. The addition of soil variables does not alter the magnitude of the coefficients on the

Table 7
Question 3: Pairwise correlation coefficients between soil analysis and AfSIS data for the four soil characteristics in Kenya.

		Soil analysis data				AfSIS data			
		C	N	pH	CEC	C	N	pH	CEC
Soil analysis data	C	1.00							
	N	0.96*	1.00						
	pH	0.13	0.07	1.00					
	CEC	0.80*	0.75*	0.43*	1.00				
AfSIS data	C	0.30*	0.23*	-0.48*	0.06	1.00			
	N	0.37*	0.29*	-0.29*	0.25*	0.82*	1.00		
	pH	0.11	0.10	0.68*	0.33*	-0.47*	-0.35*	1.00	
	CEC	0.47*	0.37*	0.26*	0.55*	0.39*	0.58*	0.31*	1.00

Note: Bonferroni-adjusted significance levels of 0.05 or less. N = 307 maize plots.

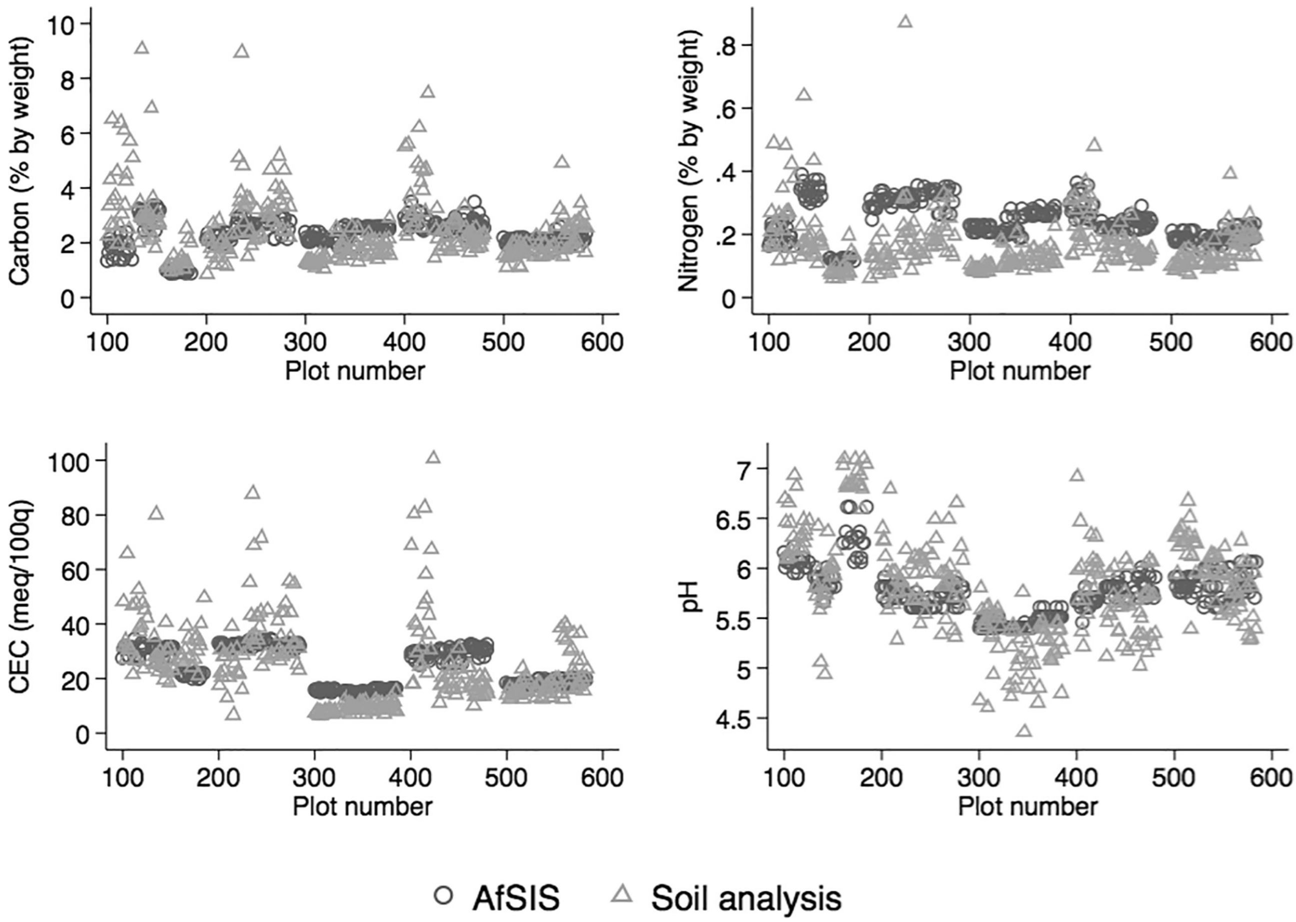

Fig. 2. Question 3: Soil analysis vs. AfSIS data by plot across the four soil characteristics in Kenya: organic carbon, total nitrogen, pH, and CEC.

Table 8
Question 3: Test of equivalence of means between soil analysis and AfSIS data in Kenya.

		Soil organic carbon		Soil nitrogen content		Soil pH		Soil CEC	
Village	Obs	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
Bumira B	21	8.49	0.00	21.77	0.00	6.09	0.00	14.98	0.00
Chamakanga	20	18.68	0.00	45.08	0.00	0.99	0.34	56.53	0.00
Chepkitin B	21	6.41	0.00	13.57	0.00	4.05	0.00	14.61	0.00
Jeveleli	21	3.22	0.00	8.58	0.00	4.74	0.00	18.28	0.00
Kagai	21	-1.82	0.08	2.94	0.01	-5.34	0.00	-2.46	0.02
Kanyibana A	17	-4.38	0.00	3.01	0.01	-10.62	0.00	-6.69	0.00
Kanyilaji B	21	6.35	0.00	14.80	0.00	-7.01	0.00	2.26	0.04
Kasagoma B	21	-3.09	0.01	3.25	0.00	2.36	0.03	-3.52	0.00
Kures	21	-4.36	0.00	8.98	0.00	-1.88	0.08	-1.99	0.06
Lelmolok A	20	3.09	0.01	7.94	0.00	2.35	0.03	6.09	0.00
Nyangera B	21	0.08	0.94	2.67	0.01	-1.96	0.06	0.46	0.65
Ogwedhi B	20	2.72	0.01	18.41	0.00	-2.60	0.02	4.99	0.00
Ratunwet	21	-6.70	0.00	-2.18	0.04	-6.80	0.00	-3.26	0.00
Tabet B	21	-0.70	0.49	5.53	0.00	0.38	0.71	0.36	0.72
Tulwet West	21	-3.78	0.00	1.88	0.07	-3.55	0.00	-3.41	0.00
All villages	308	-2.24	0.03	15.44	0.00	-2.65	0.01	-0.17	0.87

Note: Highlighted values indicate failure to reject statistical difference between soil analysis and AfSIS data.

Table 9
Question 4: Cobb-Douglas maize production function.

	Kenya				Tanzania		
Variables	(1) No soil	(2) Farmer-reported	(3) Soil analysis	(4) AfSIS	(5) No soil	(6) Farmer-reported	(7) AfSIS
LN (Labor (days/ha or adult equivalents))	0.275***	0.274***	0.280***	0.310***	0.369***	0.369***	0.366***
	(0.0807)	(0.0786)	(0.0777)	(0.0801)	(0.0206)	(0.0206)	(0.0206)
LN (Fertilizer (kg/ha))	0.0616*	0.0802**	0.0667**	0.0551*	0.113***	0.112***	0.114***
	(0.0329)	(0.0325)	(0.0321)	(0.0309)	(0.0164)	(0.0164)	(0.0164)
Perceived soil quality: 1 = average		0.155				0.0222	
		(0.111)				(0.0945)	
Perceived soil quality: 1 = good		0.448***				0.0804	
		(0.149)				(0.0982)	
Soil carbon (% by weight)			0.266***	0.240			0.0851
			(0.0775)	(0.172)			(0.0681)
Soil CEC (meq/100 g)			−0.0184***	0.0615*			0.0110
			(0.00692)	(0.0336)			(0.00934)
Constant	4.525***	4.392***	5.246***	4.085***	5.450***	5.431***	5.312***
	(1.242)	(1.224)	(1.144)	(1.331)	(0.313)	(0.329)	(0.353)
Observations	307	307	307	307	2358	2358	2358
R-squared	0.309	0.333	0.344	0.334	0.377	0.377	0.379
AIC (BIC)	750 (832)	743 (833)	738 (827)	743 (832)	6658 (7950)	6658 (7955)	6653 (7950)
Predicted yield (t/ha)	1.47 (0.05)	1.49 (0.05)	1.49 (0.05)	1.48 (0.05)	0.84 (0.02)	0.84 (0.02)	0.84 (0.02)
MPP fertilizer (kg/ha) conditional on use	1.85 (0.18)	2.41 (0.24)	2.00 (0.20)	1.66 (0.16)	2.54 (0.29)	2.53 (0.28)	2.58 (0.29)
MPP fertilizer for bad soils		1.95 (0.37)				1.71 (0.27)	
MPP fertilizer for average soils		2.27 (0.25)				2.95 (0.57)	
MPP fertilizer for good soils		3.53 (0.92)				2.27 (0.25)	
MPP fertilizer for soils with soil carbon <2			1.64 (0.25)	3.14 (0.66)			2.55 (0.31)
MPP fertilizer for soils with soil carbon ≥2			2.21 (0.27)	1.56 (0.17)			2.69 (0.77)

Note: Dependent variable = LN (Maize yield (kg/ha)). Other variables include plot altitude (km), herd size (TLU), female household head, household head age and education, indicator variables for intercropping, use of improved seeds, use of herbicides or pesticides, use of organic resources, plot ownership, soil erosion, plot slope, distance from home (km), household size (adult equivalents) for Kenya, and geographic controls (block dummies for Kenya and enumeration area and district dummies for Tanzania). Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. Yield predictions adjusted under assumption of normally distributed errors following Wooldridge (2012). In Kenya, estimation includes only plots with measured soil data. In Tanzania, estimation includes household-level sampling weights.

input variables substantially or considerably increase the models' fit, as represented by the R-squared values. However, the Akaike information criterion (AIC) values are lower for the models that include soil information than the AIC for the model without any soil information in Kenya (Table 9). More importantly, the AIC is lowest for the model that includes soil analysis data—having objective plot-level soil information improves the fit of the production function.[15]

The mean and standard error of the predicted maize yields and of the calculated marginal physical products of fertilizer, conditional on use, across all observations are reported in the bottom rows for all specifications. In neither Kenya nor Tanzania does including soil information of any type considerably change the mean of predicted yields or the magnitude of the standard errors. The estimated average MPPs of chemical fertilizer in Kenya, however, are different (statistically significant) across the four specifications in Kenya. The average values of MPP across different plot groupings—for plots with farmer-reported bad, average and good soil quality in the model with subjective soil information and for plots with low (less than 2% w/w) and high (greater or equal to 2% w/w) soil carbon in the models with objective soil information—are also different. Differences in estimated MPP at the plot level are shown in Fig. 3, where the distribution of MPPs within Kenya is explored for each model. The left panel shows the MPPs across the four model specifications that include control variables at the maize plot level across the Kenya data set, while the right panel zooms in on three villages in the Mid Nyando region (20 percent of the sample). For low values of MPP (less than five kilograms per hectare), the plot-specific MPP is nearly the same across the models; for higher values of MPP, however, the MPP calculated with different soil information differs. The use of farmers' perceptions in the estimation of MPP produces the most extreme values, followed by the soil analysis data, and no soils data; the AfSIS data produces the most conservative estimates across the board. Those plots with more extreme values also show a greater spread (variation) between estimates, suggesting that there is more noise in the extreme values overall (which we would expect from a regression coefficient). If we treat the soil analysis data as the "truth" in this setting, then farmers' perceptions offer an overestimate of the return to fertilizer and AfSIS data offer an underestimate (these differences are also statistically significant on average).

The caveats to this discussion are considerable, however. Estimation of the production function offers regression to the mean. While most soil fertility indicators (objective and subjective) are positive and statistically significant for both Kenya and Tanzania, they are small in magnitude and in Kenya correspond to soils with relatively low empirical variation. Therefore, the addition of any soil variables is unlikely to result in vast differences in estimates derived from the underlying models, at least with the methods currently employed and when analyzed in similar contexts (good soils, low empirical variation, and when prediction focuses on sample averages). However, having plot-level soil information from soil analysis improves the overall fit of the production function estimation and results in different average values of marginal physical products with our data in Kenya. Since we do not observe variation across time and are unable to control for other sources of unobserved household or plot-level heterogeneity that could bias our estimates, we are cautious to draw definitive conclusions from our estimates of the Cobb-Douglas production function. Moreover, the role of measurement error in our estimates may be non-trivial: for example, the data on yields is gathered via recall and not direct measurement and we combine all chemical fertilizer together, instead of separating by type or nutrient.

What we can conclude, however, is that when the focus is on specific plots or households, having detailed and accurate soil data

[15] Vuong's (1989) likelihood ratio test for equivalence of explanatory power in non-nested models confirms this results with the data from Kenya.

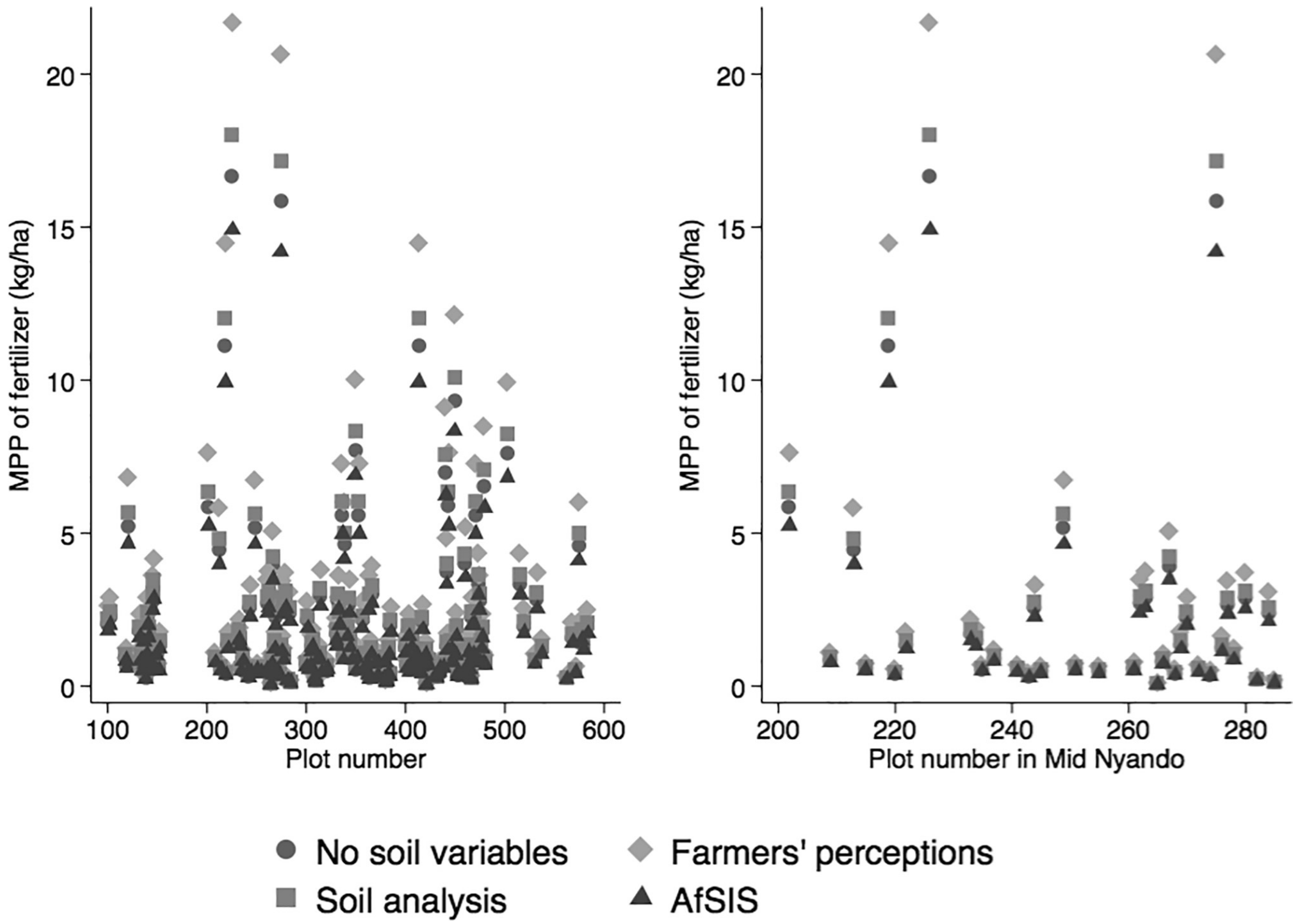

Fig. 3. Question 4: Increase in maize yield in response to one additional kilogram of fertilizer (estimated MPP of fertilizer) after the Cobb-Douglas production function with no soil variables, farmers' perceptions, soil analysis, and AfSIS soil variables for all plots in the Kenya data set and for plots in the three villages in Mid Nyando.

still matters. Using data from western Kenya that display a greater degree of soil fertility variation,[16] Marenya and Barrett (2009b), for example, find that crop production functions can exhibit von Liebig-type responses. Maize yield response to nitrogen fertilizer in their data depends on the state of soil fertility, and below some threshold the input applications are not profitable.

While the soil data did not significantly change the estimated coefficients or the R-squared values of maize production function in our two data sets, our results do not suggest that there is not a place for fine-grained soil data in agricultural research. First, by including soil information we at least partially mitigate the omitted variable bias since farmers most likely take soil information into consideration when deciding on their input use. Second, soil information changes the plot-level values and the averages of MPP of fertilizer. Such fine-grained detail provided in plot-level soil analysis data is needed to perform mechanistic and processes-based research at the plot or individual farm scales, whereas high spatial resolution estimated soil data, such as that provided by AfSIS, may be sufficient to meet the needs of those researchers interested in production functions on the country-wide or regional scales. And while farmers' perceptions or misperceptions of soil fertility may not alter all the conclusions of a production function analysis, this information can be incredibly informative to extension efforts that seek to identify and correct information gaps.

[16] Farms in this data set are sampled based on plot age (time since conversion from forest to agriculture) to capture cultivation time and, therefore, the degree of soil fertility degradation.

5. Conclusion

With a renewed appreciation for soil fertility in the international development community, particularly in Sub-Saharan Africa, this paper takes stock of the types of soil information currently available to researchers, using data from east Africa. In summary, we find that farmers' perceptions of soil fertility are more correlated with maize yields than with agricultural inputs and that these correlations hold up even when we control for plot and household characteristics. Farmers either base their soil quality perceptions on the yield from their maize fields or report obtaining greater yields from plots they believe to have good soil quality. Other than herbicides and pesticides in Kenya (greater application on good plots) and chemical fertilizers in Tanzania (greater application on bad plots), farmers are not responding to perceived soil quality with more or fewer inputs. We find few observable plot and household level characteristics that are correlated with soils assessment. In addition, our results suggest that the AfSIS data may be useful to the researcher who is interested in relatively stable soil fertility indicators—soil pH and CEC—at an aggregate scale; however, we find enough statistically significant differences at the plot, village, and data set levels to justify collection of plot-level soil data for laboratory analysis when precise plot-level soil data are important for the analysis at hand (e.g., providing context-specific recommendations to farmers) and especially when the soil chemistry is subject to change over time and with farmer investment (i.e., organic carbon and nitrogen). At the same time, the role of soil information in the estimation of simple agricultural production functions appears limited when focusing on averages and when performing the analysis in a setting with good soils and low empirical variation. However, our data from Kenya show that including plot-level measured soil information improves the overall fit of the production function and results in different values of the marginal physical product of fertilizer.

Overall, we conclude that we have much more to learn about farmers' subjective soil fertility assessments and we caution against using these assessments analytically (as not to introduce endogeneity) when more objective metrics, especially plot level soil samples, are available. But we should not stop asking these questions of farmers either. Our analysis has also only considered cross-sectional evidence and described statistical associations. However, given that farmers' perceptions can be learned and that even objective measures vary over time, particularly when and where nutrients are not added back to the soil, a dynamic analysis of any of these correlations could provide even more utility to our disciplines.

Moreover, we cannot exclusively rely on single experiment data or small samples to answer questions about the how farmers make judgments about their soil fertility. We need a major research effort to understand how farmers value and use soil information. In addition, there is continued need for survey modules that dig deeper into how subjective soil fertility perceptions are formed. Investments should be simultaneously made in (1) understanding the actual learning process farmers use to arrive at their soil fertility distinctions and (2) educating and informing farmers about soil fertility and helping them make their input and other management decisions using this knowledge. From the policy makers' stand point, there is need to invest in development of efforts that map soil fertility with more accuracy and in dissemination and use of these data by extension agents and agricultural practitioners, so that farmers and those interacting with them have the most accurate soil information possible. As time goes on, we hope to see a better convergence of farmer knowledge with objective soil fertility metrics, more reliable soil information data sets, and more personalized extension services and systems.

Additionally, questions remain about whether information on soil fertility would alter farmers' behavior in terms of inputs and cropping decisions. In other words, is soil information a limiting constraint to farm management in Sub-Saharan Africa? Investigation into such a question will also enable us to study what farmers do with soil knowledge—does it help improve their farm decisions and, ultimately, yields and welfare measures? Or are farm management decisions informed via some other process? Experimental or quasi-experimental studies, for example, could include a soil chemistry information treatment to assess farmers' willingness to pay for objective soil information and subsequent collection of panel data could help track changes (if any) in farmers' input and cropping decisions. Such studies could help identify the causal linkages between farmers' perceptions, their management

Table A1
Summary statistics.

	Kenya						Tanzania					
Variable	Mean	Std. Dev.	Min	10%	90%	Max	Mean	Std. Dev.	Min	10%	90%	Max
Household head female: 1 = yes	0.19	0.39	0.00			1.00	0.23	0.42	0.00			1.00
Household head (HH) age	51.29	15.48	20.00	31.00	72.00	90.00	49.18	15.59	18.00	30.00	72.00	98.00
HH years of education	6.73	4.54	0.00	0.00	13.00	18.00						
HH education: 1 = none							0.27	0.45	0.00			1.00
HH education: 1 = some primary or adult							0.20	0.40	0.00			1.00
HH education: 1 = completed primary							0.46	0.50	0.00			1.00
HH education: 1 = more than primary							0.07	0.25	0.00			1.00
Household size (adult equivalents)	6.02	2.44	1.00	3.00	9.00	13.00	4.70	2.61	0.72	1.88	7.96	26.32
Crop income (USD)							266	316	−1312	23	673	2040
Maize grain yield (t/ha)	1.77	1.41	0.02	0.38	3.57	8.34	1.07	1.30	0.00	0.13	2.53	5.47
Herd size (TLU)	2.35	2.74	0.00	0.03	5.60	17.66	2.38	6.38	0.00	0.00	5.87	39.00
Own plot: 1 = yes	0.95	0.21	0.00			1.00	0.88	0.32	0.00			1.00
Soil erosion: 1 = yes	0.45	0.50	0.00			1.00	0.14	0.35	0.00			1.00
Slope: 1 = flat	0.49	0.50	0.00			1.00	0.63	0.48	0.00			1.00
Slope: 1 = gentle	0.49	0.50	0.00			1.00	0.33	0.47	0.00			1.00
Slope: 1 = steep	0.02	0.15	0.00			1.00	0.04	0.20	0.00			1.00
Plot altitude (km)	1.61	0.33	1.21	1.25	2.21	2.25	1.04	0.52	0.01	0.31	1.67	2.16
Distance from home (km)	0.12	0.43	0.01	0.02	0.17	6.29	3.79	8.39	0.00	0.00	9.00	70.00
Plot size (ha)	1.92	1.86	0.05	0.37	4.42	14.35	1.23	2.36	0.00	0.12	2.68	39.26
Intercropped: 1 = yes	0.76	0.43	0.00			1.00	0.65	0.48	0.00			1.00
Chemical fertilizer: 1 = yes	0.59	0.49	0.00			1.00	0.19	0.39	0.00			1.00
Organic resources: 1 = yes	0.66	0.47	0.00			1.00	0.13	0.34	0.00			1.00
Herbicides, pesticides: 1 = yes	0.13	0.34	0.00			1.00	0.09	0.29	0.00			1.00
Improved seeds: 1 = yes	0.61	0.49	0.00			1.00	0.11	0.31	0.00			1.00
Perceived soil quality: 1 = bad	0.22	0.42	0.00			1.00	0.07	0.25	0.00			1.00
Perceived soil quality: 1 = average	0.56	0.50	0.00			1.00	0.44	0.50	0.00			1.00
Perceived soil quality: 1 = good	0.22	0.41	0.00			1.00	0.49	0.50	0.00			1.00
Perceived soil type: 1 = sandy	0.24	0.43	0.00			1.00	0.18	0.38	0.00			1.00
Perceived soil type: 1 = loam	0.54	0.50	0.00			1.00	0.65	0.48	0.00			1.00
Perceived soil type: 1 = clay	0.19	0.39	0.00			1.00	0.16	0.37	0.00			1.00
AfSIS: Soil carbon (% by weight)	2.28	0.51	0.85	1.80	2.85	3.45	1.59	0.89	0.54	0.79	2.98	5.53
AfSIS: Soil total nitrogen (% by weight)	0.24	0.06	0.11	0.17	0.33	0.39	0.12	0.06	0.03	0.06	0.19	0.47
AfSIS: Soil CEC (meq/100 g)	24.21	6.91	14.00	15.50	32.00	34.00	13.67	6.34	5.38	7.36	23.22	40.48
AfSIS: Soil pH (1–7)	5.75	0.23	5.40	5.45	6.05	6.60	6.09	0.41	5.05	5.63	6.52	8.14
Soil analysis: Soil carbon (% by weight)	2.43	1.23	0.83	1.29	3.81	9.05						
Soil analysis: Soil total nitrogen (% by weight)	0.16	0.09	0.06	0.09	0.26	0.87						
Soil analysis: Soil CEC (meq/100 g)	24.33	15.20	6.33	8.43	42.87	100.37						
Soil analysis: Soil pH (1–7)	5.81	0.52	4.35	5.18	6.46	7.09						

Note: N = 307 plots in Kenya and 2360 plots in Tanzania. Maize plot is the land area under maize cultivation (including the area where maize is intercropped with legumes); 1 TLU is equivalent to 250 kg of animal body mass (0.7 cattle or 0.1 sheep/goat). For Tanzania, maize yields and distance from home are winsorized at the 99th percentile of the raw distribution.

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Table A2
Within vs. between variation in subjective soil quality (farmer-reported): Household and village for Kenya and household and enumeration area (EA) for Tanzania.

	Plots		Households			Villages/EAs		
Soil quality	Number	%	Number	% between	% within	Number	% between	% within
Kenya: 312 households, 15 villages								
Good	124	24	98	32	75	15	100	25
Average	262	51	201	64	85	15	100	51
Bad	123	24	91	29	75	15	100	24
Total	509	100	390	125	80	45	400	33
Tanzania: 1566 households, 292 EAs								
Good	1152	49	839	54	92	258	88	57
Average	1050	44	764	49	91	258	88	57
Bad	158	7	126	8	81	93	32	23
Total	2360	100	1729	110	91	592	203	49

Note: There are 1.63 maize plots per average household and 33.93 maize plots per average village in Kenya. There are 1.51 maize plots per average household and 8.08 maize plots per average enumeration area in Tanzania.

Table A3
Kenya: Farmer-reported vs. plot-level soil analysis data.

	Carbon, C (% by weight)		Nitrogen, N (% by weight)		pH 1–7		CEC (meq/100 g)		Fertile soil** =1	
Soil quality, mean (st. err.)										
Good (n = 67)	2.56 (0.15)	a	0.17 (0.01)	a	5.85 (0.06)	a	25.26 (1.86)	a	0.22 (0.05)	a
Average (n = 173)	2.42 (0.09)	a	0.16 (0.01)	a	5.81 (0.04)	a	24.29 (1.16)	a	0.19 (0.03)	a
Bad (n = 68)	2.32 (0.15)	a	0.15 (0.01)	a	5.78 (0.06)	a	23.59 (1.85)	a	0.18 (0.05)	a
Soil type, mean (st. err.)										
Clay (n = 57)	2.86 (0.16)	b	0.19 (0.01)	a	5.90 (0.07)	a	30.65 (1.95)	b	0.40 (0.05)	a
Loam (n = 166)	2.34 (0.09)	a	0.16 (0.01)	ab	5.68 (0.04)	b	21.89 (1.15)	a	0.16 (0.03)	a
Sandy (n = 75)	2.27 (0.14)	a	0.15 (0.01)	b	6.02 (0.06)	a	24.23 (1.70)	a	0.12 (0.04)	b

Notes: Analysis at plot level for 2011–2012 long rains season. 'Other' soil type is excluded. Common letters indicate values are not statistically different at the 95% confidence level using a Tukey-Kramer test, e.g., values both marked with "a" are not statistically significantly different from each other at the 95% confidence level.

practices, and actual soil fertility to start addressing soil and human poverty dynamics.

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Appendix A

Table A1 shows summary statistics for the data used in our estimation.

Table A2 reports the variation between good, average, and bad perceived soil quality within and between plots, households, and villages in Kenya and enumeration areas (EAs) in Tanzania. The first panel of Table A1 indicates the number and percentage of plots that have been designated by their farmers as good, average, or bad in Kenya and Tanzania. In Kenya we see that little over half (51 percent) of the total plots in the data set are perceived as average while there is an even split between good and bad (24 percent each). In Tanzania, nearly half the plots are perceived as good (49 percent) and 44 percent are perceived as average. Only seven percent are perceived as bad. To better understand the source of the variation in perception, the next panels decompose soil quality designation by between and within differences among households and villages/EAs. We observe much greater variation within villages/EAs rather than within households in both Kenya and Tanzania. For example, of the households that report at least one maize plot with good quality in Tanzania, 92 percent of plots within the same household are also deemed to have good soil. On the other hand, of the EAs where someone has declared their soil as good, 57 percent of plots within that same EA have plots with good soil quality. The same applies to the average and bad classifications too.

Similar to Table 5, Table A3 displays the multiple pairwise comparisons of farmer-reported soil quality and type with soil carbon, nitrogen, pH and CEC from the AfSIS soil data.

References

Abdulai, A.-N., & Abdulai, A. (2017). Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. *Environment and Development Economics, 22*(02), 177–201.
Antle, J. M., Stoorvogel, J. J., & Valdivia, R. O. (2006). Multiple equilibria, soil conservation investments, and the resilience of agricultural systems. *Environment and Development Economics, 11*, 477–492.
Arslan, A., & Taylor, J. E. (2009). Farmers' subjective valuation of subsistence crops: The case of traditional maize in Mexico. *American Journal of Agricultural Economics, 91*(4), 956–972.
Barrett, C. B., & Bevis, L. E. M. (2015). The self-reinforcing feedback between low soil fertility and chronic poverty. *Nature Geoscience, 8*(12), 907–912.

Berazneva, J., Lee, D. R., Place, F., & Jakubson, G. (2017). *Allocation and valuation of non-marketed crop residues in smallholder agriculture: The case of maize residues in Western Kenya* Working Paper. Ithaca, NY: Cornell University.

Bui, E. (2010). Assessment of digital soil mapping products: independent ground-truthing is essential. In: *Proceedings of the 19th world congress of soil science: Soil solutions for a changing world, Brisbane, Australia, 1–6 August 2010. Working Group 1.3 Digital Soil Assessment*, 9th–12th ed. Institut fur Bodenforschung, Universitat fur Bodenkultur: International Union of Soil Sciences (IUSS).

Chivenge, P., Vanlauwe, B., & Six, J. (2011). Does the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. *Plant and Soil, 342*(1–2), 1–30.

Cozzolino, D., & Moron, A. (2003). The potential of near-infrared reflectance spectroscopy to analyse soil chemical and physical characteristics. *The Journal of Agricultural Science, 140*(01), 65–71.

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*(2), 482–488.

FAOSTAT (2017). *FAOSTAT Database Query*. Rome, Italy: Food and Agriculture Organization of the United Nations Statistics Division (FAOSTAT). http://www.fao.org/faostat/en/#home.

Greene, W. H. (2008). *Econometric analysis* (6th ed.). Upper Saddle River, N.J.: Prentice Hall.

Güereña, D. T., Kimetu, J., Riha, S., Neufeldt, H., & Lehmann, J. (2016). Maize productivity dynamics in response to mineral nutrient additions and legacy organic soil inputs of contrasting quality. *Field Crops Research, 188*, 113–120.

Hengl, T., Heuvelink, G. B. M., Kempen, B., Leenaars, J. G. B., Walsh, M. G., Shepherd, K. D., et al. (2015). Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. *PLoS ONE, 10*(6), 1–26.

Karltun, E., Lemenih, M., & Tolera, M. (2013). Comparing farmers' perception of soil fertility change with soil properties and crop performance in Beseku, Ethiopia. *Land Degradation & Development, 24*(3), 228–235.

Kimetu, J. M., Lehmann, J., Ngoze, S. O., Mugendi, D. N., Kinyangi, J. M., Riha, S., et al. (2008). Reversibility of soil productivity decline with organic matter of differing quality along a degradation gradient. *Ecosystems, 11*(5), 726–739.

Komba, C., & Muchapondwa, E. (2015). *Adaptation to climate change by smallholder farmers in Tanzania*. EfD DP 15-12. http://www.efdinitiative.org/sites/default/files/publications/efd-dp-15-12.pdf.

Lal, R. (2006). Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. *Land Degradation & Development, 17*(2), 197–209.

Lal, R. (2012). Climate change and soil degradation mitigation by sustainable management of soils and other natural resources. *Agricultural Research, 1*(3), 199–212.

Lehmann, J., & Kleber, M. (2015). The contentious nature of soil organic matter. *Nature, 528*(7580), 60–68.

Marenya, P. P., & Barrett, C. B. (2009a). Soil quality and fertilizer use rates among smallholder farmers in Western Kenya. *Agricultural Economics, 40*(5), 561–572.

Marenya, P. P., & Barrett, C. B. (2009b). State-conditional fertilizer yield response on western Kenyan Farms. *American Journal of Agricultural Economics, 91*(4), 991–1006.

Marenya, P. P., Barrett, C. B., & Gulick, T. (2008). *Farmers' perceptions of soil fertility and fertilizer yield response in Kenya* SSRN Scholarly Paper ID 1845546. Rochester, NY: Social Science Research Network.

Moebius-Clune, B. N., van Es, H. M., Idowu, O. J., Schindelbeck, R. R., Kimetu, J. M., Ngoze, S., et al. (2011). Long-term soil quality degradation along a cultivation chronosequence in Western Kenya. *Agriculture, Ecosystems & Environment, 141*(1–2), 86–99.

Mukhwana, E.J., & Odera, J. (2009). Best-bet comparison of soil fertility management recommendations in Western Kenya: Independent testing by NGOs. *10th KARI biennial scientific conference volume I.* Nairobi, Kenya: Kenya Agricultural Research Institute (KARI).

Niemeijer, D., & Mazzucato, V. (2003). Moving beyond indigenous soil taxonomies: local theories of soils for sustainable development. *Geoderma, 111*(3), 403–424.

Palacios-Lopez, A., & Djima, I. Y. (2014). *Land areas in the LSMS-ISA country datasets: An application of multiple imputation (MI) methods*. Washington, D.C.: The World Bank (WB).

Recha, J. W., Johannes Lehmann, M., Walter, T., Pell, A., Verchot, L., & Johnson, M. (2013). Stream water nutrient and organic carbon exports from tropical headwater catchments at a soil degradation gradient. *Nutrient Cycling in Agroecosystems, 95*(2), 145–158. https://doi.org/10.1007/s10705-013-9554-0.

Sanchez, P. A. (2002). Soil fertility and hunger in Africa. *Science, 295*(5562), 2019–2020.

Sanchez, P. A., & Swaminathan, M. S. (2005). Hunger in Africa: The link between unhealthy people and unhealthy soils. *The Lancet, 365*(9457), 442–444.

Sheahan, M., & Barrett, C. B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy, Agriculture in Africa – Telling Myths from Facts, 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., & Soule, M. J. (1998). Soil fertility management in west Kenya: Dynamic simulation of productivity, profitability and sustainability at different resource endowment levels. *Agriculture, Ecosystems & Environment, 71*(1–3), 131–145.

Shepherd, K. D., & Walsh, M. G. (2002). Development of reflectance spectral libraries for characterization of soil properties. *Soil Science Society of America Journal, 66*(3), 988–998.

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), 1–19.

Sherlund, S. M., Barrett, C. B., & Adesina, A. A. (2002). Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics, 69*(1), 85–101.

Sparks, D. (Ed.). (1996). *Methods of soil analysis. Part 3, Chemical methods*. Madison, WI: Soil Science Society of America, American Society of Agronomy.

Stephens, E. C., Nicholson, C. F., Brown, D. R., Parsons, D., Barrett, C. B., Lehmann, J., et al. (2012). Modeling the impact of natural resource-based poverty traps on food security in Kenya: The crops, livestock and soils in smallholder economic systems (CLASSES) model. *Food Security, 4*(3), 423–439.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79*(1), 159–209.

Terhoeven-Urselmans, Ts., Vagen, T.-G., Spaargaren, O., & Shepherd, K. D. (2010). Prediction of soil fertility properties from a globally distributed soil mid-infrared spectral library. *Soil Science Society of America Journal, 74*(5), 1792–1799.

Tittonell, P., Vanlauwe, B., Leffelaar, P. A., Rowe, E. C., & Giller, K. E. (2005). Exploring diversity in soil fertility management of smallholder farms in western Kenya: I. Heterogeneity at region and farm scale. *Agriculture, Ecosystems & Environment, 110*(3–4), 149–165.

Tittonell, P., Vanlauwe, B., Leffelaar, P. A., Shepherd, K. D., & Giller, K. E. (2005). Exploring diversity in soil fertility management of smallholder farms in Western Kenya: II. Within-farm variability in resource allocation, nutrient flows and soil fertility status. *Agriculture, Ecosystems & Environment, 110*(3–4), 166–184.

Tully, K., Sullivan, C., Weil, R., & Sanchez, P. (2015). The state of soil degradation in Sub-Saharan Africa: Baselines, trajectories, and solutions. *Sustainability, 7*(6), 6523–6552.

TZNPS (2016). *Tanzania National Panel Survey (TZNPS). Year 2 (2010–2011)*. Tanzania National Bureau of Statistics (NBS), the World Bank. http://go.worldbank.org/OOLZL0UIR0.

Vagen, T.-G., Shepherd, K. D., Walsh, M. G., Winowiecki, L., Desta, L. T., & Tondoh, J. E. (2010). *AfSIS technical specifications: Soil health surveillance*. Africa Soil Information Service (AfSIS).

Vanlauwe, B., Six, J., Sanginga, N., & Adesina, A. A. (2015). Soil fertility decline at the base of rural poverty in Sub-Saharan Africa. *Nature Plants, 1*(7), 15101.

Vitousek, P. M., Naylor, R., Crews, T., David, M. B., Drinkwater, L. E., Holland, E., et al. (2009). Nutrient imbalances in agricultural development. *Science, 324*(5934), 1519–1520.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica, 57*(2), 307–333.

Wooldridge, J. M. (2012). *Introductory econometrics: A modern approach* (5th ed.). South-Western College Pub..