Modeling climate smart soil health investments in Sub-Saharan Africa

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Abstract

Investing in productivity-enhancing inputs is complicated by unknown *ex ante* economic returns that can vary widely over space and time. Nevertheless, decision makers in Sub-Saharan Africa must choose where to invest scarce agricultural budgetary resources. To assist decision makers with soil health investments, we estimate a fertilizer response model using an experimental crop trial metadataset (which includes around 20,000 observations spanning 18 countries and nine years) with geocoded rainfall and temperature data and newly available soil map data. We use a machine learning algorithm to select a heterogeneous fertilizer response model specification that performs well in predicting fertilizer response outside of the estimation sample. Using this fertilizer response model and a synthetic climate dataset, we simulate site-specific, forward-looking predictions of fertilizer response across Sub-Saharan Africa. The resulting profitability assessment tool allows decision makers to visualize the site-specific probability of achieving profitability objectives when climate conditions are unknown. We find that, while there are many sites where fertilizer use is likely to be profitable even where fertilizer is relatively expensive, there are also some places where fertilizer use is unlikely to be profitable even if fertilizer is relatively inexpensive. We explore the implications for decision makers who are designing and geographically targeting soil health interventions.

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1 Introduction

Three out of every four poor people in developing countries live in rural areas, and most of these people depend on agriculture for their livelihoods (World Bank 2008). African governments, NGOs, and the international community have responded to agriculture's importance within Sub-Saharan Africa (the region of the world where poverty remains the most concentrated) by investing heavily in agricultural development in recent decades. Despite large increases in investments, agricultural development budgets are still limited and decision makers must target these resources.

One way to resolve the difficulty of targeting is to develop better ways to identify interventions that are likely to be profitable. Defining profitability in the context of agriculture is not simple, though. Returns to input use are site specific, determined by soils, elevation, slope, prevailing climatic conditions, and crop management. Prices vary from site to site, with location and infrastructure quality determining the costs of procuring inputs at the farm level. Output prices are determined by local market conditions, depending on the balance of supply and demand, storage infrastructure, and transportation costs to other markets (Benin and Yu 2013). Furthermore, farmers must purchase inputs at the time of planting, before climatic conditions and output prices are known, forcing them to gamble on whether or not inputs will be profitable (Chavas and Holt 1996). In short, returns to agriculture are driven by spatial heterogeneity in growing conditions and uncertainty about climate conditions (Jayne and Rashid 2013).

In this paper, we develop a forward-looking profitability assessment tool that can be used to generate site-specific, probabilistic distributions of the returns to fertilizer use. Previous targeting efforts generally do not account for as many sources of spatial heterogeneity, nor do they account for uncertainty in weather realizations. Typical fertilizer response studies are location and time specific, meaning the conclusions of the study apply only to that location (or a very similar location) and if the weather repeats itself. We extend this approach by integrating extensive agronomic trial data with high resolution weather data and newly collected soil data to estimate the conditional yield response to inorganic fertilizer treatment in maize. We use a machine learning algorithm to identify the yield response model that performs best outside of the estimation sample.

To support investment planning and priority-setting in the face of climatic risk, we pair this fertilizer response model with a synthetic weather dataset to similate site-specific, *ex ante* fertizer profitability predictions across Sub-Saharan Africa. This forward looking tool allows users to visualize the probability of achieving a user-defined profitability objective, given stochastic realizations of climate conditions and heterogeneous growing conditions. Such a tool can play a central role in planning climate smart agricultural investments, especially as the underlying distributions for key climate variables are evolving with climate change (Burke, Lobell, and Guarino 2009).

We find that this *ex ante* profitability assessment, which explicitly incorporates probability-oriented and spatially explicit factors, leads to different profitability conditions compared to "business as usual." We define "business as usual" as taking regionally estimated responses to fertilizer (derived from experimental or observational studies) and valuing the costs and benefits according to recent prices. In about 70% of African sites where maize is grown, fertilizer profitability predictions do not change based on whether an *ex ante* or an *ex post* measure is used. However, in the remaining 30% of the sites, the *ex ante* profitability assessment is different than the *ex post* one. Decision tools like the one we have created can support policy planners' efforts to develop interventions that are robust in the face of climate uncertainty, and that account for the highly variable growing conditions present in their domains. With better decision tools, planners can make climate-smart agricultural productivity investments while more efficiently using limited resources.

2 Modeling Fertilizer Returns

The profitability of an agricultural technology is a key determinant of its adoption and use by farmers (Feder, Just, and Zilberman 1985). Holding all else equal, it is unreasonable to expect farmers to adopt a technology if the value of the increased output generated is less than the cost of the technology. The Value-to-Cost Ratio (VCR) is a single measure that incorporates the private benefits and costs that a farmer faces when using an input or technology (Equation 1). Here, the change in output for crop y is depicted by Δy. The input, in this case, is inorganic fertilizer applied in quantity q (f_q), as compared to no fertilizer use. The output price is p^y, and the fertilizer price is p^f.

$$VCR_y(f_q) = \frac{\Delta y \cdot p^y}{\Delta q \cdot p^f} \qquad (1)$$

While profitability is a very powerful concept in economic analysis, VCR is often used quite bluntly. Calculations of VCR are often based on aggregate area statistics or a few data points from model farms. This is problematic for several reasons. Profitability of input use varies systematically from site to site, with geographical features such as slope, aspect and elevation that influence temperature and precipitation; with underlying soil properties; with the farmer's transport costs, which affect farm gate prices for inputs and outputs; and over time, as management practices affect productive capacity. As a result of site-specific heterogeneity in the determinants of profitability, farmers who are located in agriculturally less favorable and remote locations will systematically face lower profitability than the regional average, while farmers in more favorable and less remote locations will face higher than average profitability. Decision-makers can refine their predictions of profitability by accounting for these geographical determinants of profitability. Because determinants of input use profitability, i.e., agricultural favorability and market access, are often correlated with socioeconomic variables such as poverty (Chamberlin and Schmidt 2012; Harou et al. 2013; Dercon and Christiaensen 2011), improved intervention targeting has both efficiency and distributional implications.

A second problem with profitability assessment is that it does not explicitly account for the uncertainty that farmers face when determining, in expectation, whether adopting a technology or input is likely to be profitable. It is important to recognize that farmers make their decisions in the presence of uncertainty regarding the marginal value of output that will result from use of a technology or input. Uncertainty can be found in crop responses depending on stochastic climate realizations and also in market fluctuations of input and output prices, since farmers generally do not know the market price they will receive for their crop at the time inputs are purchased. According to economic theory, farmers will optimally use less fertilizer when the output distribution faced is more variable

(Anderson and Hardaker 2003). Point estimates of profitability necessarily imply that the crop response and output prices are certain (Spielman, Kelemwork, and Alemu 2011; Morris et al. 2007). However, assessing profitability in this way is only helpful for determining *ex post* whether using an input was profitable. Since farmers do not have the benefit of hindsight when they must decide whether or how much to invest in an input, using a deterministic profitability measure, rather than a probabilistic one that incorporates uncertainty, could lead one to conclude that farmers are under-using a technology when they are not.

The limitations of VCR as a metric to predict input use profitability and input demand by farmers are well known to researchers. Often, researchers will account for shortcomings of the VCR measure by adjusting the target profitability threshold. That is, even though a VCR need only exceed 1 for use of technology to be profitable, researchers look for a VCR greater than 2 to be confident that the benefits of using an input outweigh the costs (Morris et al. 2007; CIMMYT Economics Program 1988). The assumption is that if the VCR is big enough on average, then profitability is robust, even though many farmers will have lower than average VCR, and risk may also play an important role in farmers' decisions. Our concept of robustness, by contrast, relates not only to how profitability, on average, compares to a threshold but also how uncertain that profitability outcome is. Given the same expected profitability, one would expect farmers to perceive a technology to be more robust if profitability falls below the threshold once every ten years compared to once every three years.

In Equation 2, we introduce a site- and year- specific value-to-cost ratio (VCR) for a representative farmer in location i at time t applying q quantity of fertilizer (f) at unit price p_{it}^{f} to crop y:

$$VCR_{it}^{y}(f_q, \bar{\theta}, X_i, \omega_{it}) = [y(f_q, \bar{\theta}, X_i, \omega_{it}) - y(f_0, \bar{\theta}, X_i, \omega_{it})] \cdot \frac{p_{it}^{y}}{q \cdot p_{it}^{f}} \tag{2}$$

$\bar{\theta}$ refers to a vector of inputs and technologies used (e.g., seeds, non-fertilizer inputs), X_i is a vector of time-invariant location conditions (soils, elevation, slope, etc.), and ω_{it} is a vector of climate variables in location i and period t. The VCR contains the expression for the average agronomic efficiency per kg of fertilizer applied compared with an application of zero fertilizer, $(y(f_q) - y(f_0))/q$.

In the *ex ante* framework, VCR is a random variable with probability distribution $f(VCR)$. The intent is not to study farmer behavior under risk, but to understand the distributional aspects of returns to fertilizer within a given location. Input use decisions, both regarding fertilizer use f_q and other inputs $(\bar{\theta})$, are determined exogenously in this framework, meaning that the fertilizer response function applies to a model farmer who is hypothetically assigned to either use or not use fertilizer, and the fertilizer use decision is not modeled. Within each location, VCR_i is a function of a vector of climate variables, ω_{it}. Prices (p^y_{it}) are assumed to be orthogonal to climate variables, which is consistent with grain price behavior in a small, open economy.

For a given profitability threshold T, we will evaluate robustness according to the probability that VCR is expected to exceed that threshold. This can be derived from the cumulative distribution function for VCR in location i:

$$PR(VCR_i > T) = 1 - F(VCR_i(T)) \tag{3}$$

Because ω_{it} is a vector rather than a scalar, it makes sense to use a Monte Carlo approach to derive the CDF of VCR_i in each location, sampling from a synthetic climate dataset generated from historic precipitation and temperature data (ω) that spans all of the sites. We describe the process by which the synthetic weather data are generated in the next section.

2.1 Understanding fertilizer response

In order to estimate the CDF of VCR in a given location, we must first estimate the parameters of a representative farmer's production function, $y(\cdot)$. Of particular interest is the extent to which crops' response to fertilizer, $y(f_q) - y(f_0)$, varies with site characteristics (X), with climate realizations (ω_{it}), and with the other technologies and management practices employed $(\bar{\theta})$. There is ample agronomic evidence, from Sub-Saharan Africa and other regions of the world, that the agronomic response to fertilizer depends on rainfall and temperature, soil conditions, technologies used, and other soil health practices (Yanggen et al. 1998; Vanlauwe and Giller 2006).

Soil organic matter (SOM) can influence soil structure, moisture retention, and nutrient retention in soil, which is important because applied nitrogen leaches readily through the soil profile, becoming unavailable to crops (Magdoff and Van Es 2000). Marenya and Barrett (2009) show that the yield response to fertilizer varies with SOM in Western Kenya. An intensive soil mapping effort in Ethiopia suggests low SOM levels in the highlands. Soil pH also influences nutrient retention and availability to plants, with fertilizer-SOM and fertilizer-mineral interactions typically weakened as soils become more acidic. Soil micronutrients generally become more soluble in acidic soils, which can increase their availability to crops (Sarkar and Wynjones 1982).

This spatial heterogeneity in precipitation is important to consider when assessing the returns to fertilizer in a given location. The majority of agriculture in Sub-Saharan Africa is rain-fed, and empirical evidence suggests that rainfall is the common yield-limiting factor among all major cereals (You et al. 2010). Haefele et al. (2006) show that fertilizer response decreases with increasing water stress during the growing season. To the extent that crop responses to soil health interventions are determined by rainfall levels, rainfall conditions in a single year will be a strong determinant of the profitability in that year of soil health interventions such as fertilizer application.

Temperatures also vary in space and are important determinants of crop growth. Lobell et al. (2011) show that there is a nonlinear response between temperature (growing degree days) and yields in African maize. Their results suggest that nitrogen application can help mediate the effects of heat stress. Using side by side comparison of fertilizer treated and non-treated on-farm experimental plots across a large sample of Malawi model farms over multiple growing seasons, Harou et al. (2017) find that fertilizer response varies with temperature and rainfall. Uyovbisere and Lombim (1991) repeat agronomic trials over multiple years and also find that fertilizer responses vary with rainfall and temperature.

2.2 Estimating parameters of a fertilizer response function

Because of the important interactions between fertilizer response, site-specific characteristics, management practices, and climate realization, empirical measurement of the fertilizer response requires estimating the parameters of a production function that is sufficiently flexible to allow for key interactions. Particularly, the production function should not be additively separable with respect to fertilizer use and the other variables – climate, location characteristics, and other technologies – or the specification will assume away the possibility of these interactions.

There are four typical approaches to estimating the parameters of a fertilizer response function. First, agronomic trials are commonly used to compare two plots with different fertilizer doses while holding all other variables constant. Some agronomic trials address a few additional management practices, such as crop variety or irrigation, through a factorial design. Measures of agronomic efficiency of fertilizer used on maize in East Africa exhibit a large spread. "High" responses are typically around 25 kg maize per kg nitrogen, while low responses are around 5 kg maize per kg nitrogen (Heisey and Mwangi 1997). Agronomic trials are typically characterized by very small sample sizes, low variation in climate and soil conditions, and a limited number of treatment doses from which a crop response curve can be derived.

It can be difficult to capture the interactions between fertilizer use and other variables using an agronomic trial dataset, either because the other variables are not recorded or because they do not vary across the observations. Though rainfall and temperature may not be recorded as part of an experimental study, they can be recovered from historical data by matching the location and time of the trial with historical climate data. However, one may not be able to confirm that supplemental water was not added to the crops under the trial. Furthermore, one cannot fully identify the contributions of different interactions between fertilizer and other variables to the local average treatment effect. The fertilizer response parameter, therefore, has limited validity outside of the trial setting. Furthermore, agronomic trial datasets are not well-suited for estimating parameters of a production function apart from the treatment effect on which the trial focuses.

Another concern about using agronomic trial data to estimate production function parameters is that, often, they are not conducted in locations that are representative of farmers' fields (Nelson, Voss, and Pesek 1985). Yield responses are typically higher in experimental stations than on farmers' fields (Yanggen et al. 1998). Higher use of complementary inputs, more intensive weeding, and optimal timing of planting and fertilization could bias fertilizer response upwards in experiment stations relative to farmers' fields (Heisey and Mwangi 1997). Studies have found nutrient responses often tend to be larger in "depleted" soils, where nutrients are limiting. If nutrients are more likely to be limiting on farmers' fields than on experiment stations, then the fertilizer response at experiment stations will be biased downwards relative to farmers' fields.

Model farm trials are a second source of data from which to estimate fertilizer response parameters. These trials typically involve side-by-side comparisons between fertilizer treatments on different farmers' fields. Usually, but not always, the crop production is managed by farmers rather than scientists supervising the studies. Fertilizer practices are randomly assigned at the farm level, and typically the farms cover varying soil and climate conditions, allowing one to estimate key parameters of the fertilizer response function. This was the approach followed by Harou et al. (2017). The main concern with these datasets is that model farmers do not represent the farming population as a whole. Typically, they are better educated, more closely tied in with the extension system, and may differ in other characteristics. Fertilizer response parameters generated from model farm trials tend to be smaller in magnitude than those from experimental trials (Yanggen et al. 1998). Another concern is that these trials typically run for one to two growing seasons, so it is difficult to separately identify the effects on production of time-invariant characteristics, such as soil type, from the effects of temperature and precipitation variation.

Observational farm surveys comprise a third source of data that can be used to estimate the parameters of a crop production function by exploiting crosssectional variation. The main challenge with this approach is that the decision to use fertilizer is not randomly assigned, and is likely correlated with unobservable farm and farmer characteristics, such as expected returns to fertilizer use and farmer ability, which then can bias the parameter estimates. Fertilizer response measures from observational data tends to be the smallest (compared to estimates based on agronomic trials or model farms) (Yanggen et al. 1998). A recent comparison of nitrogen use efficiency measures derived from surveys with those from agronomic trials in Malawi suggests that farmer management practices, such as weeding, crop rotation, and timing and intensity of inorganic fertilizer application, can explain why nitrogen responses are lower on farmer fields than in research stations (Snapp et al. 2014).

The last approach to estimating fertilizer response is through the use of a fully mechanistic crop growth model. These models are generally highly sensitive to their data inputs (e.g., timing of fertilizer application, daily rainfall and solar radiation). Furthermore, crop models are typically not calibrated to local conditions, which would require additional experimental or observational data anyway. Mechanistic crop models underlie estimates of returns to input use in the Global Agro-Ecological Zones assessments and the Harvest Choice platform (Guo, Koo, and Wood 2009; Fischer et al. 2012).

Drawing on the strengths and weaknesses associated with the different approaches available, we assemble a meta-experimental dataset, pairing individual trial data points with their respective rainfall, locational, and management practice control variables. We then use the meta dataset to estimate production function parameters, following Lobell et al. (2011). Thus our dataset spans a wide range of climate and soil conditions, allowing us to estimate the interactions between climate and soil conditions and fertilizer response. Because fertilizer treatment is experimentally assigned within these trials, we avoid bias arising from selection into fertilizer use, which would be an issue if the data came from observational datasets.

3 Data

We estimate the parameters of the crop response to fertilizer using the dataset of multiple maize trials across Eastern and Southern Sub-Saharan Africa compiled by Lobell et al. (2011). The dataset includes trials managed by the International Maize and Wheat Research Institute (CIMMYT), national agricultural research institutes, and private seed companies. The trials span 9 different years (1999-2007), 18 different countries, and 9 different agro-ecological zones. We focus on maize, which is the most widely grown crop in Sub-Saharan Africa, accounting for 27% of all cereal area, 34% of all cereal production, and 31% of all calories from cereals in the region (Smale, Byerlee, and Jayne 2013).[1]

The crop trials were conducted to test performance of new maize varieties in various conditions, and the metadataset was compiled in order to study maize response to water and temperature stress (Bänziger et al. 2006; Lobell et al. 2011). The data were not collected in order to estimate fertilizer response, although many of the varieties were tested under a low-nitrogen management regime, in which crops were planted on fields that were depleted of nitrogen due to continuous cropping of maize over previous seasons, removing all stover after previous harvests, and witholding application of organic and inorganic fertilizers. In optimal-management trials, the recommended amounts of nitrogen fertilizer were added. All other crop management practices were held constant between low-nitrogen and optimal-management trials.

Using the location of each experiment site, we match each crop trial observation with climate data. We use daily temperature and precipitation data at 0.25 degree resolution from the United States National Aeronautics and Space Administration (NASA) AgMERRA climate forcing dataset for agricultural modeling.[2] In the crop growth period, which we define as five months after planting

[1]This approach could be expanded to other crops with additional trial data.

[2]AgMERRA falls under the Agricultural Modeling dataset that is part of the Modern-Era Retrospective Analysis for Research and Applications effort. It can be accessed via: https://data.giss.nasa.gov/impacts/agmipcf/agmerra/

(Bänziger et al. 2006), we calculate monthly total precipitation and average temperature for each site. The third month generally coincides with flowering and silking, a period that is considered especially sensitive to water and temperature stress. For temperature data, we use the average monthly temperature, while for precipitation, we use the accumulated monthly precipitation.

We match the trial sites with soil data from the Africa Soil Information Service (AfSIS).[3] The 250 meter resolution soil data include estimates of several soil characteristics at different soil depths, such as soil cation exchange capacity, pH, texture, and water retention capacity. Finally, we match the trial data with Agro-ecological zone (AEZ) classifications from GAEZs.[4] In the estimation dataset, trial observations that fell under the low-pH, drought management, or streak virus management regimes were not included in the analysis. The fertilizer elimination treatment was extremely scarce under these management scenarios. [5]

The first two columns of Table 1 show mean descriptives for both no-fertilizer and optimal-fertilizer observations from the trial dataset. The third column shows the normalized difference between fertilizer treatments for each variable.[6] Yields in the no-nitrogen sites are 1.92 t/ha, about half of yields in optimally managed sites, which average 4.31 t/ha.

The no-nitrogen trial sites differ from the optimal fertilizer sites in climate and soil conditions. While the trial occurs over 123 different trial sites, the no-fertilizer treatment takes place in only 23 of those sites. On average, the sites that include no-fertilizer observations tended to be slightly warmer and slightly drier than the sites where low-nitrogen treatment was not used. To account for this imbalance, we estimated the probability that each site in the dataset included some no-fertilizer trial observations, using the site level mean temperature, precipitation,

[3]http://www.isric.org/content/african-soilgrids-250m-geotiffs

[4]These are accessed through the Harvest Choice platform, available at http://harvestchoice.org/maps/agro-ecological-zones-sub-saharan-africa.

[5]We lose 5,629 observations that are under low pH, drought, or maize streak management. The remaining estimation sample contains 20,513 observations.

[6]The normalized difference is the difference in average between the two groups scaled by the square root of the sum of variances across groups.

and soil characteristics as predictors. The summary statistics, re-weighted by the site-level predicted probability of conducting no-fertilizer trials, are depicted in columns 4-6 of Table 1.

After weighting observations by the site-level probability that the no-nitrogen treatment occurs at the site, the normalized difference between no-fertilizer and optimal-fertilizer sites for all variables is smaller than the 25% that would cause treatment effect estimates to be sensitive to model specification (Imbens and Rubin 2015). Even though the differences are statistically significant for almost all of the climate and soil variables, they are not especially large in magnitude. Because nitrogen treatment was experimentally assigned, rather than selected by farmers based on expected response, prior knowledge, or a financing constraint, a clean identification of the effect of nitrogen on crop growth is ensured.

Table 1: Summary statistics of model variables by fertilizer management strategy.

	No Fertilizer	Optimal Fertilizer	Normalized Difference	No Fertilizer (weighted)	Optimal Fertilizer (weighted)	Normalized Difference (weighted)
Yield (t/ha)	1.92	4.31	0.81	2.07	3.82	0.62
	(1.28)	(2.67)		(1.28)	(2.51)	
Fertilized plot (dummy)	0.00	1.00		0.00	1.00	
	(0.00)	(0.00)		(0.00)	(0.00)	
Temp months 1-2 (mean, $^\circ$ C)	22.78	22.26	-0.11	23.74	23.20	-0.14
	(3.59)	(3.14)		(2.87)	(2.73)	
Temp month 3 (mean, $^\circ$ C)	22.11	21.77	-0.07	22.98	22.58	-0.10
	(3.67)	(3.31)		(2.82)	(2.85)	
Temp months 4-5 (mean, $^\circ$ C)	20.45	20.33	-0.03	20.96	20.76	-0.05
	(3.38)	(3.03)		(2.57)	(2.69)	
Precip months 1-2 (tot, mm)	298.80	321.81	0.12	277.62	291.31	0.08
	(111.58)	(152.88)		(100.69)	(149.75)	
Precip month 3 (tot, mm)	158.59	144.75	-0.10	165.79	146.26	-0.13
	(97.83)	(107.50)		(107.29)	(108.70)	
Precip months 4-5 (tot, mm)	125.63	130.41	0.03	119.92	114.53	-0.03
	(115.27)	(119.25)		(110.57)	(109.65)	
Soil cation exchange capacity (centimol charge per kg soil)	11.94	12.60	0.06	11.02	11.73	0.08
	(7.42)	(8.62)		(5.79)	(7.38)	
Soil pH (pH determined in soil/water mixture)	5.92	5.99	0.11	6.00	6.06	0.10
	(0.43)	(0.42)		(0.41)	(0.41)	
Soil clay (share by volume)	0.35	0.27	-0.29	0.31	0.26	-0.23
	(0.22)	(0.13)		(0.20)	(0.11)	
Soil silt (share by volume)	0.15	0.16	0.10	0.15	0.15	0.09
	(0.06)	(0.07)		(0.04)	(0.05)	
Poor drainage (dummy)	0.13	0.17	0.06	0.13	0.18	0.08
	(0.34)	(0.37)		(0.34)	(0.38)	
N	2599	16164		2599	16164	

4 Results

In estimating the agronomic response to fertilizer use, we begin with a yield model specification that includes a full set of possible regression variables. In addition fertilizer use, we include soil characteristics (pH, cation exchange capacity, clay and silt content, and soil drainage), and precipitation and average temperature for three different periods within the growing season. We also include all possible interactions between these variables and second order polynomials for each continuous variable. Equation 4 depicts the full yield model, with X depicting the matrix of j explanatory variables, Y depicting yields in tons per hectare,[7] and F representing fertilizer use.

Optimal fertilizer management sites are assigned a fertilizer treatment dummy equal to one, while low-nitrogen management sites were assigned a fertilizer treatment dummy of zero. The design does not allow for estimating a continuous fertilizer dose effect on crop growth. It is, however, appropriate for estimating the binary impacts of adopting fertilizer at the level recommended by agronomists. In order to identify the heterogeneity of the response to fertilizer across different soil types and climate realizations, we interact the fertilizer treatment dummy with all of the other yield function variables.

$$Y_{it} = \beta_0 + \sum_j \beta_j X_{jit} + \sum_j \sum_k \frac{1}{2}\beta_{jk} X_{jit} X_{kit} + \beta_F F_{it} + \sum_j \beta_{Fj} F_{it} X_{jit} + \varepsilon_{it} \quad (4)$$

From the list of possible regressors specified in Equation 4, we use a stepwise leaps and bounds algorithm to select a subset of regressors based on the Akaike information criterion (Lindsey and Sheather 2013). In order to balance in-sample fit with out of sample predictive power, we use k-fold cross-validation to evaluate model performance. We divide our sample randomly into 5 partitions of roughly

[7]We estimate both the log-log version of the model (with log dependent variable and log independent variables) and the level-level form (with both dependent and independent variables in level form). The results are materially quite similar, and very few predicted yield values are negative, so we use the level form. The log form model is available on request

equal size, keeping all observations from the same site in the same partition. For each of the 5 partitions, we run a variable selection algorithm withholding that partition. Then we predict yields for the left out partition and calculate the root mean square error of predict yields for that left out sample. In each regression, we include, as weights, the predicted probability that the trial's site included some no-fertilizer trial observations, as described in the previous section.

We then have five possible models, one for each of the k data partitions.[8] For each model, we report the regression coefficients, the average RMSE for predicted yields when the model is estimated on each of the k partitions, and the average adjusted R^2 when that model is estimated on each of the five partitions. These parameters, as well as the in-sample and out-of-sample performance metrics, are shown in Table A.1. Table A.2 shows the parameter estimates when the selected model is run on the full trial dataset. Because trials occur in a limited set of sites, within which regressors are correlated, we wish to cluster our standard errors at the site level. We estimate a feasible generalized least squares regression, which is more efficient than an OLS model with robust standard error corrections. We also include site-specific weight reflecting the probability that the trial site includes some no-fertilizer observations. It is not possible to use our approach in a fixed effects modeling framework given that model selection relies on predicting yields in sites from a left out data partition. Furthermore, we would not be able to obtain coefficients for any time-invariant variables, such as soil characteristics, with a fixed effects model.

The marginal effects of the explanatory variables at the median values of the data are shown in Table 2 for each of the specifications described above. The standard errors are generated by repeatedly sampling parameter vectors from the variance-covariance matrix. At the median values of the variables, yields are decreasing in temperature in the beginning of the growing season and increasing in temperature in the middle end end of the growing season. When fertilizer is not used, the yield response to temperature is also decreasing in the early part of the

[8]The k^{th} data partition is the subset of the full dataset that excludes group k, so it includes 80% of the observations.

Table 2: Marginal effects at the dataset medians of explanatory variables (soil and climate characteristics) on yield, with and without fertilizer use.

	No Fertilizer Margin at data median	Fertilizer Margin at data median
Temp months 1-2 (mean, degrees C)	-0.1901	-0.3223
	(0.2980)	(0.8557)
Temp month 3 (mean, degrees C)	1.5149	0.0018
	(0.9212)	(0.9785)
Temp months 4-5 (mean, degrees C)	-1.0965	0.2657
	(0.7576)	(0.6093)
Precip months 1-2 (tot, mm)	-0.6175	0.0757
	(0.3646)	(0.1979)
Precip month 3 (tot, mm)	0.9611**	0.9594***
	(0.3006)	(0.2356)
Precip months 4-5 (tot, mm)	0.0467	0.0467
	(0.2384)	(0.2384)
Soil cation exchange capacity (centimol charge per kg soil)	0.7917	0.4947
	(1.3798)	(1.0584)
Soil pH (pH determined in soil/water mixture)	-0.3414	-0.1026
	(0.5553)	(0.3582)
Soil clay (share by volume)	0.5675	1.1104*
	(0.7726)	(0.5665)
Soil silt (share by volume)	0.7183	0.0179
	(1.1853)	(0.3981)

season and increasing in the middle of the season. However, at the end of the growing season, the yield response to temperature is negative when fertilizer is not used. The yield response to early season precipitation is positive when fertilizer is used and negative when it is not. The yield response to middle and late season precipitation is similar with or without fertilizer use (positive, and larger in magnitude in the middle of the season than at the end). Yields are more strongly increasing in soil clay content when fertilizer is used than when it is not. They are more strongly decreasing in soil pH when fertilizer is not used than when it is. They are more strongly increasing in soil silt content when fertilizer is not used than when it is not.

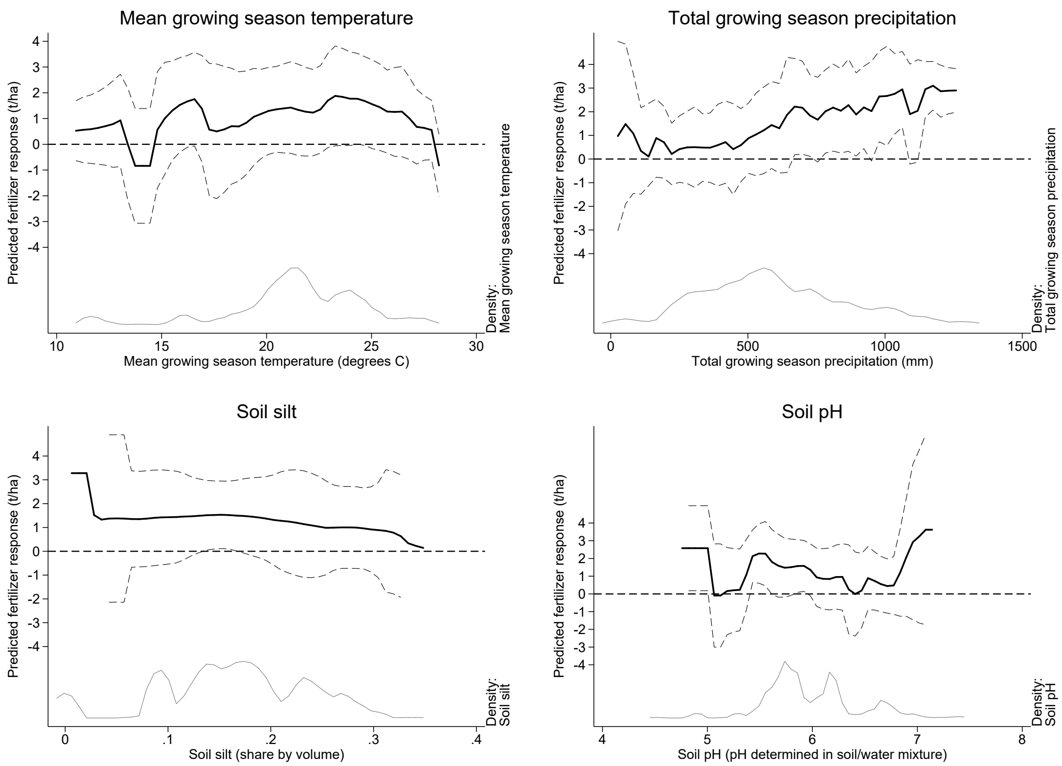
In order to better understand how fertilizer response varies under different growing conditions, we predicted the difference between an optimal-fertilizer yield and a no-fertilizer yield for each trial observation, holding all climate and soil characteristics to the values observed in the dataset. The predicted fertilizer response is then graphed non-parametrically over climate and site characteristics (Figure 1). The densities of the climate and site characteristics are depicted at the bottom of each graph. The graphs show that expected fertilizer response is roughly U-shaped over average growing season temperature and is increasing over growing season precipitation. The fertilizer response is positive and increasing, on average, when mean growing season temperature is between 17 and 22 degrees, and decreasing above that. When temperatures reach the high end of the distribution, above 23 degrees, the fertilizer response is decreasing in temperature. Expected fertilizer response is decreasing in soil silt content and decreasing over the majority of the soil pH distribution (between 5.5 and 7), and more variable at the tails.

Generally, fertilizer is considered a risk-enhancing input with respect to temperatue and precipitation. Using the trial dataset, we compare the coefficient of variation on yields between fertilized and non-fertilized sites by temperature and preciptation quantile (Table 3). This conventional wisdom is not supported by the data, which suggest that there is no clear pattern between yield variability of fertilized or unfertilized sites and temperature or precipitation (or their combination).

4.1 Predicting fertilizer response

Using the production function parameters estimated above, we next simulate the agronomic response to fertilizer across African geographies. We generate a gridded map of soil characteristics, AEZ, and maize planting date for Sub-Saharan Africa, masking out areas where maize is not grown or where the temperature and precipitation distributions fall outside of the range used to estimate the fertil-

Figure 1: Mean predicted fertilizer yield response over total growing season precipitation (top left), average growing season temperature (top right) soil pH (bottom left), soil silt content (bottom right).



izer response.[9] Then, for each African site, we generate a 200-year long synthetic climate dataset using each site's historical climate distribution. Using the planting date for each site, we create monthly growing season temperature and precipitation variable for each of the 200 growing seasons in the synthetic dataset.

For each site and year in the simulated dataset, we predict the agronomic response to fertilizer. Combining years in the synthetic climate dataset, we then generate a site-specific, probabilistic distribution of fertilizer response. For illus-

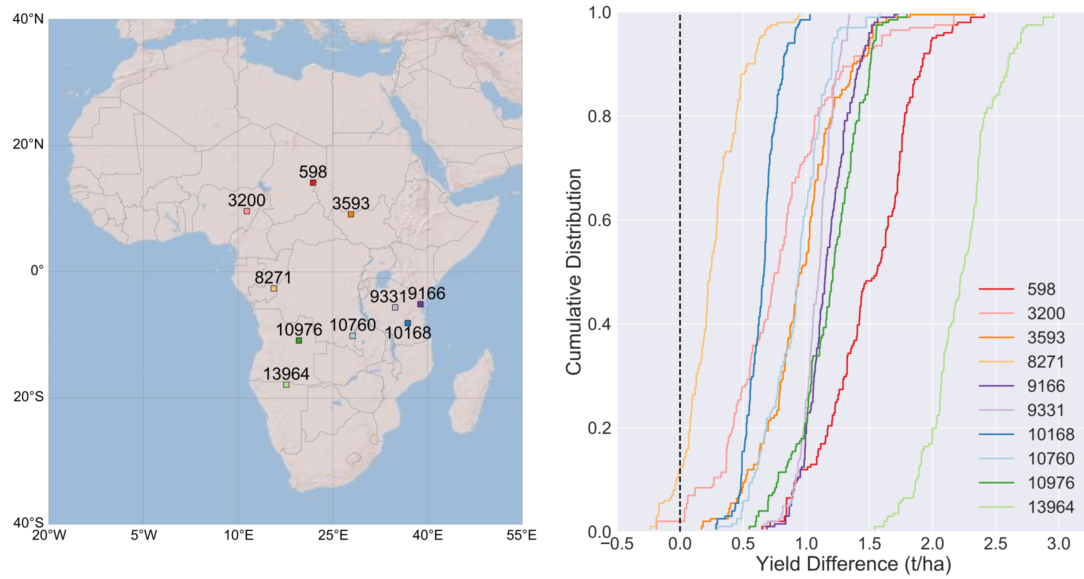
[9] We use Harvest Choice to screen out areas where maize is not grown, and the GAEZ dataset for maize planting date. We also screen out sites that have low probability of fertilizer elimination testing based on the criteria used to generate probability weights in the estimation dataset.

Table 3: Comparison between the coefficient of variation between fertilized and non-fertilized sites, by temperature and precipitation quantile.

			Average Temperature				
			Q1	Q2	Q3	Q4	Q5
Total Precipitation	Q1	No fert				26.27	56.34
		Optimal fert	72.54	48.49	79.64	44.98	62.35
	Q2	No fert	42.29			41.65	65.06
		Optimal fert	79.07	57.78	105.60	47.81	58.89
	Q3	No fert	46.74	51.55	50.98	54.09	
		Optimal fert	50.53	107.31	72.89	45.71	36.74
	Q4	No fert	58.25	59.82	39.72		
		Optimal fert	56.10	61.38	43.96	53.36	58.91
	Q5	No fert	44.37	46.14	26.19	39.57	33.28
		Optimal fert	37.05	36.32	29.47	42.49	47.28

trative purposes, Figure 2 depicts the cumulative distribution of the fertilizer response in 10 randomly selected locations in sub-Saharan Africa. The site locations are mapped in the left side of the figure. In two of the sites, the fertilizer response is predicted to be negative for at least some years. In the best site, the fertilizer response ranges from 1.5 t/ha in the worst year to 3 t/ha in the best year. In most of the years and most of the the sites, the fertilizer response ranges between 0.75 and 1.25 t/ha. The distribution of the fertilizer response is different in every site, due to fixed site differences in soil characteristics, the site-specific climate distribution, and interactions between the two.

Figure 2: The left figure depicts the location of 10 randomly selected sites in Sub-Saharan Africa. The right figure depicts the cumulative distribution of yield response to fertilizer over realizations of stochastic temperature and precipitation conditions for these 10 locations.



5 Fertilizer Profitability

Next, we turn to analysis of the profitability of fertilizer use. We convert the predicted yield difference described above into a value cost ratio (VCR) measure using an assumed fertilizer price and maize price.[10] We then analyze profitability, *ex ante*, according to properties of the distribution of the stochastic VCR variable (see Equation 5). For the purposes of this analysis, we assume that a farmer seeks

[10]We expect local and fertilizer prices to vary across sites due to transportation costs and local market conditions. For the sake of this profitability analysis, we ignore site- and even year- specific prices and assume a fertilizer price of $665 per MT and a maize price of $250 per MT.

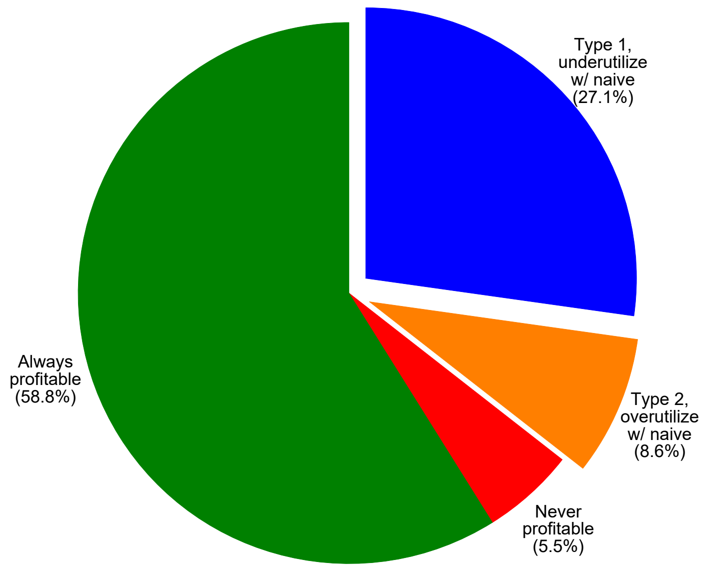
at least a 30% return on the fertilizer investment (T=1.3) at least 70% of the time (P=0.7).

$$1 - F(VCR = T) > P \tag{5}$$

We then characterize sites in Sub-Saharan Africa by whether the robust profitability criteria specified in Equation 5 are met and explore the implications for decision makers. For the sake of comparison, we define a "naive" profitability measure based on what is commonly used in practice – fertilizer use is deemed profitable if the average yield difference between fertilized and non-fertilized trial sites in the country is valued at least double the cost of the fertilizer. If trial data are not available in a given country, we use the average yield difference for trial sites in the same agro-ecological zone (AEZ). This measure is analogous to an *ex post* measure of profitability as commonly applied in the literature. After constructing a profitablility assessment for each site using both the naive and the robust definitions, we then compare the two assessments.

At the desired profitability incidence of 70%, we find that fertilizer use deemed profitable by both "naive" and "robust" criteria in the majority of sites in which maize is grown (Figure 3). In almost 60% of the sites, fertilizer use is profitable using both "naive" and "robust" criteria. In 5.5% of the sites, fertilizer use is profitable using neither "naive" nor "robust" criteria. In 8.6% of the sites, fertilizer use would be considered profitable according to "naive", *ex post* criteria, but not according to robust, *ex ante* criteria. In these cases, characterized by type 2 error, one might over-predict the returns to fertilizer use if one does not fully consider stochastic weather realizations. In about 27% of the sites, fertilizer use is considered profitable according to "robust", *ex ante* criteria but not "naive", *ex post* criteria. In these cases, a planner might under-predict the profitability to fertilizer use with the rule of thumb profitability measure. Because the very recent years tend to be worse, on average, than the full climate record, the Type 1 classification, characterized by under-estimation of fertilizer profitability using the naive

Figure 3: Comparison of profitability between two different criteria – "naive", based on the most recent climate realization in a site, and "robust", based on simulation of climated conditions.



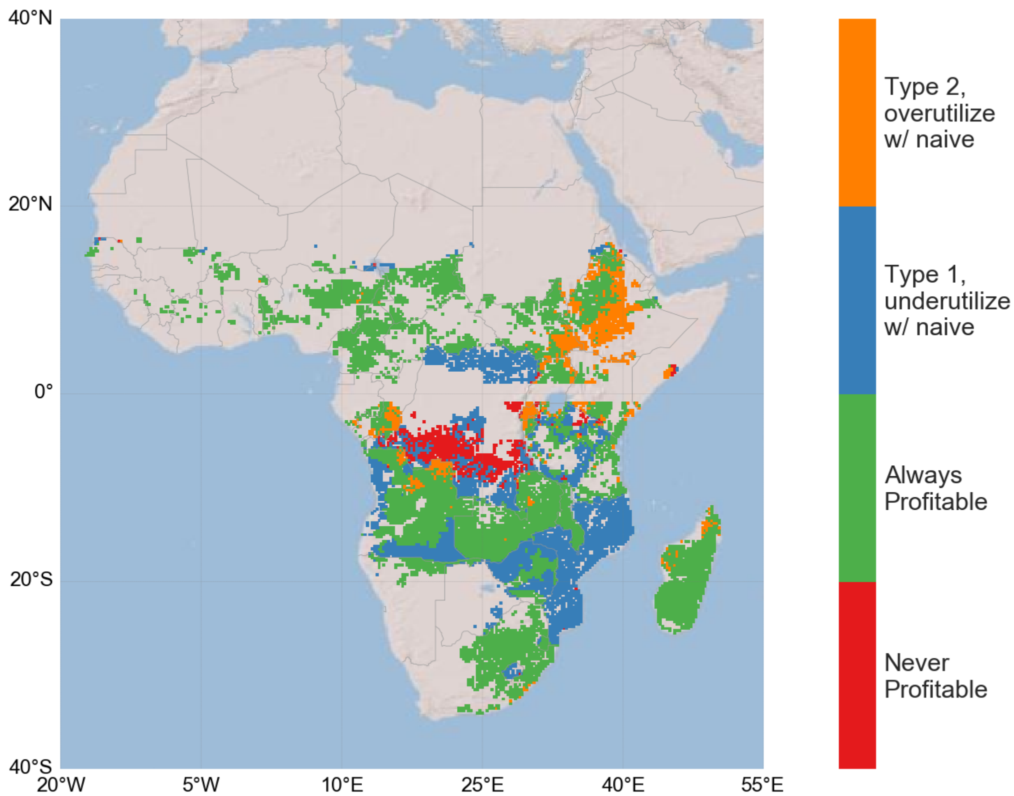
approach, is more common. [11]

We depict the spatial distribution of "robust" and "naive" profitability in Figure 4. The "never profitable" sites are concentrated in the Democratic Republic of the Congo. Sites that tend to be profitable according to either the robust or the naive criteria are found throughout the Sahel, the southern part of Central Africa, South Africa, and Madagascar. Sites where farmers are likely to over-utilize fertilizer based on very recent climate realizations tend to be concentrated in Ethiopia and around Lake Victoria, while sites where farmers are likely to under-utilize fertilizer if they are influenced by very recent climate realizations are spread throughout the region and are especially concentrated around Mozambique.

Next, given the difficulty in assessing site-specific prices for both maize and

[11] The implications of shifting trends in the underlying distributions of climatic variables are not considered in this analysis.

Figure 4: Map of site level profitability assessment according to the "naive" and "robust" criteria.



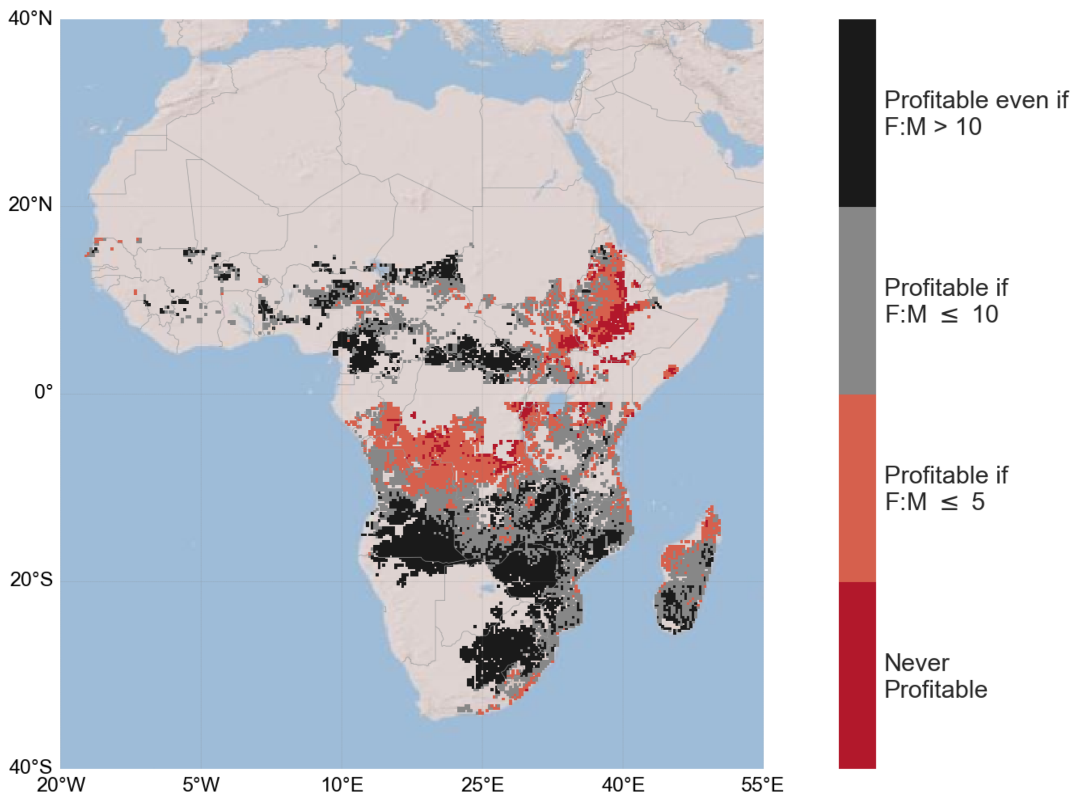
fertilizer, we consider what ratio between fertilizer and maize prices would be required in order for fertilizer use to be profitable according to the robust criteria. We solve for, and then map, the price ratio that ensures $VCR \geq 1.3$ in at least 70% of years (Figure 5). In a few sites fertilizer response is not predicted to be large enough in enough scenarios that profitability is achievable, no matter what the ratio between fertilizer and maize prices. These sites are concentrated in Ethiopia and in Central Africa. These sites give way to others where fertilizer use would be profitable only if fertilizer is priced very inexpensively, at less than 5 times the price of maize. We also highlight sites where fertilizer use would be profitable if the price ratio were between 5 and 10, which is a more realistic scenario. Finally, we show where fertilizer use is expected to be profitable even if fertilizer is very expensive – over 10 times as much as maize. In these sites (colored black), the profitability of fertilizer use is more robust to high fertilizer or low maize prices.

6 Conclusion

We have proposed a flexible approach to assisting decision makers in assessing the returns to soil health investments in the face of climate uncertainty and spatial heterogeneity. Predicted fertilizer response in an agronomic trial setting may not perfectly correspond with fertilizer responses that farmers will observe on their fields. However, it is nevertheless informative to explicitly examine the interactions between fertilizer response, climate realizations, and site characteristics. Our analysis indicates that, in many parts of the sub-continent, profitability is likely to be sensitive to the criteria by which decision-makers define profitability. In particular, by ignoring climate variability and soil characteristics in certain parts of the region, one could systematically underestimate the probability that a smallholders' investment in fertilizer won't pay off. Similarly, by fine-tuning our understanding of climate-fertilizer interactions, we can better target fertilizer use. By using the "rule of thumb" decision criteria, which assumes that responses that are large enough are robust, we would ignore sites characterize by smaller yet very reliable responses. It is important to better understand these criteria when calibrating decision support tools or fertilizer promotion programs.

This approach, as a platform, can be strengthened as more data become available. Additional fertilizer response trials in cool and dry regions would be especially useful, in order to extend the range of conditions under which fertilizer profitability can be reasonably predicted. Starting to trace out a continuous fertilizer response would also be quite interesting, as fertilizer response per kilogram

Figure 5: Map of the ratio between fertilizer and maize prices that would be required in each given site in order for profitability to be considered "robust."



applied is likely to be higher when fertilizer is applied at low quantities than at the full recommended dose. Understanding the continous fertilizer response will require a major effort to collect fertilizer dosing data over multiple sites and years.

One feasible expansion involves conditioning the synthetic climate data draw on underlying trends in the historical dataset, thereby incorporating climate change trends into the synthetic dataset used to forecast returns to fertilizer use. It is also possible to incorporate medium range climate forecasts, such as the ENSO signal, which is available at the time of planting, in order to help decision makers refine their predictions of fertilizer profitability in El Nino and La Nina years, when climatic patterns tend to differ (Korecha and Barnston 2007).

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Appendix

Table A.1: Selected model variables and parameters for all five dataset partitions. The parameter estimates depicted for each partition correspond with a regression that excludes that partition. The R^2 value shows the in-sample fit for each regression, and the RMSE shows the "out of sample" root mean square error of predicted yields for the left-out partition.

	K1 (Best)	(se)	**K2**	(se)	**K3**	(se)	**K4**	(se)	**K5**	(se)
precip p1	-0.260	0.532	-0.277	0.439	-1.044	0.335**	-0.382	0.333	-0.285	0.473
fert	2.155	0.295**	1.448	0.418**	1.042	0.428*	1.927	0.410**	1.663	0.318**
claypct x fert	3.030	0.760**	0.555	0.465	0.544	0.392	0.484	0.377	0.566	0.332
precip p2 x fert	0.323	0.276	0.528	0.235*	-0.314	0.410	0.037	0.208	-0.350	0.188
claypct x claypct	-5.526	1.273**	-0.897	0.322**	-1.314	0.278**	-0.734	0.428	-0.346	0.322
precip p2 x siltpct	0.832	0.362*	0.632	0.367	0.577	0.479	0.628	0.418	1.360	0.432**
claypct x siltpct	0.858	1.720	-0.101	1.221	-1.100	1.027	-3.683	1.604*	-0.236	1.253
precip p3 x siltpct	-2.797	0.833**	-0.945	0.526	-1.133	0.443*	-1.512	0.541**	-0.440	0.567
temp p3 x precip p3	-0.881	0.434*	-0.613	0.450	-0.726	0.680	-0.931	0.403*	-0.763	0.378*
temp p1 x precip p3	0.675	0.800	2.127	0.616**	1.716	0.819*	1.596	0.694*	0.540	0.850
temp p1 x temp p1	2.050	1.700	-0.485	1.277	0.106	1.706				
soilph x poordrain	3.172	1.371*	-0.022	1.966	2.325	2.805	-0.230	1.225	1.483	1.206
precip p3 x poordrain	3.302	1.350*			3.919	2.978	2.232	1.300	2.402	1.300
temp p1 x soilcec	-0.916	1.346	1.279	1.163	-0.520	1.461	-0.618	1.141	2.226	1.483
precip p3 x claypct	1.051	0.835	-0.221	0.162	-0.243	0.334	0.204	0.303		
precip p1 x poordrain	-0.291	0.603	-0.262	0.696	0.713	0.854	-0.439	0.705	0.303	0.555
soilph x soilph	0.635	0.261*	0.309	0.166	-0.131	0.219	0.202	0.196	0.304	0.193
soilph x fert	0.537	0.597			1.527	0.850			0.578	0.484
temp p1 x fert	-1.229	0.641			1.438	0.689*			0.201	0.855
claypct	-2.025	0.858*	1.924	0.821*	1.543	0.765*	0.520	0.820	-0.654	0.653
soilph x siltpct	-0.551	0.451	-0.363	0.384	-0.943	0.479*	-0.437	0.611	-1.075	0.635
temp p1 x soilph	-0.819	0.722	-1.120	0.778	0.040	0.986	-1.361	0.647*	-0.371	0.722
precip p3 x soilcec	0.802	0.584	1.030	0.683	0.763	0.628	1.123	0.704	0.340	0.608
claypct x poordrain	-10.349	5.288	-7.322	2.452**	-6.479	4.135	-3.919	3.192	-1.945	4.520
soilcec x claypct	3.204	1.559*	0.502	0.879	0.209	0.989	4.008	1.567*	1.327	1.126
temp p2 x temp p2	1.333	1.792	-1.027	2.108	-2.984	2.177	-1.177	1.696	-0.879	1.286
precip p1 x claypct	0.217	0.574	-0.455	0.312	0.476	0.277			0.688	0.341*
precip p1 x precip p3	-0.213	0.187	-0.151	0.175					0.521	0.233*
siltpct x fert	-0.545	1.002	-1.275	0.677	3.950	2.350			-1.496	0.840
poordrain	3.172	1.255*			4.593	3.056	2.613	1.006**	0.992	1.919
temp p2 x siltpct	-2.522	1.141*	-2.703	1.283*	-0.702	1.475	-4.155	1.780*	3.584	1.819*
temp p3 x siltpct	0.757	0.831	1.416	0.872	-1.061	0.898	1.099	1.257	-1.353	1.052
siltpct	-0.044	1.015			-5.017	2.140*	-0.053	0.698	3.103	0.760**
temp p3 x poordrain	-3.877	0.982**	-3.406	1.064**	-0.367	1.489	-1.346	1.467	-1.233	1.140
precip p2 x soilcec	-1.238	0.449**	-0.840	0.331*	-0.299	0.360	-0.850	0.355*	-1.193	0.385**
temp p2 x poordrain	4.009	1.590*	-1.707	2.079	-1.598	2.594	0.884	2.099	0.530	1.805

(continued on next page)

(continuation of Table A.1)

	K1 (Best)	(se)	**K2**	(se)	**K3**	(se)	**K4**	(se)	**K5**	(se)
soilcec x poordrain	4.229	1.466**	1.547	2.388	1.478	2.930	4.265	1.632**	0.605	1.632
siltpct x poordrain	-3.224	1.630*	1.530	1.164	0.710	2.638	-2.300	1.964	1.781	3.746
precip p1 x fert	0.643	0.557	0.665	0.419	1.109	0.347**	0.726	0.371	1.191	0.464*
soilcec x soilph	-0.571	0.721	0.191	0.650	1.608	0.563**	1.318	0.533*	0.519	0.622
precip p2 x soilph	0.348	0.300	0.636	0.256*	0.245	0.292	0.371	0.310	0.178	0.256
temp p2 x precip p2	0.173	0.776	-0.405	0.714	-0.723	0.722	0.455	0.695	-0.964	0.808
temp p3 x fert	0.389	1.178			-0.314	1.338	-0.410	0.316	1.624	0.739*
soilph	-0.870	0.547	0.866	0.280**	-1.333	0.995	0.621	0.368	-0.125	0.498
temp p2	-0.748	1.170	0.698	0.979	0.165	1.634	0.681	0.856	1.306	1.271
temp p2 x soilph	-0.164	0.759	1.214	1.022	0.423	1.115	1.790	0.695**	1.773	1.024
siltpct x siltpct	0.607	0.684	-0.489	0.543	0.466	0.881	0.600	0.750	-1.107	0.617
precip p1 x siltpct	0.579	0.435			0.166	0.523	0.420	0.494	-0.740	0.461
precip p2 x precip p2	-0.155	0.164			-0.149	0.183			-0.116	0.165
temp p3 x precip p2	0.896	0.609	0.242	0.471	1.254	0.522*	0.953	0.493	0.554	0.637
precip p3 x precip p3	0.104	0.115	0.063	0.076	0.101	0.110	-0.087	0.174	0.197	0.086*
precip p3	-0.181	0.252	0.090	0.261	0.367	0.529	-0.099	0.269	0.354	0.241
temp p1 x temp p2	-4.489	3.404	1.118	3.029	2.133	3.265	0.944	1.351	1.360	1.089
temp p1 x precip p2	-0.969	0.645	-0.037	0.805	-0.446	0.802	-1.011	0.625	0.727	0.806
temp p2 x precip p1	0.854	1.011	-0.171	0.629	0.987	1.113	1.288	0.673	0.935	0.896
temp p1 x precip p1	-0.541	0.662	0.494	0.535	-0.547	0.841	-0.464	0.581	-0.453	0.531
temp p3 x temp p3	0.030	0.217	-0.257	0.424	-1.096	0.567	-0.534	0.553	0.156	0.634
soilph x claypct	-0.185	0.607	0.625	0.487	-0.628	0.718	-0.804	0.794	-0.457	0.668
precip p2 x claypct	0.470	0.444	0.511	0.228*	0.121	0.231	0.608	0.262*	0.418	0.227
precip p1 x precip p1	0.085	0.112	-0.110	0.115	-0.011	0.158	0.162	0.147	0.125	0.163
temp p2 x precip p3	-0.564	0.696	-1.304	0.632*	-1.063	0.723	-0.638	0.700	0.321	0.841
precip p1 x soilph	0.218	0.246	-0.140	0.257	0.154	0.328	0.534	0.310	0.846	0.334*
soilcec x soilcec	-0.854	0.775	-1.554	0.953	-1.923	0.675**	-2.980	0.788**	-1.186	0.580*
temp p3 x claypct	0.206	1.281	-0.795	0.577	0.788	0.605	-0.137	0.846	-0.279	0.591
soilcec	1.833	1.213	-0.163	0.874	5.079	2.082*	0.958	0.921		
soilcec x fert	-1.440	1.201	1.021	0.597	-4.516	2.005*			-0.750	0.717
temp p1 x siltpct	1.327	1.420	0.724	1.083	0.748	1.522	1.916	1.306	-1.287	1.539
precip p2	0.300	0.375	0.111	0.252	1.083	0.454*	0.634	0.247*	0.717	0.351*
precip p2 x precip p3	-0.176	0.279	-0.073	0.169	-0.214	0.271	-0.400	0.207	-0.209	0.221
temp p3 x soilcec	0.491	0.790	-0.232	0.807	0.240	0.759	-0.912	0.808	1.164	0.830
temp p2 x claypct	0.398	1.663	5.613	1.891**	-1.253	1.510	4.249	1.999*	3.464	1.402*
temp p3	0.659	1.169	-0.172	0.450	0.284	1.291			-1.578	0.701*
temp p2 x fert	0.463	1.394			-0.633	1.673			-2.267	1.432
temp p1 x poordrain	-0.393	1.385	3.906	2.053	1.013	1.596				
precip p2 x poordrain	-0.139	0.583			-0.721	0.484	-0.573	0.440		
temp p3 x precip p1	-0.110	0.505			-0.431	0.508	-0.717	0.401	-1.026	0.627
precip p3 x fert			0.192	0.333	-0.361	0.607	0.391	0.385		
temp p1 x temp p3			-0.744	1.095	-3.032	1.160**	-1.496	1.202	-1.940	0.936*
precip p1 x precip p2			0.467	0.187*	-0.118	0.187	0.050	0.215	-0.309	0.306
fert x poordrain			0.955	0.868	-2.314	1.609			-0.552	0.860

(continued on next page)

(continuation of Table A.1)

	K1 (Best)	(se)	**K2**	(se)	**K3**	(se)	**K4**	(se)	**K5**	(se)
temp p2 x temp p3			0.703	1.640	3.965	1.791*	1.368	1.951	0.654	1.694
soilcec x siltpct			1.802	1.593	1.648	1.455	1.339	1.284	2.533	1.013*
precip p1 x soilcec			0.703	0.344*	-0.513	0.532	-0.023	0.478	-0.553	0.519
precip p3 x soilph			-0.551	0.287	-0.413	0.377	-0.470	0.315	0.648	0.416
temp p1 x claypct			-3.678	1.220**	-0.459	1.081	-2.244	0.907*	-0.642	0.778
temp p1			-1.112	0.804	-2.055	0.925*	-0.906	0.677	0.793	0.891
temp p3 x soilph			-0.158	0.350	-0.512	0.572			-0.836	0.553
temp p2 x soilcec			-1.173	1.707	0.782	1.534	0.552	1.625	-4.670	1.851*
cons	3.259	0.513**	4.216	0.643**	5.128	0.688**	4.065	0.647**	3.063	0.469**
RMSE (out)	0.347		0.380		0.370		0.370		0.381	
Parameters	77		78		85		75		81	

* $p < 0.05$; ** $p < 0.01$

Table A.2: Parameters of selected model estimated using full trial dataset.

	Coefficient	(se)
Precip months 1-2 (tot, mm)	-0.457	0.316
Fertilized plot (dummy)	1.543	0.363**
claypct x fert	0.550	0.496
precip p2 x fert	0.066	0.237
claypct x claypct	-0.789	0.275**
precip p2 x siltpct	0.673	0.320*
claypct x siltpct	-1.427	0.840
precip p3 x siltpct	-1.276	0.441**
temp p3 x precip p3	-0.634	0.390
temp p1 x precip p3	1.725	0.621**
temp p1 x temp p1	-0.570	1.316
soilph x poordrain	2.892	1.232*
precip p3 x poordrain	1.747	1.303
temp p1 x soilcec	-0.939	0.913
precip p3 x claypct	0.159	0.173
precip p1 x poordrain	0.495	0.546
soilph x soilph	0.113	0.157
soilph x fert	0.197	0.548
temp p1 x fert	-0.145	0.685
Soil clay (share by volume)	0.720	0.800
soilph x siltpct	-0.042	0.392
temp p1 x soilph	0.542	0.611
precip p3 x soilcec	0.647	0.507
claypct x poordrain	-8.575	3.481*
soilcec x claypct	1.731	0.717*
temp p2 x temp p2	-0.195	1.377
precip p1 x claypct	0.063	0.331

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(continuation of Table A.2)

	Coefficient	(se)
precip p1 x precip p3	0.116	0.155
siltpct x fert	-0.527	1.202
Poor drainage (dummy)	2.073	0.912*
temp p2 x siltpct	-0.536	0.642
temp p3 x siltpct	0.472	0.772
Soil silt (share by volume)	0.366	1.232
temp p3 x poordrain	-0.834	1.017
precip p2 x soilcec	-0.737	0.268**
temp p2 x poordrain	-1.450	2.087
soilcec x poordrain	1.336	1.126
siltpct x poordrain	-1.549	1.425
precip p1 x fert	0.709	0.341*
soilcec x soilph	0.705	0.441
precip p2 x soilph	0.316	0.225
temp p2 x precip p2	-0.525	0.683
temp p3 x fert	1.036	0.597
Soil pH (pH determined in soil/water mixture)	0.093	0.477
Temp month 3 (mean, degrees C)	0.795	0.883
temp p2 x soilph	-0.287	0.626
siltpct x siltpct	0.843	0.490
precip p1 x siltpct	0.130	0.382
precip p2 x precip p2	-0.089	0.146
temp p3 x precip p2	1.233	0.508*
precip p3 x precip p3	0.097	0.091
Precip months 4-5 (tot, mm)	0.215	0.267
temp p1 x temp p2	0.412	2.609
temp p1 x precip p2	-0.713	0.713
temp p2 x precip p1	0.909	0.771
temp p1 x precip p1	0.020	0.510
temp p3 x temp p3	-0.261	0.212
soilph x claypct	-0.593	0.485
precip p2 x claypct	0.340	0.224
precip p1 x precip p1	0.084	0.117
temp p2 x precip p3	-1.366	0.624*
precip p1 x soilph	0.166	0.227
soilcec x soilcec	-1.135	0.320**
temp p3 x claypct	0.224	0.453
Soil cation exchange capacity (centimol charge per kg soil)	0.698	1.082
soilcec x fert	-0.445	1.093
temp p1 x siltpct	0.380	0.967
Precip month 3 (tot, mm)	0.697	0.357
precip p2 x precip p3	-0.338	0.243
temp p3 x soilcec	-0.141	0.595
temp p2 x claypct	0.416	0.949

(continued on next page)

(continuation of Table A.2)

	Coefficient	(se)
Temp months 4-5 (mean, degrees C)	-0.871	0.667
temp p2 x fert	-1.071	1.057
temp p1 x poordrain	0.011	1.538
precip p2 x poordrain	-0.606	0.451
temp p3 x precip p1	-0.808	0.451

* $p < 0.05$; ** $p < 0.01$