Impact of Information of Expected Effectiveness Based on Soil Quality on Farmers' decision of Fertilizer Use: Evidence from Madagascar

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Abstract:

Increasing the use of chemical fertilizer is the key to a sustained growth of agricultural productivity in sub-Saharan Africa. However, it has been shown in previous studies that crop yield response to fertilizer depends on soil characteristics. This study examines how information about expected effectiveness (EE) of fertilizer application based on soil characteristics affects farmers' decisions as to fertilizer allocation based on a randomized controlled trial (RCT) conducted in the central highland zone of Madagascar. More specifically, this study investigates whether simply designed binary information based on the result of soil analysis helps farmers to optimize their fertilizer use in terms of adoption and application rates. The results reveal that high EE information significantly increases the rates of nitrogen fertilizer application in responsive plots while low EE information decreases the probability of nitrogen fertilizer adoption and its application rates in non-responsive plots. One important implication of these findings is that the interventions that target the adoption of chemical fertilizers are more likely to succeed if additional information about soil characteristics is provided to farmers.

Keywords: Randomized Control Trial, Chemical Fertilizer, Soil quality information

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1 Introduction

It is widely recognized that sustained growth of agricultural productivity in sub-Saharan Africa (SSA) requires increase in chemical fertilizer application (Vlek, 1990; Morris et al., 2007; Xu et al., 2009; Holden, 2018). The pace of increase in nitrogen fertilizer use in agriculture has been substantially slower in SSA than other parts of the world (FAO, 2020). A large body of literature has proposed various factors that help to explain the low use of fertilizer in SSA. The education level of the heads and other household members affects adoption decisions of fertilizer (Asfaw, 2004). The poor accessibility to input and credit markets are constraints (Croppenstedt et al., 2003). Bold et al. (2015) proposed that low quality of inputs sold in markets discourage farmers to adopt fertilizer.

Another group of research shed light on the relationship between soil characteristics and crop yield response to fertilizer which contributes to the heterogeneous rate of returns to fertilizer use. For instance, soil carbon content (SCC) (Marenya and Barret, 2009), phosphorus (Asai et al., 2020), and other factors related to soil chemistry including pH and carbon exchange capacity (CEC) (Burke et al., 2019) on crop yield response to fertilizer application have been studied. In addition to soil characteristics, Duflo et al. (2008) pointed out that application rates affect crop yield response and profitability of fertilizer use.

Findings from these studies suggest that suitable types of fertilizer and appropriate application rates may be largely different from plot to plot, depending on inherent soil conditions. More importantly, farmers usually do not have accurate information about their soil characteristics and thereby they make decisions without knowing how to optimize the use of fertilizer. Some studies such as Harou et al. (2018) have paid attention to the role of site-specific recommendations about fertilizer application rates. These studies commonly examine the effect of information on plot-level optimization, focusing on how much extent information could close the gap between required rates and actual rates of application. The recommendation is made based on the deficiency of nutrient in soil as well as required types and amount of fertilizer to fill the gap between ideal and actual levels of soil nutrition. The required amount is naturally larger in nutrient poorer soils.

However, under financial and physical limitation of access to fertilizers, applying the appropriate types of fertilizer at required level following site-specific recommendation in all plots may not be feasible for farmers, especially if the degree of deficit is high. Thus, an alternative approach is taken to help farmers optimize fertilizer use at farm level, which is a novelty of this study. We provide farmers with the information related to effectiveness of fertilizers in the main plots for rice production. This information is expected to allow farmers to take a better strategy by diverting fertilizer from plots that do not response positively to those more responsive to it. This viewpoint has rarely been presented in existing literature.

This study aims to contribute to the literature by providing new empirical evidence of the role of information. More specifically, this study is to answer the question: does site-specific information about expected effectiveness (EE) of nitrogen fertilizer application affect farmers' decisions as to fertilizer allocation? The hypothesis is that information based on soil characteristics helps farmers to optimize fertilizer allocation in terms of its adoption and its application rates. Information of high EE will contribute to increase in the probability of adoption of nitrogen fertilizer as well as its application rates at targeted plots and low-EE information will have opposite effects. In the case of low EE plots, farmers might utilize the information to select another plot as a place to use nitrogen fertilizer. Eventually, both types of information ideally will increase in the total rice yield at farm level and improve household welfare.

Using evidence from the agronomic experiment by Asai et al. (2020) that nitrogen fertilizer does not increase paddy yield when the amount of phosphorus in soil is less than 100 mg/kg, we designed a simple binary information about EE of nitrogen fertilizer application. Then, a randomized controlled trial (RCT) was conducted in the central highland zone of Madagascar. Treated farmers receive information of either "high" or "low" in terms of the EE about one main lowland rice plot before planting time in addition to nitrogen fertilizer for free, while farmers in control group receive free nitrogen fertilizer only. Results reveal that high EE information significantly increases the rates of nitrogen fertilizer application and low EE information decreases the probability of adoption of nitrogen fertilizer and its application rates. We further find that high EE information about only one plot for each household increases total nitrogen application rates and total rice yield at farm level.

The rest of this paper is organized as follows. Section 2 is used to explain the context of the study site. Experimental design is proposed in section 3. Section 4 explains econometric specification applied in the analysis. Results are presented in section 5, followed by conclusion.

2 Context

2.1 Madagascar

Madagascar is an island nation located in the Indian Ocean with a population of 25.67 million people as of 2018 (INSTAT, 2019). Rural population accounts for 80.7% of the total population (INSTAT, 2019). Poverty head count ratio reaches over 75%, which is one of the highest in the world (World Bank, 2019). In Madagascar, rice is historically the main staple food crop and it is the major income source for rural population. 89% of the rural households are engaged in rice cultivation and 56% of agricultural land is devoted to it (World Bank, 2019). Therefore, the improvement of rice productivity has long been one of the central issues in national policies for poverty reduction and food security.

2.2 Study sites

The study site is located in the Vakinankaratra region which is in the central highland zone. The study site was selected because it is one of the major rice-producing regions. The Vakinankaratra region has an asymmetric landscape: The altitude in its eastern part is high up to near 1,800 meters above the sea level and there is a long mild slope descending towards the western end of the region. This asymmetry affects agroecological environment and thus agricultural practice although rice production in lowland is a common practice.

The selection of the Vakinankaratra region has another advantage. The findings of Asai et al. (2020) are highly applicable to this study since their agronomic experiment was implemented within this region.

3 Experimental design

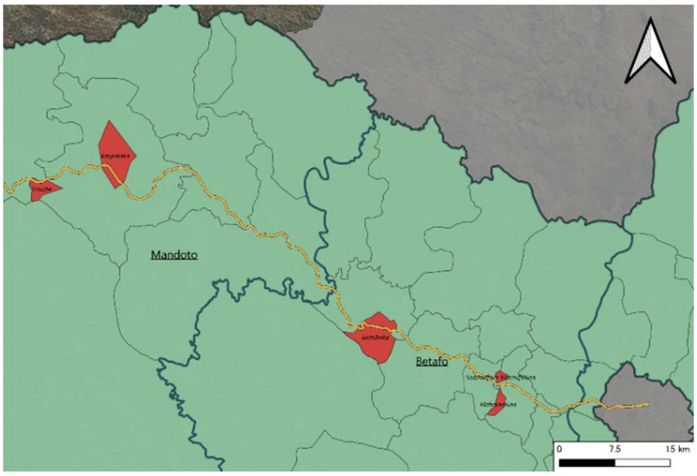
3.1 Sampling procedure

Five villages across three districts in the Vakinankaratra region were chosen. Purposively, two villages from the eastern part, another two villages from western part, and the other one in between the two groups of villages were selected to evenly represent the agroecological diversity. All the five villages are located along the national road that runs east and west in the middle of the region (Figure 1).

Each village has several smaller administrative units. Based on the units, two enumeration areas (EAs) were chosen in each village. The two EAs in a village have similar characteristics in terms of distance from the national road, population, and rice cultivation practices based on information collected in a preliminary field survey[1]. Then, we randomly selected farmers who grew rice in lowland plots in 2018-19 rainy season. Before intervention, all the sample farmers were asked to list all the agricultural plots used in that season and then to choose one most important lowland rice plot. We visited each plot selected and measured its location and size by GPS. In addition, soil was taken from three points in each plot to obtain composites of soil sample. All the soil samples were sent to national laboratory to examine phosphorus amount. Based on the result of this soil analysis, all the plots selected as the most important lowland rice plot were classified as either high EE or low EE.

[1] When the national road passes through the target village, we selected one EA from the northern side of the national road, the other EA was selected from the southern side of the road.

Figure 1: Location of target villages



Source: Authors created based on data obtained from Humanitarian Data Exchange (HDX) https://data.humdata.org/dataset/madagascar-administrative-level-0-4-population-statistics

3.2 Randomization

Figure 2. Assignment Structure

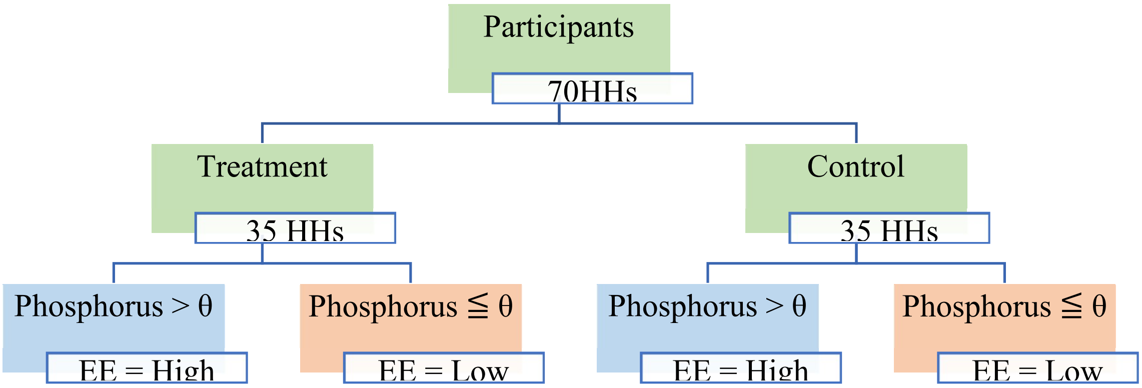


Figure 2. shows assignment structure. The total number of participants was 70. Randomization was done at EA level to minimize the risk of interaction between treatment and control groups to take place. Randomization at EA level was more suitable than at household level because communication with treated participants might let ones in control group learn from information given to the treated if both the treated and the control groups exist within an EA. Since two EAs in a village are geographically apart

and farmers in control EAs had no information about treated EAs, spillover of information could be prevented by randomization at EA level.

After randomization, treatment and control groups had 35 households for each. Regardless of the assignment status, we provided all participants with common inputs that consisted of free fertilizer (5kg of urea), the size of the targeted plot, and general recommendation about timing and rates of urea application. There was no restriction on the usage of the free fertilizer. Participants were clearly informed that they would be able to use it to any crop at any plot, keep it, sell it, or even give it to others. The distribution was implemented in October in 2019.

Then, when the common inputs were distributed, only farmers in treatment group were additionally provided with information about the result of soil analysis including phosphorus amount and EE of urea application of not only each farmer's own targeted plot but also of all other participants' targeted plots in the same EA. As a result, although both treatment and control groups were divided into two sub-groups by EE status, only the treated farmers could know which sub-group they belong to and make decisions about whether and how much they would use urea on the targeted plot based on the EE. Farmers in control group had to decide how to use the given fertilizer without knowing EE status of their targeted plots.

4 Analytical framework

4.1 Definition of expected effectiveness to nitrogen fertilizer

Table 1 presents the summary of results of soil analysis by EA. The amount of phosphorus was measured as oxalate phosphorus. The averages largely vary across study area from 36.96 mg/kg of Tsarazaza as the lowest to 482 mg/kg of Befaritra as the highest.

One possible explanation of such a huge difference is that a volcano affects soil in its surrounding EAs including Befaritra, Amohimilemaka, Mahazina, and Morafeno. Volcanic soil contains rich phosphorus, but most of the phosphorus exists in a form which plants cannot absorb and utilize. According to a publicly available guideline for fertilizer application in Japan, required amount of phosphorus in volcanic soil is three times larger than that in non-volcanic soil (MAFF, 2008).

Table 1. Summary of variation of phosphorus amount by EAs

Name of EA	Mean	S.D.	Min	Max	Volcanic soil	θ
Befaritra	482.48	219.91	228.27	823.08	Yes	300
Ambohimilemaka	321.31	196.94	24.49	615.74	Yes	300
Mahazina	335.71	134.06	94.16	586.60	Yes	300
Morafeno	316.25	117.60	136.88	481.96	Yes	300
Ampotaka Afovoany	74.29	44.68	23.48	184.22	No	100
Ambany Ravinkazo	58.76	27.42	27.50	97.57	No	100
Tsarazaza	36.96	12.69	20.30	60.58	No	100
Soanotohizana	38.87	22.83	24.44	113.50	No	100
Antanetibe	90.20	38.00	42.54	166.81	No	100
Antohobe	70.52	26.31	34.99	135.99	No	100

Note: Unit is mg/kg of dried soil. Phosphorus amount is measured as oxalate phosphorus. S.D. stands for standard deviation.

Following Asai et al. (2020), phosphorus amount of 100 mg/kg was used as the base threshold (θ) to define EE of soil to nitrogen fertilizer use. Then, the base threshold was applied except for the 4 EAs where soil is affected by the volcano. For the 4 EAs, 300 mg/kg was employed as the threshold to deal with influence of volcanic soil. Eight out of 10 EAs embrace both sub-groups, implying that there exist substantial variations of soil quality even within a village.

4.2 Econometric specification

In RCT setting, the average treatment effects are estimated by using OLS. The basic specification is given as equation (1) as below.

$$Y_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i' + \alpha_3 village' + u_i \dots (1)$$

where Y_i is one of outcome variables at plot i, T is assignment status, X is a vector of control variables that include plot characteristics, previous year experiences of fertilizer use, and household characteristics. Dummy variables to control unobserved factors attributable to village characteristics are included. However, this model is not suitable to test the hypotheses that two types of information have effects differently on fertilizer adoption and application rates. Therefore, we mainly use equation (2) in which two treatment variables are separately included.

$$Y_i = \beta_0 + \beta_1 T_i^{high} + \beta_2 T_i^{low} + \beta_3 X'_i + \beta_4 village' + u_i \dots (2)$$

where both $\beta_1$and $\beta_2$are parameters of interest.

The major concern of this research is the small number of observations and villages which are used as clusters in estimation process. To deal with the small number of observations a typical strategy is to conduct bootstrap. However, it is also known that the ordinary bootstrap method that performs replications by resampling a pair of outcome variables and covariates at cluster level may work poorly when the number of clusters is only a few or the number of observations largely vary across clusters (Roodman et al., 2018). Since this study has only 5 villages as clusters, wild cluster bootstrapping (WCR) method is employed to make results as rigorous as possible.

5 Results

5.1 Descriptive statistics about households

Table 2 presents summary statistics about participants' household. The size of household is 5 people on average. More than 90% of households are headed by a male.

Farmers cultivate two or more lowland plots for rice. This implies that most of them have options to diverge plots for fertilizer use. In the season of 2018-19, nearly a half of participants cultivated rice on upland plots as well as lowland plots. Lowland plots accounts for 83.2% of the total rice plots on average, and therefore, lowland rice is the main production. This table confirms that there is no systematic difference between treatment and control groups.

Table 2. Descriptive statistics about participants' household

Variables	Unit	Total	Control	Treatment	Pr (|T|>t)
Household size	People	5.21	5.29	5.14	0.746
HH head's sex	%	92.86	94.29	91.43	0.648
HH head's age	Years old	46.57	46.03	47.11	0.711
HH head's education	Years	6.0	6.31	5.69	0.416
Total No. of parcels	Number	5.67	5.80	5.54	0.678
Total No. of lowland rice plots	Number	2.74	2.83	2.66	0.612
Upland rice cultivation	%	48.57	48.57	48.57	1.00
Proportion of lowland rice plots	%	83.23	80.49	85.97	0.32
Value of asset per capita	1,000MGA	146.46	131.50	161.42	0.545
Value of consumption in 3 months	1,000MGA	246.99	282.19	211.79	0.437
Agricultural income per capita	1,000MGA	167.21	172.37	162.05	0.820
Observations		70	35	35	

Source: Authors.
Note: MGA is local currency, standing for Malagasy Ariary, HH stands for household.

5.2 Descriptive statistics about targeted plots

Table 3 shows descriptive statistics of targeted plots. The number of plots is the same as the number of households because we targeted one plot for each household. The percentage of plots which had high EE was 31.4%. Although it was 34% and 28% in control and treatment group, respectively, no statistically significant difference was found. The mean plot size is 15.3 Ares, implying participants are typically small farmers. As for experiences of fertilizer use in the previous year, the percentage of targeted plots where farmers had applied urea was 17% and that for NPK was only 8%. Due to free distribution of urea, the percentage of urea use increased to 61.4% in total. This suggests that accessibility to input is a major constraint for fertilizer adoption in the context of study site. In addition to chemical fertilizer, manure use is an important input in rice cultivation. 31.4% of the targeted plots had received manure in the previous year and the percentage did not largely change after intervention. The average rice yield is 51.09kg per Are. Although this seems relatively higher than publicly available data, it is probably because of the inverse relationship between plot size and yield as literature has shown (Desiere and Jolliffe, 2018). Between plots from treatment group and those from control group, no statistically significant difference was observed.

Table 3. Descriptive statistics

Variables	Unit	Observation	Total	Control	Treatment	Pr(|T|>|t|)
Expected Effectiveness	%	70	31.43	34.28	28.57	0.61
Plot size	are	70	15.29	12.81	17.76	0.18
Production shock	%	70	44.29	37.14	51.43	0.24
Urea use	%	70	61.43	68.57	54.29	0.23
NPK use	%	70	8.57	5.71	11.43	0.40
Manure use	%	70	35.71	37.14	34.29	0.81
Urea application	kg	70	4.19	4.76	3.62	0.38
Nitrogen application	kg	70	2.1	2.19	2.01	0.81
Urea use in the previous year	%	70	17.14	14.28	20	0.53
NPK use in the previous year	%	70	8.57	5.71	11.43	0.40
Manure use in the previous year	%	70	31.43	31.43	31.43	1.00
Yield	kg/are	68	51.09	52.82	49.37	0.69

Source: Authors

Note: the number of observations is 68 for yield because the two targeted plots were not used for rice cultivation.

Table 4. Urea adoption by assignment status

	Adopt	Not Adopt	Total	%
	Panel A: Low EE plots			
Treatment	12	13	25	48.0
Control	13	10	23	56.5
Total	25	23	48	52.1
	Panel B: High EE plots			
Treatment	7	3	10	70.0
Control	11	1	12	91.7
Total	18	4	22	81.8

Table 4 summarizes the numbers of the targeted plots by adoption behavior in each group of treatment assignment. Panels were prepared to show the numbers separately by different status of EE. Panel A shows that on 12 targeted plots, urea was used although participants received the information that EE was low. However, the share of such plots was no more than 50 % among the treatment group and it was less than that of plots among the control group. Panel B also shows that the share of plots on which urea was applied is smaller in treatment group than control group, while the shares among high EE plots (Panel B) are higher than those among low EE plots (Panel A) regardless of the treatment status.

5.3 Impact of intervention on fertilizer application at targeted plots

Table 5 presents the results of regression of fertilizer use at targeted plots on treatment variables. The first two columns focus on urea use. Receiving information of high EE did not increase probability of adoption and application rates. However, low EE information resulted in significant decrease in the probability of urea use by 19.6% as well as its application rates by 0.18 kg per Are. In the third and fourth columns, it examined the impact of information on the total nitrogen amount including not only nitrogen from urea but also from other fertilizer product such as NPK. As for effects of low EE information, similar results to the columns 1 and 2 were observed. In addition, information of high EE shows a significant positive impact on nitrogen application rates by 0.29 kg per Are.

Table 5: Impact of treatment on urea and nitrogen fertilizer application at targeted plots

	Urea		Nitrogen		Manure	Nitrogen
Dependent Variables	Adoption (1/0)	Application rate (kg/are)	Adoption (1/0)	Application rate (kg/are)	Adoption (1/0)	Additional purchase (1/0)
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory Variables						
Treated and High EE (1/0)	-0.278	0.142	-0.279	0.290**	-0.238	-0.072
Treated and Low EE (1/0)	-0.196***	-0.179*	-0.182***	-0.141*	-0.044	-0.142*
Plot size (Ares)	-0.002	-0.002	-0.003	0.001**	0.004	0.005**
Proportion of lowland rice plots in size	0.648	0.458	0.641	0.301	-0.267	-0.029
Urea use in the previous year (1/0)	0.263					
Urea application rate in the previous year (kg/are)		0.539*				
Nitrogen use in the previous year (1/0)			0.131			0.007
Nitrogen application rate in the previous year (kg/are)				0.919*		
Manure use in the previous year (1/0)					-0.167	
Size of household	0.007	0.011	0.006	0.020	-0.048	0.022
Education level of household head (years)	-0.019	-0.005	-0.021	-0.005	-0.019	0.010
Log of value of total asset per capita (MGA)	0.687	0.945*	0.597	0.797	-0.578	0.326
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.430	-2.355	-1.125	-2.263	3.120	0.577
Observations	67	67	67	67	67	67
R-squared	0.37	0.75	0.35	0.72	0.38	0.35

Note: ***, ** and * indicate p<0.01, p<0.05 and p<0.1, respectively. Standard errors were recalculated using wild-bootstrap method to deal with the small number of clustering. MGA represents local currency, standing for Madagascar Ariary. 3 observations were excluded either because the targeted plot was not used for rice or because a only very small portion of the plot was used for rice cultivation.

In the fifth column, impact of treatment on manure use was tested because factors to change fertilizer use may also influence the use of other types of inputs. No significant effects appeared. Finally, in the sixth column, whether information motivated (crowding-in) or demotivated (crowding-out) farmers to purchase nitrogen fertilizer was explored. The amount of urea distributed for free was 5 kg regardless of plot size. Considering that the average plot size is 15.3 Ares and farmers had received the instruction that 5 kg of urea would be good for 5 Ares of plot, the free urea may not be enough to cover the targeted plot for most farmers. Then, if information motivated or demotivated farmers to purchase additional fertilizer to follow the instruction is of interest. On the one hand, low EE information reduced the probability of purchasing additional fertilizer by 14.2%, implying that the information contributed to saving money. On the other hand, no significant impact, either positive or negative, was found for high EE information.

5.4 Impacts on rice yield at targeted plots

Next, whether treatment had impact on rice yield at targeted plots is examined and the first column of Table 6 presents the results. Receiving information of high EE increased rice yield by 19.1 kg per Are, which is equivalent to more than a third of the average yield. This positive effect is consistent with increase in nitrogen fertilizer application rates which was presented in Table 5. In the second column, it was examined whether urea application on high EE plot was in fact more effective than on low EE plot. Although the coefficient of the interaction term of the amount of urea and being high EE plot is positive, it is not statistically significant. A simple average of urea use of two years is included to control pre-existing status of soil condition that affect yield and urea use.

Table 6. Regressions of rice yield at targeted plots

Dependent variables:	Rice yield (kg/are)	
	(1)	(2)
Explanatory variables		
Treated and High EE	19.10**	
Treated and Low EE	4.35	
High EE plots		2.09
Amount of Urea applied		6.70
Amount of Urea applied * High EE		13.75
Average amount of Urea in 2 years		5.98
Average amount of Urea in 2 years * High EE		-18.16
Production shock	-16.97**	-10.99
Plot size	-1.44*	-1.38*
Plot size squared	0.01	0.01
Terrace	-11.99	-10.38
Rice variety dummy	Yes	Yes
Household level control variables	Yes	Yes
Village dummy	Yes	Yes
Constant	-1.83	-43.372
Observations	67	67
R-squared	0.53	0.53

Note:** and * indicate $p<0.05$ and $p<0.1$, respectively. Standard errors were recalculated using wild-bootstrap method to deal with the small number of clustering. 3 observations were excluded either because the targeted plot was not used for rice or because only a very small portion of the plot was used for rice cultivation.

5.5 Impact of intervention on rice yield and fertilizer use at farm level

The first two columns of Table 7 show the impact of treatment on rice yield at farm level. The outcome variable is the average rice yield that is calculated with weight of plot size. Overall, the results are similar to those presented in previous tables. Information of high EE contributed to increase in farm-level rice yield by 15.5 kg per Are. The reason is probably because high EE information increased total nitrogen application rates as well. It is noteworthy that at farm level, no significant negative effect of low EE information on nitrogen use was detected while it showed significantly negative effects at the targeted plot. It implies that farmers reallocated urea to other rice plots when they received low EE information about one specific plot.

Table 7: Impact of treatment on rice cultivation at farm level

Dependent Variables (kg/are):	Rice yield (weighted)		Urea application rate (weighted)		Nitrogen application rate (weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
Treated household (1/0)	6.13		0.01		0.07**	
Treated and High EE (1/0)		15.50*		0.10		0.27*
Treated and Low EE (1/0)		0.53		-0.02		-0.001
Total size of rice plots (Ares)	-0.27**	-0.26**	-0.001**	-0.001***	-0.001**	-0.001***
Proportion of lowland rice plots in size	15.37	16.76	0.16*	0.18**	0.05	0.09
Production shock	-35.29*	-39.39*				
Log of asset value per capita (MGA)	4.29	4.27	0.03	0.03*	0.01	0.02
Years of education of head	1.47	1.54	0.01	0.01	0.001	0.003
Household size	1.93	2.17	0.02*	0.02**	0.01	0.02*
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-15.88	-20.62	0.23	-0.17	0.21	0.07
Observations	67	67	67	67	67	67
R-squared	0.54	0.55	0.58	0.60	0.40	0.47

Note: ** and * indicate p<0.05 and p<0.1, respectively. Standard errors were recalculated using wild-bootstrap method to deal with the small number of clustering. MGA represents local currency, standing for Madagascar Ariary.

5.6 Impact of intervention on household welfare variables

To see whether the intervention contributed to welfare improvement of treated households, two outcome variables are regressed on treatment variables. First, crop income per capita is used because rice yield increase as a result of farm-level optimization is supposed to have had a positive impact on crop income. Second, consumption per capita during 3 months after rice harvest is measured in monetary value and used as the other outcome variable. Although hypotheses expected positive effects, neither high EE nor low EE information had significant effects in any of these variables probably because the impact was too small to see at farm level.

Table 8. Impact of treatment on household welfare indicators

Dependent Variables (1000MGA):	Crop income per capita		Consumption per capita for 3 months after harvest	
	(1)	(2)	(3)	(4)
Explanatory variables				
Treated household (1/0)	-33.65		-26.79	
Treated and High EE (1/0)		-54.93		111.46
Treated and Low EE (1/0)		-26.21		-75.15
Production shock (weighted average)	-253.27	-243.14	-75.40	-141.21
Age of head (years old)	1.87	1.89	-0.10	-0.23
Sex of head (=1 if male)	54.32*	56.38	-24.78	-38.72
Years of education of head (years)	3.75	3.48	4.19	5.96
Household size (no. of member)	-8.09	-8.83	-26.99*	-22.23
Log of total asset per capita	43.42**	43.36**	30.85	31.24
Village dummy	Yes	Yes	Yes	Yes
Constant	-408.73	-509.72	-64.68	-114.41
Observations	67	67	67	67
R-squared	0.33	0.33	0.10	0.14

Note: ** and * indicate $p<0.05$ and $p<0.1$, respectively. Standard errors were recalculated using wild-bootstraping method to deal with the small number of clustering. MGA represents local currency, standing for Madagascar Ariary.

6 Conclusion

The objective of this paper is to provide new empirical evidence of the role of information in optimal fertilizer management. In Madagascar, like in other SSA countries, fertilizer use has been limited to insufficient level.

A randomized controlled trial was implemented in one of the major rice-producing regions of Madagascar. Using agronomic findings that phosphorus amount in soil has the critical role in effectiveness of nitrogen fertilizer, a simple binary information about expected effectiveness (EE) was designed. We examined whether the information of either high or low EE would affect the probability of nitrogen fertilizer use and the rate of its application. First, this study revealed that phosphorus amount in soil largely varies across study site and even within a village. This large variation of soil characteristics emphasizes the importance of site-specific advices as conventional blanket recommendations about fertilizer management might lead to disappointing outcome in some plots where crop yield response is low due to soil quality. Second, this study found that high EE information significantly increases the rates of nitrogen fertilizer application in responsive plots while low EE information decreases the probability of nitrogen fertilizer adoption and its application rates in non-responsive plots. With a viewpoint that giving up or reducing the fertilizer use in low EE plots is one way of optimization under limited accessibility to fertilizer, the results of regressions provided evidence that farmers utilize information to optimize fertilizer allocation.

To improve farmers' accessibility to fertilizer, various attempts including subsidy program, credit lending, training about how to use have been implemented in SSA. Some studies have proposed that combination of subsidy and other inputs have led to better outcome. Then, this study showed that combination of information based on soil characteristics, even a simple information as used in this study, and conventional policies with focus on accessibility to inputs has potential to enhance effectiveness of fertilizer promotion policies.

Limitations of this study are as follows. First, the experiment was implemented in only a few villages in the region and the number of observations is small. Considering criticism about external validity of many RCT studies in addition to the small sample problem, generalization of the results of this research requires a particular care. Similar intervention with larger scale will be important to reconfirm the key findings. Second, this study only examined the impact of information in the season of intervention. Additional data in the following seasons would be useful to see whether the impacts would last without free fertilizer provision. Finally, this study would also face the same criticism that Burke et al.

(2019) made against Marenya and Barret (2009) as we dealt with only phosphorus, ignoring complicated structure of soil that affects crop yield response. Inclusion of multiple soil characteristics in information design will make a similar intervention more meaningful both for researchers and farmers.

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