Pre-analysis Plan - The impact of hyper-localized fertilizer recommendations based on site-specific soil tests: Experimental Evidence from Malawi

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Abstract

Raising agricultural productivity among smallholder farmers in Sub-Saharan Africa is widely recognized as an important component of inclusive wealth creation and structural transformation. Central to this endeavor will be the adoption of sustainable soil and land management to improve the sustainability, resilience and productivity of agriculture. As such, government advise farmers to increase soil productivity by embracing the use of fertilizers and implement proper soil health management practices. However, these recommendations mostly come in the form of blanket one-size-fits-all recommendations that ignore heterogeneity in soil characteristics that individual farmers face. Using a cluster randomize control trial, we evaluate the impact of a bundled intervention that involves offering farmers a soil test on a plot they select and, using the results of this soil test, provide them with tailored fertilizer recommendation and access to agricultural advice on the proper application of the recommended fertilizer to attain a desired yield for a particular crop the farmer chooses to plant on the plot. Furthermore, we also explore resources constraints as a potential barrier to the adoption of site specific fertilizer blends by providing a subsidy tied to the recommended fertilizer blend.

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O33, Q12,Q16

1 Introduction

Increasing agricultural productivity in Sub-Saharan Africa's smallholder farms is vital for inclusive economic growth and transformation. Sustainable soil and land management practices are essential for improving the sustainability, resilience and productivity of agriculture. The USAID Bureau for Resilience and Food Security (RFS) has led a partnership with the International Fertilizer Development Center (IFDC) and other partners to build a low-cost "Space to Place" (S2P) approach for developing and disseminating localized fertilizer guidance. The S2P approach revolves around the delivery of spatially appropriate soil fertility management recommendations, guided by digitized soil maps (Space) combined with farm(er)-level characteristics (Place), for effective agronomic and fertilizer recommendations that increase fertilizer use efficiency to maintain or surpass current productivity levels, and reduce fertilizer wastage.

IFPRI was tasked in 2023 to do a rigorous impact evaluation of the S2P approach. However, at the start of the project it quickly became clear that the S2P application was not going to be ready in the first operational year of the evaluation (during the 2024/25 growing season). A full and rigorous evaluation of the S2P approach was therefore deferred to the 2025/26 growing seasons and beyond. As such, we decided that the 2024/25 growing season could be used to generate learning to inform S2P's theory of change.

Building on recent rigorous impact evaluations, we decided to assess the impact of a bundled intervention. This intervention offers farmers a soil test on a selected plot, followed by tailored fertilizer recommendations based on the test results. In addition, farmers receive agricultural advice on the proper application of the recommended fertilizer to achieve a desired yield for the crop they choose to plant on that plot. Furthermore, we also explore resources constraints as a potential barrier to the adoption of site specific fertilizer blends by providing a subsidy tied to the recommended fertilizer blend.

2 Motivation

Governments in developing countries are trying to increase adoption of Green Revolution technologies, seed of improved varieties and mineral fertilizer in particular, through agricultural extension advice. In general, these extension systems provide blanket recommendations. One important reason why farmers fail to adopt seemingly profitable yield improving technologies is heterogeneity in the farmer's ability and context. For instance, high transacting costs may make a technology unprofitable for a farmer even though on average the technology would be profitable (Suri, 2011). A similar argument can be made for soil—

another key production factor in agricultural production (Arouna et al., 2021). Also here, differences in soil composition and nutrient content may mean that blanket fertilizer recommendations are sub-optimal.

Information and Communication Technologies (ICTs) provide an opportunity to deliver advisory services that are more tailored to the specific needs of farmers (Spielman et al., 2021). Numerous Site Specific Nutrient Management (SSNM) Decision Support Tools (DST) have been developed with the promise to reduce inefficiencies coming from grossly simplified recommendations, thereby raising the productivity and profitability from adopting improved inputs (Arouna et al., 2021).

However, decision support tools for tailored nutrient recommendations have generally fallen short of expectations. This is illustrated by the numerous apps and tools available that fail to scale effectively (Sida et al., 2023). Several factors may explain why these tools have not had more impact, and they relate to some unresolved questions:

One such issue is spatial resolution, or how site specific these tools really are. Many rely on models that predict soil composition and nutrients availability over relatively large area. As a result, it has been argued that, often, "...the numerous laboratory services and digital applications providing field-specific recommendations appear to promise more accuracy than soil analysis can realistically deliver" (Schut and Giller, 2020).

Another limitation is that many of these apps implicitly assume that providing farmers with information alone is sufficient to change their behavior. What is missing is an en extension component - specifically, a human intermediary who can help guide farmers through the decision-making process.

Moreover, decision support tools often take several pre-conditions for granted, with one of the most critical probably being that the recommended blend of soil macro- and micro-nutrients are available to the farmer at reasonable cost. Indeed, as we will discuss below, most RCTs that study the effectiveness of DSTs include at least one treatment arm to investigate the importance of a particular pre-condition, such as access to insurance, financial resources, or information.

3 Related literature

Recent literature on site-specific nutrient management has focused on providing tailored fertilizer recommendations to improve agricultural productivity. Among the studies employing plot-level soil tests, Beg, Islam, and Rahman (2024) examined rice farmers in Bangladesh, comparing three types of fertilizer recommendations: community-level, plot-specific based on individual soil tests, and standard government recommendations. They find limited effects on quantity of fertilizer use, except perhaps for a reduction in application error (difference between recommended quantity of a particular nutrient and quantity used). That is, some farmers were using more than the recommended TSP (phosphate fertilizer) and as a result of the intervention cut back. Some even appear to over-react and stop using TSP altogether, leading to lower yield. They also find indications that farmers adapt seed use to match baseline fertilizer use.

Similarly, Gars, Kishore, and Ward (2022) demonstrated that plot-level soil testing and tailored input recommendations changed farmers' fertilizer usage and increased the adoption of recommended practices, leading to improved yields. This aligns with findings by [Harou et all (2018)] who studied maize farmers in Tanzania. Their study testes the joint effects of information and financing constraints on fertilizer adoption. Specifically, they investigated if farmers use more fertilizer with site-specific soil test provided and they also investigated if only this information is not sufficient due to financing constraints. They have three treatment arms: an arm which receives site-specific soil test information, another arm which also receives a subsidy with the site-specific soil test information and a third arm which receives only a subsidy. The found that only those who received both the site-specific soil test information and the subsidy increase fertilizer application and yields. Their study is comparable to ours, except that we additionally offer agricultural extension services alongside the soil test results as in Bag et al. (2024) and gars(2022).

Corral et al. (2020) implement a field experiment that combines tailored input recommendations based on soil sample tests, extension services and an in-kind grant. The grant comes in two flavors: in one treatment arm, the grant can only be spent on the recommended fertilizer blend; in the second treatment arm, the farmer can decide what inputs to get. They find that the intervention reduces overuse of fertilizer, and the effect is sustained more if the farmer was free to choose how to spend the grant.

Murphy et al. (2019) investigated whether site-specific soil testing, using a low-cost testing kit, influenced farmer's demand for inorganic and organic fertilizers. Their auction-based study before and after disseminating soil test information revealed significant impacts on farmer's willingness to pay for fertilizers.

Other studies on site-specific nutrient management did not rely on soil test but still provided insights into the potential of customized approaches. Arouna et al. (2021) evaluate the effectiveness of a mobile application that provides personalized advice on rice nutrient management in Nigeria. In particular, they evaluate RiceAdvice, an Android-based application to provide personalized recommendations on nutrient management (type, quantity, and timing of fertilizer) in rice production. They find that the intervention increases yields by 7 percent. They also have a treatment that combines personalized advice with a grant that provides the recommended level of fertilizer. Here they estimate a treatment effect of 20 percent. They also found a 10% increase from the intervention on profit which increased to 23% when the intervention is combined with the grant. The mechanism behind the increase in yield and profitability seems to be a reallocation in the fertilizer mix, with farmers using less NPK and more Urea.

Ayalew, Chamberlin, and Newman (2022) evaluate the impact of targeted site-specific fertilizer blend recommendations to Ethiopian smallholder farmers on fertilizer usage, farm productivity, profits from maize production, and household welfare using a cluster randomized control trial. They also have a treatment arm that adds insurance to the recommendation. They find significant reduction of the application error, which in turn affects yields. In particular, they report a 13 percent increase in yield (437 on baseline yield of 3250 kg/ha) and a very similar increase in farmer profit.

Oyinbo et al. (2022) study maize in Nigeria. They study the impact of Site Specific Soil Nutrient Management extension advice through the Nutrient Expert tool. They have two treatment arms and one business-as-usual blanket recommendations control. One treatment arm with farmers who are exposed to SSNM information interventions on nutrient application rates and fertilizer management, and anther treatment arm with farmers who are exposed to the same SSNM information and additional information on the variability of expected returns to fertilizer investment under different price scenarios. They find modest effects on yields and profits.

Others to include: Maertens et al. (2023) and Fishman et al 2016.

Cited by many Suri 2011

4 Research Questions

Our research aims to look at a prototype S2P intervention, as well as assess the relative importance of two of the key components. It will also investigate the role of resources constraints as a potential enabling factor. In particular, we will answer the following research questions:

1. Does the provision of site-specific soil nutrient information derived from a soil test and the recommendation of a specific fertilizer blend based on this information change outcomes of interest?

2. Does the provision of site-specific nutrient recommendations combined with a subsidy to buy these nutrients at a local agro-dealer, change the outcomes of interest? This research question looks at the importance of cash/credit constraints in the effectiveness of S2P.

Other issues we will investigate are:

3. Do farmers face substantial heterogeneity in soil nutrient profiles? This will be done by comparing variability in soil macro and micro-nutrients across different areas (eg within villages, between village and between regions).[1]

4. Do farmers know their soils? This will be done by asking farmers what they think their soil is missing and comparing this with results from the soil tests. We also can use the revealed version of this by comparing what farmers are actually putting on their fields and what would be recommended by the soil tests.

5 Experimental Design

The study employs a randomized controlled trial (RCT) design involving 113 villages across four districts in Malawi (Lilongwe, Dowa, Ntchisi, and Mchinji).

[1] This can be done through standard analysis of variance or multilevel modeling.

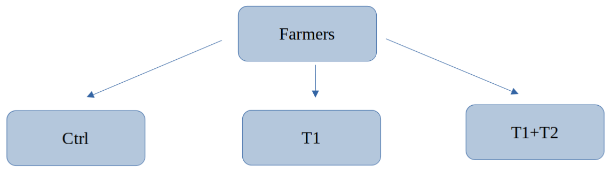


Figure 1: Experimental layout

The villages are randomly assigned to one of the following three groups and the layout of the experiment is illustrated in Figure 1.

- **Farmers in the first group, Treatment 1 (T1)**, receives a soil report based on a soil test conducted on a plot chosen by the farmer for a specific crop the farmer plans to grow on the selected plot.
- **Farmers in the second group, Treatment 2 (T2)**, receives everything farmers in T1 get in addition to a voucher that can be redeemed to buy the recommended fertilizer blend.
- **Farmers in the third group, Control (C)**, do not receive a soil test offer, a customized fertilizer recommendation, and a voucher.

For the treatments, (T1 and T2) we cooperate with Meridian's Farmer Support Unit (FSU). This private-sector player offers farmers spectral soil tests and site- and crop-specific recommendations. The model underlying the test was calibrated on wet-chemistry analyses conducted on 22,000 samples from across Malawi. The tool is part of a private-sector business model in which FSU Meridian forms a recommendation for a package of nutrients, which is then supplied through their network of 400 agrodealers. After the soil tests are conducted by Meridian, the results are communicated in a follow up visit to farmers, along with an agricultural extension/advice service on the proper use (the 4 Rs) of the recommended fertilizer blend from a private sector-trained extension agents, known as "agronauts.

Specifically, farmers in the T1 group of villages are visited by an enumerator accompanied by a private sector trained extension agents called “agronaut” and is offered the opportunity for a soil test on a plot chosen by the farmer.[2] The farmer is also asked what crop he/she plans to cultivate on this plot, as well as

[2] The fact that the farmer can choose the plot themselves (as opposed to the experimenter choosing the plot in some systematic way) has important consequences for the analysis. In particular, it makes it hard to compare information at the plot level, as the choice of the plot may be influenced by the treatment, and so the plot on which outcomes are collected for the treated farmers may differ in more respects from those of control farmers than just information about soil quality. We have thought hard about ways to assure a comparable plot level counterfactual, such as also doing soil tests in the control group but keeping farmers in the dark about when they will receive feedback (as is done in Corral et al) or randomly choosing a plot for the soil test, but eventually decided to keep the treatment as realistic as

the target yield that the farmer would like to get from the crop on that plot. The soil sample is then analyzed, which results in a soil report (see example in Appendix 1) that is provided to the farmer. The report indicates the soil's texture, pH level, cation exchange capacity, percentage organic matter, total nitrogen, carbon to nitrogen ratio, as well as the parts per million of available P, exchangeable K, calcium, magnesium, iron, manganese, boron, copper and zinc. Beyond the exact measurements each soil property is given a score on a 4-point Likert scale (very low, low, high, very high), with emojis, color coding and bar charts indicating where the soil is deficient and where the levels are sound. After the results the soil test are communicated with extension service on the proper use of the recommended fertilizer, farmers are then informed where and how to obtain these nutrients (in the form of a particular fertilizer blend). We use open route service to link sample villages to the nearest agro-dealer. We assume farmers go to agro-dealers by motorbike or bicycle.

Farmers in the T2 group of villages receive a subsidy that they get in the from of a voucher that can be redeemed at a nearby Farmer World agro-input shop. The subsidy is tied to T1 in that it will be specific for the recommended fertilizer blend. The amount of the subsidy is determined based on Malawi's Agricultural Input Program (AIP) subsidy which allows farmers to buy one bag of UREA and one bag of NPK fertilizer for a fixed amount of 15,000 MWK each. In particular, we aim at making the total amount of money transferred to farmers through our subsidy be equal to the amount of transfer a farmer receives through the AIP program. Up on deciding the amount of the transfer, the total cost for a bag of Urea and a bag of NPK was around 200,000 MWK. Therefore, the total amount of the subsidy farmers get through AIP is around 170,000 MWK which is also the amount of our subsidy for this study. This will allow us to directly compare our bundle as an alternative to Malawi's AIP.

Farmers in the C group of villages do not receive any of the treatments that T1 and T2 groups of farmers get. This group serves as a pure comparison group with which the T1 and T2 groups are compared to arrive at the estimates of the impact of the treatments. T

6 Empirical Specifications

Due to the random assignment of participants to treatment and control groups, comparing outcome variables averages of treated and control participants provides unbiased estimates of the average treatment effects. We compare averages using OLS regression of the following form:

$$Y_i = \alpha + \beta_{T1} T1_j + \beta_{T2} T1_i T2_i + \varepsilon_i \tag{1}$$

possible, which gives the farmer substantial agency in terms of what plot to choose and crops to cultivate. The trade-off is that it will become harder to compare plot level outcomes (eg fertilizer use on the plot on which the soil test was done versus control). At the same time, there are now also interesting household level outcomes that we can investigate, such as crops cultivated.

where Y_i is the outcome of interest (agronomic practices, profits, return on investment, etc—see Section 8 below) of farmer i. $T1_i$ and $T2_i$ are treatment indicators at the village level that take the value of one if the farmer was located in a village that was allocated to the respective treatment group, and zero otherwise. The parameter estimate of β_{T1} is the treatment effect of the soil test treatment, β_{T2} is the incremental effect of adding the voucher to the combined treatment.[3]

For outcome families with more than one outcome (knowledge, adoption, input use, and effort), we compute outcome indices, which is a common way to account for multiple hypothesis testing. To do so, we follow Anderson (2008), where each index is computed as a weighted mean of the standardized values of the outcome variables. The weights are derived from the (inverse) covariance matrix, such that less weight is given to outcomes that are highly correlated with each other. For these indices, signs of outcomes were switched where necessary so that the positive direction always indicates a "better" outcome.

7 Statistical Power and Sample Size Determination

We run a simulation analysis to determine sample size for the design presented in section 6. Simulation, which involves instructing a computer to conduct an experiment thousands of times and tallying the frequency of significant outcomes under specific assumptions, is a considerably more flexible and intuitive approach to conceptualizing power analysis.[4]

Power calculations require the choice of an outcome variable. Normally, this outcome is assumed to be normally distributed, with a particular mean and standard deviation. However, when simulation is used, it is possible to draw from an actual distribution of the outcome variable if data is available. The outcome we consider in this study for our power calculations is maize yield. As such, we draw random samples from farmer level data that was collected for a study on smallholder market participation in the central region of Malawi (De Weerdt et al., 2024). Using this data, we find that average yield is 2,574 kilogram per hectare (with standard deviation of 1145 kg per hectare).

Power is determined in the following way. Our sampling frame is drawn from the previous study on smallholder market participation (De Weerdt et al., 2024). We set the number of villages to the maximum number of villages that

[3] To estimate β_{T1}, we will also estimate an alternative specification that boosts power by exploiting the fact that farmers T2 is provided on top of T1 (that is, farmers in the second treatment arm also receive T1). To do so, we consider T2 as covariate and enter it in deviations from its mean in the following way (Lin, 2013):

$$Y_i = \alpha + \beta_{T1} T1_j + \beta_{T2} T1_j \left(T2_j - \overline{T2} \right) + \beta_C \left(T2_j - \overline{T2} \right) + \varepsilon_i \quad (2)$$

See also this blog post: https://blogs.worldbank.org/en/impactevaluations/what-should-you-do-experiments-factorial-designs

[4] See also this methods guide: https://egap.org/resource/10-things-to-know-about-statistical-power/

was used in this study, as this is a clustered design and we want to exploit inter-cluster variation to the maximum extent. We then search in two dimensions. First, we vary the share of villages that is allocated to the control (and equally divide the remaining villages to T1 and T2). In the second dimension, we vary the number of households that will be interviewed in each village. We model similar effects for T1 and T2 (a 13 percent increase over baseline yield). We run 1000 simulations and use 5 percent significance level and .8 is our target for power.

Figure 2(a) shows that when we allocate 25 percent of villages to the control group (and 75 percent to the treatments) and include about 16 households per village, we hit the 80 percent power level for the joint hypothesis that both β_{T1} and β_{T2} are significantly different from zero. However, to avoid that we are focusing on an isolated peak in the distribution, it seemed safer to move closer toward 30 percent in control (and hence 35 percent in T1 and 35 percent in T2) and aim for about 18 households per village. Figure 2(b) shows that at such a sample, we will get 85 to 90 percent power to identify a significant effect on T1. Figure 2(c) shows power to detect a significant difference between T1 and T2. From this, we conclude that we need about 30 percent in control (and hence 35 percent in T1 and 35 percent in T2) and aim for about 18 households per village. This results in a total of 2034 households with 738 households in T1, 756 households in T2, and 540 households in C.

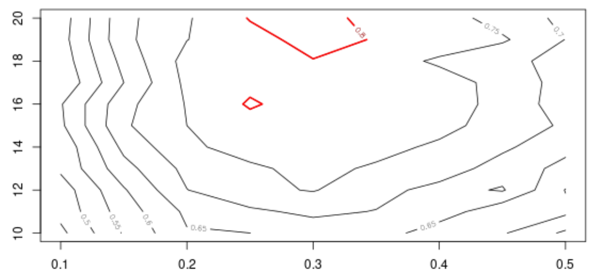
The sample for this study is drawn from a previous longitudinal study that involved 113 villages.[5] This gives us the opportunity of leveraging two years' worth of data on Maize, Groundnut, and Soyabean growing farmers for our study design and analysis. In doing so, we ensure that we do not lose external validity as we are relying on a specific sample drawn for a different purpose. The sample for the previous study was selected using the same approach we would have applied for this study—randomly drawing districts, villages, and households within villages—we believe that using this sample does not compromise external validity. Additionally, we ensure that an intervention that was conducted during the previous survey doesn't compromise the effect of our treatments. Specifically, we are assigning our treatments at the village level while the previous survey had a light touch intervention randomly assigned to

Using the data from the previous study, which was collected in May and June 2022, we can already test balance on fifteen pre-specified variables. First, we assess balance on the following five variables that are unlikely to be affected by the treatments: farmer's age (in years), sex of farmer, household size, land area for crop production (acres), and whether the household had difficulty in meeting food needs in the year preceding the survey. Results are in Table 1. The table shows not a single significant difference for the five outcomes for pairwise comparisons between the different treatment groups. Joint tests of orthogonality confirm that we have good balance judged by these five outcome variables that were collected before the treatment administration.

Second, while we do not plan to do a dedicated baseline, we will collect

[5] This is also the case in Beg et al. (2024).

(a)



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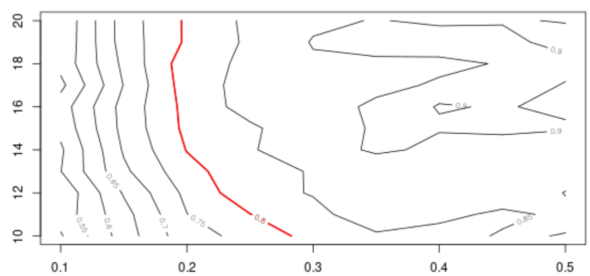

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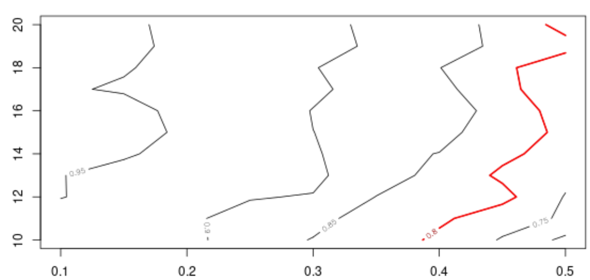

Figure 2: Power Plots

Table 1: Balance table

	mean ctrl	T1	T2	nobs
Household head age (years)	42.434	1.158	-0.022	2007
	(14.76)	(0.867)	(0.901)	
Household head is male (1=yes)	0.781	0.012	0.01	2034
	(0.414)	(0.025)	(0.025)	
Household size (number)	4.902	0.129	0.159	2032
	(1.927)	(0.125)	(0.135)	
Land area (ha)	0.999	0.011	0.007	2033
	(0.627)	(0.053)	(0.051)	
Had difficulties feeding familiy in last year (1=yes)	0.276	0.041	0	2034
	(0.447)	(0.037)	(0.038)	
F-test C/T1 (p-value)	1.348	(0.241)		
F-test T1/T2 (p-value)	0.462	(0.805)		

Note: First column reports control group means (and standard deviations below); second column shows different between control and T1 (and standard errors clustered at the village level below); third column shows different between T1 and T2 (and standard errors clustered at the village level below). F-test test for joint significance in a regression with treatment status on the left hand side (T1/C or T2/T1). Likelihood ratio test is derived from a multinomial model where the left hand side has three levels (C,T1,T2).

data on some background characteristics on the previous season a few weeks after treatment administration. This will include whether the household was AIP recipient in the previous season, total land size use for cultivation, and number of crops grown. We also include five variables from among the outcomes of interest to test balance at baseline, in particular: use of organic fertilizer (yes/no), amount of fertilizer by type (kg), yield, profit, crop in previous season was legume. At this time, we will also ask detailed questions on what the farmer thinks the soil quality is to answer the fourth research question. This will help us in establishing if farmers under or overuse fertilizer when they do not know the soil quality.[6]

8 Outcomes of interest

We plan to assess the impact of the intervention on **fertilizer use, production, and farm profit outcomes.**

- **Fertilizer use:**
  - Primary indicator: application error - measured by the difference between the quantity used and quantity recommended (Beg et al

[6]Note that we can not use treatment versus control to answer this question given the fact that the farmer can select the plot on which the soil test is performed making it hard to identify an appropriate counterfactual.

(2024), Corral et al. (2020)).

  - Secondary indicators
    * Fertilizer adoption - measured by a binary indicator with a 1 for Yes, 0 otherwise. (Beg et al 2024, Gars et al. (2022)),
    * Proper application of fertilizer - measured by indicator with 1 for yes on applying on time and 0 otherwise (Gars et al (2022)

- **Other inputs and crop choice**
  - Farm expenditure: measured by the sum of expenditure on seeds, pesticides and fungicides, irrigation and hired labor. Expenditures including fertilizer can also be computed to see if agricultural intensification happened due to the treatment **(Beg et al. (2024))**.
  - Adoption of other SNM practices - measured by a binary indicator with a 1 for Yes if farmers uses organic fertilizer (e.g., manure), 0 otherwise and similarly for other SNM practices like minimum tillage, mulching, crop rotation, and residue incorporation.
  - Crop mix **-** measured by share of area on which site and crop specific fertilizer recommendations are made**.**

- **Production**
  - Value of production per hectare (MWK/ha)

- **Profits:** measured by total value of production less the total farm expenditures (Beg et al 2024),

9 Timeline

- September/October - taking soil samples, conducting soil test and disseminating the soil test results.
- End of October (or after the treatment administration is completed) - we will conduct the "first survey" in which we validate treatment administration and collect information about the previous season on fertilizer use, agricultural practices and other key outcomes.
- April 2025 - endline data will be collected.

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