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Optimizing fertilizer use by providing soil quality information: experimental evidence from Madagascar

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Abstract

Background Improving food security in sub-Saharan Africa (SSA) requires increasing agricultural productivity. The increased and effective use of chemical fertilizers is widely recognized as one of the key strategies for achieving this goal. However, many smallholder farmers in SSA still grow crops without using fertilizer, and even when they do use fertilizer, the amount applied is often less than the recommended level. In addition to various constraints related to input markets and farmers' socioeconomic characteristics, uncertainty about crop yield response is known to discourage fertilizer use. The purpose of this study was to investigate how site-specific information on soil characteristics can help farmers optimize their fertilizer application decisions by reducing uncertainty in yield response. Our unique approach uses simple binary information about the expected effectiveness of nitrogen fertilizer based on a single soil parameter.

Methodology The simple binary information was generated for a focal rice plot of each 70 household. Based on the evaluation of oxalate-extractable phosphorus content in the soil composites collected from each of these plots, each plot was categorized into either high or low in terms of the expected effectiveness of nitrogen application. A randomized controlled trial was conducted to estimate the impact of providing this simple binary information primarily on nitrogen application rate and, consequently, on rice yield and income at plot-level and household-level.

Results The results showed that first, compared to those in the target plots of the control households, the nitrogen application rate was greater in the target plots of the treatment households who were informed of the high expected effectiveness. Second, information that the expected effectiveness was high increased the amount of nitrogen fertilizer in the target plot compared to that in other plots with no information about expected effectiveness within a household. Third, this change in fertilizer allocation led to higher rice yields and higher rice incomes at the household level.

Conclusions These results highlight how the binary information about the expected effectiveness with a single soil parameter can improve fertilizer allocation among rice plots and its use efficiency to increase rice productivity and income.

Keywords Chemical fertilizer, Randomized controlled trial, Rice, Soil property, Madagascar

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Background

Improving crop productivity and enhancing food security in sub-Saharan Africa (SSA) will require a substantial increase in chemical fertilizer use [1–4]. A large body of literature has identified factors explaining the low use of fertilizers in SSA, focusing mainly on the socio-demographic as well as market-related factors [5–7]. Additionally, recent publications show that site-specific information on soil characteristics can influence fertilizer application by smallholder farmers in SSA. Providing plot-specific information along with input vouchers significantly increased farmers' investment in mineral fertilizer and productivity [8]. Farmers face two main information deficits: technical knowledge about modern input use and information about the returns to technology adoption [9]. Information on expected returns has been shown to play a more prominent role in improving farmers' productivity [9]. Moreover, mismatches between the nutrients farmers applied and those that are actually insufficient in soils highlight the importance of site-specific information to improve productivity [10]. These findings are particularly relevant for smallholder farmers in SSA as their fields are known to be highly heterogeneous in terms of soil fertility or responses to nutrient inputs even within small distances due to the influence of topography and past management practices [11–13].

Statement of the problem

Thus, there is no doubt that site-specific information will improve productivity. Nonetheless, what kind of information should be provided remains to be further investigated. The present study aimed to answer this question. Prior studies have typically provided information based on comprehensive soil analysis to bridge the gap between required and actual fertilizer application rates (e.g., [8, 10, 14]). However, this approach is costly and time-consuming. It does not necessarily ensure effective fertilizer management due to the complex relationship between soil analysis information and crop response to fertilizer application [3].

Objectives of this study

The novelty of our study lies in providing simplified soil characteristics information and examining its impact on farmers' fertilizer use. Specifically, we provided binary information about the effectiveness of nitrogen fertilizer in a focal plot for rice production. The plot-level effectiveness was assessed by the content of oxalate-extractable phosphorus (Pox), an appropriate indicator for assessing phosphorus deficiency in lowland rice fields in the tropics [15]. Nitrogen deficiency is the most limiting factor for rice yield in SSA [16–18]. Instead of addressing nitrogen deficiency directly, we used Pox as an indicator of nitrogen fertilizer effectiveness. This approach was based on the following agronomic findings in our study region: first, the phosphorus deficiency status varies greatly from field to field [19, 20]; second, rice plants respond minimally to nitrogen fertilizer when Pox value is low because the phosphorus deficiency becomes the primary limiting factor for rice growth [21]. This strategy can be applied in the other parts of SSA where soil phosphorus deficiency is a primary yield-limiting factor for rice production, in addition to N deficiency [17]

We assumed that suboptimal allocation of fertilizer occurs because farmers are unaware of the heterogeneous distribution of phosphorus in the soil. Expected Effectiveness (EE) information on nitrogen fertilizer is expected to reduce uncertainty in fertilizer responses and help farmers optimize fertilizer allocation. Therefore, we hypothesize that farmers will increase (decrease) nitrogen fertilizer application on plots with high (low) EE. In this regard, our idea of optimizing fertilizer application differs from that of existing studies that adjust fertilizer application to the recommended level [14, 22]. For smallholder farmers in SSA, who often cannot afford large amounts of fertilizer, the practical question is how to allocate available fertilizer effectively. We further expected that optimized fertilizer allocation would increase rice yield in plots with high EE because of more intensive nitrogen fertilizer uses than in plots with low or unknown EE. Thus, our second hypothesis is that the provision of EE information will lead to a greater rice yield at the household level and, in turn, greater household welfare than otherwise.

The remainder of this paper is organized as follows: the "Methods" section describes the setting of the study and explains the sampling procedure as well as the experimental design and econometric strategies for comparison; the results and discussions are presented along with cost benefit analyses; and the conclusion and policy implications follow.

Methods

Setting of the study

The present study was conducted in Madagascar, where rice is the main staple crop and the main source of income for the rural population [23]. Improving rice productivity remains a central focus of national poverty reduction and food security policies. We chose the Vakinankaratra region, which is located in the Central Highlands zone, the largest rice-producing area in the country, for our study. Our recent study revealed that the increases in rice productivity contribute to the improvement of income via rice sales as well as human nutrition via increased

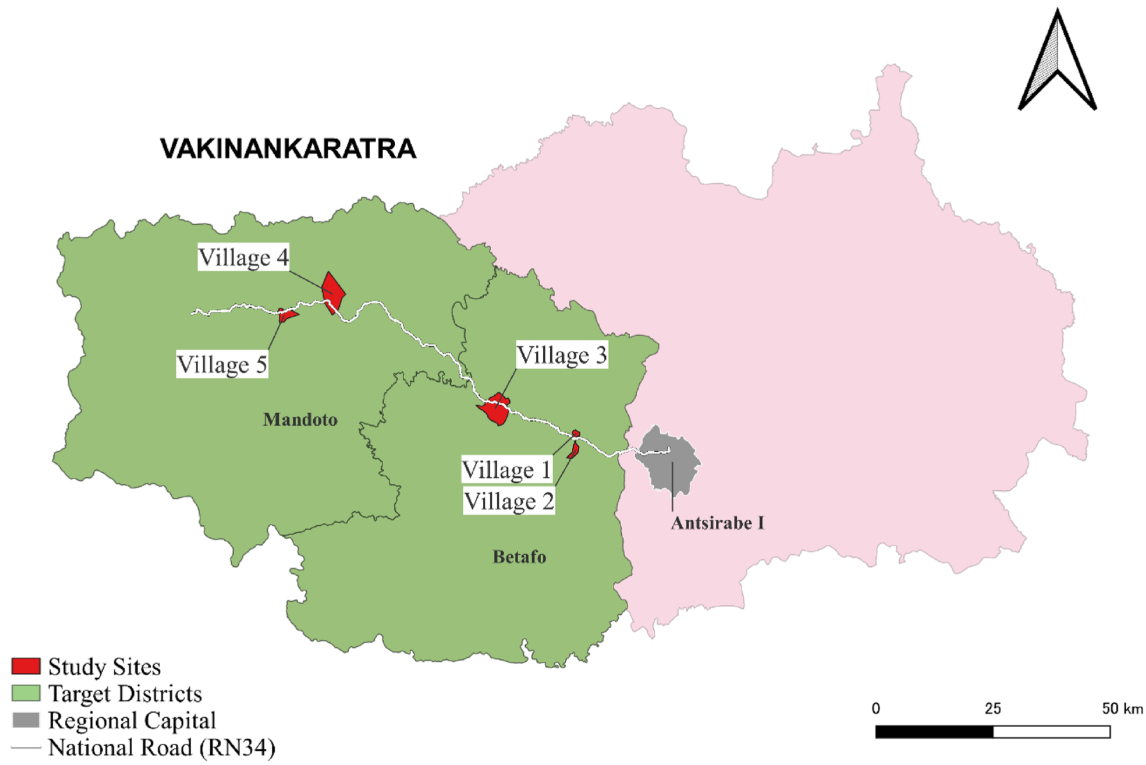

Fig. 1 Location of the study sites in the Vakinankaratra region. Source: Authors creation based on data obtained from [27]

intake of energy and micronutrients of zinc, iron, and vitamin A [24].

Although enhancing rice productivity has such a welfare effect in this region, the majority of farmers do not use chemical fertilizers in lowland rice production [25]. The poorly developed fertilizer market and the inaccessibility of the fertilizer retailers, especially for those living in remote areas, appear to explain a substantial part of the low adoption rate of chemical fertilizer. However, the assumption that farmers are willing to use chemical fertilizers on their lowland rice plots if they have access to the fertilizer market and can afford to buy them may be misleading. According to the qualitative study by International Rice Research Institute (IRRI), farmers claimed negative effects of continued use of chemical fertilizer on soil quality, such as making topsoil shallower and harder[26].[1] This belief, regardless of its origin, has led to skepticism about the overall benefit of chemical fertilizer use in lowland rice production. Therefore, encouraging farmers to change their practices requires not only improved market access, but also new and reliable information that can update their knowledge, countering long-standing beliefs and experiences. This context is crucial for our study as it highlights the necessity of scientific site-specific information.

Data collection and sampling procedure

Five villages in the Vakinankaratra region were purposively selected from two considerations. First, the five villages were chosen to represent the agroecological diversity of the region. Since the altitude of the highland region declines westward from 1500 m to 800 m, two villages were selected from relatively high-elevation areas, another two villages were selected from relatively low-elevation areas, and another village was selected from the area between them (Fig. 1). Second, to assure farmers of access to the local fertilizer market, the five villages were on the national road running from the regional capital, Antsirabe (Fig. 1).

Each village consists of several smaller administrative units. Based on these units, two enumeration areas (EAs) were selected from each village. The 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. Using the list of rice producers provided by the

[1] This IRRI's report is based on a survey conducted in 1988, which may seem outdated. However, the authors heard similar claims from several farmers during the fieldwork for this study.

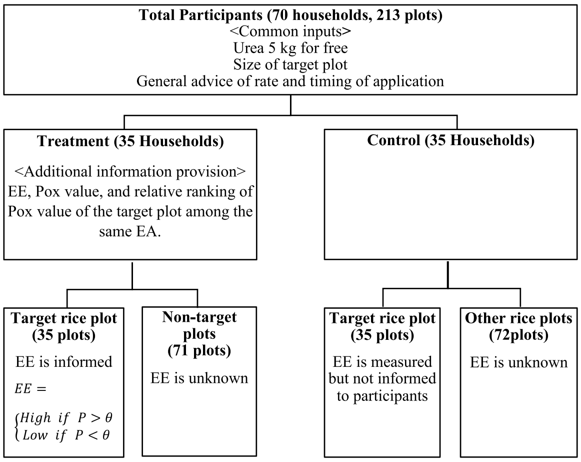

Fig. 2 Assignment structure. P denotes the amount of phosphorus in soil in mg/kg. Phosphorus was measured as oxalate-extractable phosphorus following Asai et al. (2020) [21]. Theta (θ) is the threshold value which defines the soil sample as either high expected effectiveness (EE) or low EE. Two different thresholds were used because soils in 4 out of 10 EAs were considered to be affected by a volcano

village leaders, we randomly selected 8 farmers who had grown rice in lowland plots during the 2018–19 rainy season.[2] Before the intervention, the sample farmers were asked to list all the agricultural plots they had used in that season, and then to select the most important lowland rice plot (we refer to this plot as the "target plot"). We visited each of these target plots and measured their location and size using a GPS (Garmin eTrex 30×model). In addition, surface soil at a depth of 0–15 cm was collected from three points in each plot to obtain soil composites. All the soil samples were subsequently sent to a national laboratory for soil Pox analysis according to Schwertmann (1964) [28]. Based on the results of this analysis, all the target plots were classified as either high-EE or low-EE plots. Note that the EE of "non-target" plots remained unknown for farmers with multiple rice plots.

Randomization

Figure 2 shows the assignment structure. A total number of 70 participants cultivated a total of 213 rice plots, including upland ones during the season of our intervention (2019–20 rainy season). Randomization at the EA level was more appropriate than randomization at the household level to avoid information spillover between households within each EA. Because the two EAs in a village are geographically separated and farmers in the control EAs had no information about the selection of the treated EAs, information spillover across EAs was prevented. After randomization, 35 households were included in both the treatment and control groups, and the number of rice plots were 106 and 107, respectively. We provided all participants with nitrogen fertilizer (5 kg of urea), the size of the target plot as determined by GPS, and general advice on the timing and rates of urea application[3] as common inputs. All of them were free of charge. Because we intended to test whether farmers would allocate nitrogen fertilizer based on EE information, we provided them with urea for free to alleviate the financial constraints of obtaining fertilizer. During the distribution of the common inputs, participants were explicitly informed that there were no restrictions on the use of the urea; therefore, they could apply it to any crop on any plot, keep it, sell it, or even give it to others.

After the common inputs were distributed, only the farmers in the treatment group received additional information regarding the EE status coupled with the Pox value in the soil sample of the target plot (mg/kg), and the relative ranking of the Pox value among the participants in the same EA[4] (see Figure A3). This intervention to the treated farmers removed the uncertainty of the yield response to urea application on the target plot, which should have facilitated them in deciding where to apply the nitrogen fertilizer more efficiently. Farmers in the control group had to decide how and where to use the distributed urea without knowing the EE status of their target plots.

The interviews for baseline data collection, soil sampling, and plot measurement were conducted in September 2019. In early November 2019, enumerators revisited the sample villages to distribute the common inputs to all the participants and the EE information generated based on soil sample analysis to the participants in the treatment group. The follow-up data collection was conducted in August 2020, approximately three months after the harvesting month of the year.

[2] We ended up with having 70 households in total due to some dropouts during soil sampling and interview.

[3] We recommended the rate of 1 kg of urea for 1 are of land (100 kg/ha). The recommended timings were 14 to 20 days after transplanting as basal fertilizer application, and 40 to 50 days after transplanting as top-dressing application. The actual paper distributed to all participants is presented in Appendix (see Figure A1, A2, and A3).

[4] Although our main objective was to give information on the EE status, we also provided the farmers in the treatment group with the Pox value and its ranking among the participants in the same EA because farmers in the same EA tend to know each other's plots, and the additional information might help them relate the results of soil examination to the actual situations they observed.

Table 1 Summary of variation in phosphorus amounts by EAs

Villages	EA	Mean	S.D.	Min	Max	Volcanic soil	θ
1	1	547.53	228.82	262.08	823.08	Yes	300
1	2	335.54	175.34	66.56	576.31	Yes	300
2	3	321.71	145.13	94.16	586.36	Yes	300
2	4	316.25	117.60	136.88	481.96	Yes	300
3	5	122.38	38.51	98.60	166.81	No	100
3	6	74.74	26.55	44.61	108.24	No	100
4	7	64.13	29.81	26.69	116.71	No	100
4	8	57.29	22.09	30.26	89.78	No	100
5	9	37.14	11.97	22.76	57.83	No	100
5	10	36.13	12.04	25.02	63.22	No	100

Unit is mg/kg of dried soil. Phosphorus amount is measured as oxalate-extractable phosphorus. S.D. stands for standard deviation. Theta (θ) is the threshold value which defines the soil sample as either high expected effectiveness (EE) or low EE. Two different thresholds were used because soils in 4 out of 10 EAs were considered to be affected by a volcano

Expected effectiveness of nitrogen fertilizer

Table 1 summarizes the variation in soil Pox according to EA. The mean Pox values varied considerably among the EAs, ranging from 36.13 mg/kg in EA10 to 547.53 mg/kg in EA1. Relatively high Pox levels were observed in EA1–EA4 probably because of the volcanic soil.[5] Based on the findings of Asai (2020) [21], Pox was used as the threshold to indicate the effectiveness of nitrogen fertilizer. Specifically, a Pox value of 100 mg/kg was used as the threshold (θ): the plot was considered to have high EE of nitrogen fertilizer use when Pox was above the threshold; the plot was considered to have low EE when Pox was below the threshold because phosphorus becomes the primary limiting factor for plant growth. Moreover, as phosphorus is abundant in volcanic soils but it in volcanic soils exists in the form unavailable for plants to observe, applying the same threshold of Pox value to these four EAs leads to overestimation of phosphorus availability in the plots. A public fertilizer application guideline for Japanese farmers suggests increasing the amount of phosphorus applied three times when soils are affected by volcanoes [29]. Therefore, following this recommendation, a Pox value of 300 mg/kg was used as the threshold (θ) for evaluating the EE in these four EAs. For the remaining EAs, using these thresholds, both high- and low-EE plots were found in 7 out of 10 EAs, indicating that the soil P deficiency status varies even within a village.

Econometric specification

The analysis used three specifications. The first model compares outcome variables between the target plots of the treated households and those of the control households. In our RCT setting, where whether a household received EE information was exogenously determined according to the random treatment assignment to each EA, the impact of intervention can be obtained by simple comparisons of mean values. However, it is still possible that the type of information the treated household received was correlated with observed and unobservable characteristics of the target plot and the household due to non-random selection of target plot from each household. Therefore, some control variables that explain characteristics of the plot and the household were included. Furthermore, to address the unobservable plot-level characteristics, we employed an analysis of covariance (ANCOVA) model that includes the outcome variable in the pretreatment period, or lagged dependent variable, as one of the explanatory variables. The lagged dependent variable is useful to deal with the potential omitted variable bias [30] and increases the power of the analysis, especially when using outcome variables that typically have high autocorrelations [31]. The specification is as follows:

$$Y_{h2020} = \alpha_0 + \beta_1 T_h^{high} + \beta_2 T_h^{low} + \beta_3 Y_{h2019} + \beta_4{}' Controls_h + u_h, \tag{1}$$

where Y_{h2020} is an outcome variable that is either the total amount of nitrogen[6] used or the rice yield in the target plot of household h in the rainy season of 2019–2020. The source of nitrogen can be either the distributed urea or any other nitrogen-containing chemical fertilizer prepared by farmers by themselves. Thus, the variable of the total amount of nitrogen does not differentiate these

[5] Nishigaki et al. (2020) conducted a soil survey covering our study sites, and found sporadic volcanic soil in Betafo district where the four EAs are located [12].

[6] Nitrogen application rate was calculated from the typical nutrient composition in each type of fertilizer product. It is 46% in the case of urea and 11% in the case of NPK fertilizers commonly available in the study area.

sources. With regard to the treatment variables, our treatment would affect farmers' decisions differently, depending on whether the information contained high or low EE. Therefore, two dummy variables indicating the type of information provided to the treated household were used instead of using one dummy variable for the treatment. Y_{h2019} is the outcome variable at the target plot in the previous rainy season. As additional control variables, plot size in ha, its squared value, household size, and age and years of education of the head of household were included.

Since EAs were the units of randomization, the standard errors were clustered at this level. However, the number of EAs is too small to apply the standard method of clustering standard errors. To address this problem, we employed wild cluster bootstrapping (WCB) to estimate standard errors [32].

The second model examined the impact of the intervention on fertilizer allocation within a household by comparing the target plot with non-target plots of a household. Thus, all the rice plots cultivated by the sample households, including upland rice plots, were used for this analysis. The model specification is as follows:

$$Y_{ih} = \beta_1 I_{ih}^{high} + \beta_2 I_{ih}^{low} + \beta_3 NI_{ih}^{high} + \beta_4 NI_{ih}^{low} + \beta_5 size_{ih} + \beta_6 size\_sq_{ih} + \beta_8 uprice_{ih} + HH_h + u_{ih}, \tag{2}$$

where Y_{ih} is an outcome variable for plot i of sample household h in the rainy season of 2019–2020. The outcome variables included the nitrogen application rate in kg/ha, which was defined as in the previous model; the rice yield in kg/ha; and the rice income in each plot in MGA/ha.[7] Income was calculated by subtracting the sum of expenses for seeds, hired labor, chemicals such as herbicides and pesticides, if used, and chemical fertilizers, including both the distributed urea and self-procured fertilizers, from the value of the rice paddy, which was calculated by multiplying the quantity of rice produced in kg by the average farmgate selling price of rice at the EA level.

In this specification, the target plots were further classified into four categories according to the two EEs of nitrogen fertilizer status and the two treatment statuses: target plots with a high EE of the treated households; those with a low EE of the treated households; those with a high EE of the control households; and those with a low EE of the control households. The corresponding binary dummy variables are denoted as $I_{ih}^{high}, I_{ih}^{low}, NI_{ih}^{high}$, and NI_{ih}^{low}. It should be noted that in the case of households in the treatment group, the information about EE was provided to the households before planting rice, whereas in the case of those in the control group, this information was not provided even though the soil was sampled, and the Pox values were obtained in the laboratory. Thus, these four dummy variables in specification (2) capture all possible patterns of the assignment status of target plots, setting non-target plots as the reference category. In this specification, β_1, β_2, β_3, and β_4 are the parameters of interest. Each parameter indicates whether and how each type of assignment status affects the outcome of target plots compared with non-target plots of the same household. In general, we expect that β_1 will be positive and significantly different from zero, because farmers are likely to follow the abovementioned information regardless of their subjective assessment of soil characteristics, unless they have very strong beliefs about the information. On the other hand, β_2 can be negative, but may not be significantly different from zero. The reason for the expected insignificant impact of the low EE information is that such information will not help farmers choose plots to use urea; hence, their decisions will not differ from those of control farmers who receive no information. In contrast, β_3 and β_4 will not be significantly different from zero.

Plot-level control variables were also included. $size_{ih}$ and $size\_sq_{ih}$ represent the plot size in ha and its squared value for plot i of household h, respectively. $uprice_{ih}$ is a dummy variable that takes the value of 1 if the plot is a rice plot in the upland. Given that upland rice cultivation is common in the study area [33], and many farmers in this dataset had rice plots both in lowlands and uplands, the non-target plots included both types of rice plots. Because the growing conditions differ between the two types of rice plots, this dummy variable aims to capture the effect of planting in uplands. HH_h is the household fixed effect that captures unobserved effects of household h's traits that commonly affect all the rice plots of household h. u_{ih} is the error term.

The third model was used to measure the household-level impact of the intervention:

$$Y_{h2020} = \alpha_0 + \beta_1 TREATMENT_h + \beta_2 \prime HC_h + \beta_3 \prime village + u_h, \tag{3}$$

where Y_{h2020} is one of outcome variables that include the intensity of nitrogen application in kg/ha, the rice yield in kg/ha, rice income in MGA/ha. All of them are at the household level. The household-level rice yield was calculated as the total rice quantity in kg produced divided by the total size of land devoted to rice cultivation in ha.

[7] MGA stands for Madagascar Ariary, the local currency in Madagascar.

Table 2 Results of t-test for variables related to household characteristics. Source: Authors calculation from the dataset

Variables	Unit	All	Control	Treatment	Pr(T > t)
Expected effectiveness (= 1 if High)	%	31.42	34.29	28.57	0.613
Household size	people	5.21	5.29	5.14	0.746
Sex of household head (= 1 if male)	%	92.86	94.29	91.43	0.643
Age of household head	years old	46.57	46.03	47.11	0.711
Education level of household head	years	6.00	6.31	5.69	0.416
Total size of rice plots	hectare	0.53	0.45	0.61	0.276
The number of rice plots	number	3.49	3.54	3.43	0.761
Size of the target rice plot	ha	0.15	0.14	0.17	0.384
Value of asset per capita	10^3 MGA	633.39	628.74	638.03	0.961
Observations		70	35	35	-

MGA is local currency

$TREATMENT_h$ in Eq. (3) is a dummy variable that equals to 1 if household h is in the treatment group, meaning that those who received either high or low EE information about their target plot, and 0 otherwise. Since our hypothesis is that the household-level outcome variables are positively affected by receiving information regardless of the type of information, this variable does not need to be decomposed, unlike in specification (1). HC_h is the vector of household-level covariates: total size of rice plot in ha, its squared value, and age and years in education of the head of household. Village dummy variables (*village*) were also included to control for unobserved factors attributable to village characteristics. β_1 is the parameter of interest, α_0 is the constant term, and u_h is the error term.

Because we did not collect baseline data on the household-level outcome variables, the ANCOVA model could not be applied to this household-level analysis. However, in the case of rice yield and fertilizer application, which are considered to have relatively high autocorrelation, we used the previous year's values in the target plot to control for preintervention levels.[8] As in the specification (1), we employed WCB.

Results and discussion

Characteristics of participating households

Table 2 provides descriptive statistics for the participating households. In addition to the mean values for all participating households in the first column, those of the control and treatment groups are presented in the second and third columns, respectively. In terms of EE status, 22 out of the total of 70 target plots, or 31.4%, were classified as high-EE plots, meaning that an increase in nitrogen fertilizer would result in a greater rice yield in these plots. A household typically consisted of 5 people and cultivated rice on an average area of 0.49 ha. The number of rice plots per household was on average 3.5, of which one was the target plot with a mean size of 0.15 ha. The description indicates that participants were typically small-scale but had multiple choices of plots for fertilizer allocation. It is also implied that the amount of the distributed urea was still not sufficient to cover the average size of the target plot. Thus, most farmers were expected to add urea or other nitrogen-containing fertilizer in order to thoroughly follow the recommendation. Since all the EAs are located along the national road by design of this study, farmers could procure additional fertilizer as needed without significant variability in accessibility. The last column in Table 2 shows that there were no systematic differences between the treatment and control groups with respect to these variables.

Descriptive statistics of plot-level outcomes

Panel A of Table 3 shows the descriptive statistics of rice yield and fertilizer use in the target plots. Before the intervention, urea was applied in merely 17% of the target plots. After the intervention, the percentage of plots where farmers applied urea increased to 61%. However, the average rice yield across all the target plots did not change much: 4384.31 kg/ha before the intervention and 4487.16 kg/ha after the intervention. After the intervention, urea was applied to 70% of the target plots in the treatment group when the plots were categorized as having high EE while the share was 48% when the plots were categorized as having low EE (Table 3). The mean urea application rate in the target plot of the treated households whose target plot was categorized as high EE was 167.86 kg/ha. This rate was greater than the recommendation provided regarding application rate, 100 kg of urea per ha. In addition, this rate was greater than the mean application rate in the non-target plots of the same group (see urea application rate in Panel B in the same

[8] In the case of rice income, the model was estimated without data prior to the intervention because they have low autocorrelation.

Table 3 Descriptive statistics of plot-level variables by assignment status. Source: Authors

Variables	Unit	All	Treated HHs (EE = High)	Treated HHs (EE = Low)	Control HHs
Panel A: target plots					
Before intervention (2018–19 season)					
Rice yield	kg/ha	4384.31 (2336.03)	6518.91 (2285.41)	3444.52 (2467.45)	4445.70 (1844.16)
Urea use	(0/1)	0.17	0.40	0.12	0.14
Urea application rate	kg/ha	159.78 (153.40)	123.05 (58.54)	152.44 (1.97)	193.57 (243.56)
Nitrogen use	(0/1)	0.20	0.50	0.12	0.17
Nitrogen application rate	kg/ha	68.34 (68.07)	54.02 (32.38)	74.18 (7.91)	77.35 (104.22)
After intervention (2019–20 season)					
Rice yield	kg/ha	4487.16 (2632.74)	6434.99 (3683.90)	3646.50 (2330.20)	4531.11 (2236.91)
Urea use	(0/1)	0.61	0.70	0.48	0.69
Urea application rate	kg/ha	96.89 (124.00)	167.86 (93.61)	55.10 (49.35)	97.08 (148.94)
Nitrogen use	(0/1)	0.61	0.70	0.48	0.69
Nitrogen application rate	kg/ha	47.05 (60.31)	91.53 (57.48)	25.43 (22.63)	44.90 (68.44)
Number of plots		70	10	25	35
Panel B: non-target plots					
After intervention (2019–20 season)					
Rice yield	kg/ha	3557.69 (2567.02)	4972.64 (2394.60)	3114.51 (2420.42)	3607.60 (2632.46)
Urea use	(0/1)	0.48	0.47	0.43	0.53
Urea application rate	kg/ha	53.62 (42.47)	49.27 (34.84)	39.73 (33.37)	63.19 (46.93)
Nitrogen use	(0/1)	0.58	0.47	0.55	0.62
Nitrogen application rate	kg/ha	22.32 (19.83)	27.71 (17.31)	15.54 (15.27)	26.16 (21.93)
Number of plots		143	15	56	72

Standard deviations for continuous variables are shown in parentheses. Nitrogen use and nitrogen application rate are separately presented from urea because sources of nitrogen include not only urea, but also other fertilizer products. The urea application rate and nitrogen application rate are the mean values only among plots where a positive amount of urea and nitrogen were applied, respectively

column). These differences seem to indicate that, on average, households who received EE information about their target plot adjusted their application rate and allocation although the adjustment was not necessarily accurate. We expected the proportion of urea-applied plots in the control group to be between the shares in the two treatment subgroups. Although 69% was in between, this percentage was very close to that of the high-EE group. The mean nitrogen application rate increased in the high-EE target plots from 54.02 kg/ha to 91.53 kg/ha after the intervention while it decreased in the low EE target plots of the treatment group.

These figures may seem perplexing at first glance. There was no statistically significant difference in the mean rice yield between before and after the intervention. For the treated target plots with high EE it was even slightly less after the intervention. However, these values do not mean the absence of the impact of the intervention because other factors such as plot size and household characteristics are not controlled for in the mean comparison. Therefore, the impact of the intervention should be estimated using econometric models that control for these covariates.

Panel B of Table 3 summarizes the same set of variables in the non-target plots after the intervention. The means of all these variables were lower than those in the target plots, i.e., the mean rice yield was 3557.69 kg/ha, the proportions of plots where urea was used and any nitrogen-containing chemical fertilizer was used were 48% and 58%, respectively, and the mean application rates were 53.62 for urea and 22.32 kg/ha for nitrogen. Moreover, the difference in the proportion of plots where urea was used between the target and non-target plots was the largest for the treated households that received high EE information.

Impact of intervention

Table 4 reports the regression results of Specification (1). The first row shows the impact of providing high EE information: the high EE information significantly increased the amount of nitrogen applied to the target plots by 34.09 kg/ha when the outcome variable in the season before the intervention, the plot-level covariates, and the village fixed effects were included in the model as shown in column (2). The high EE information encouraged farmers to use nitrogen fertilizer. Consequently, the rice yield

Table 4 Impact of soil quality information on nitrogen fertilizer in target plots

Dependent variables	Nitrogen quantity[a] (kg/ha)		Rice yield (kg/ha)	
	(1)	(2)	(3)	(4)
Treatment variables				
Treatment (high EE) (0/1)	49.87 (20.14)	34.09 (22.76)**	3119.95 (563.34)**	1082.50 (401.93)*
Treatment (low EE) (0/1)	−9.12 (10.89)	−6.42 (5.59)	−735.52 (464.90)	143.75 (289.29)
Plot-level covariates				
Nitrogen quantity in the previous season (kg/ha)[a]		0.48 (0.31)		
Rice yield in the previous season (kg/ha)				0.64 (0.15)***
Plot size (ha)		−28.18 (29.80)		−5946.96 (2908.25)
Plot size squared		13.40 (13.02)		−877.88 (979.56)
Age of the head of household		−0.04 (0.23)		31.60 (19.45)
Years of education of the head of household		0.60 (0.84)		71.23 (63.51)
Constant	21.32 (8.27)	19.92 (9.45)	4382.02 (384.13)	640.48 (938.90)
Village fixed effect	No	Yes	No	Yes
Observations	68	68	65	65
(Adj.) R-squared	0.29	0.50	0.18	0.47
F-value	4.55	15.12	18.15	142.48

[a] The amount of nitrogen is calculated from any type of chemical fertilizer products that contain nitrogen. For calculation, urea (N46–P0–K0) and NPK (N11–P22–K16) were used as major compositions of nutrients of each fertilizer product based on our field observations

Robust standard errors clustered at EA level are in parentheses

*** , ** and * indicate p < 0.01, p < 0.05 and p < 0.01 after wild bootstrapping, respectively

in the target plot significantly increased by 1082.50 kg/ha for those who received high EE information compared with that of the control group as shown in column (4). Note that three households were excluded because they experienced production failure in the target plots before the flowering stage of rice plants due to drought for the two of those and an unknown non-weather related factor for the other one. Since these events affected rice yield after the timing of nitrogen fertilizer application, the inclusion of these households may mask the impact of the providing EE information on rice yield via change in fertilizer use. The second row shows that receiving low EE information did not result in statistically significant differences in the nitrogen fertilizer use while the coefficient was negative as expected. Consistently with insignificant effect on the nitrogen use, the rice yield in the target plot of households that received low EE information was not different from that of the control group.

Table 5 presents the results of specification (2), which compares the outcome variables between the target plot and non-target plots in the same households that had multiple rice plots in the intervention season. The first four rows correspond to the four treatment categories of the target plot. The results showed that the amount of nitrogen fertilizer applied in the target plot was 31.89 kg/ha greater than that applied in the non-target plot only when the household received high EE information (column (1)). The difference in rice yields between the target plot and non-target plots in the same households was 1318.03 kg/ha on average after controlling for the case of upland plots and unobserved household characteristics as shown in column (2). By receiving high EE information, farmers significantly increased their rice income from the target plots compared with that from their non-target plots by 755,19 MGA/ha.

The second row of Table 5 presents the effect of low EE information on the target plots. As expected, there were no significant differences between the target and non-target plots in terms of nitrogen application or rice yield. This insignificant effect is as expected because the low EE information does not indicate to which plots a farmer should apply urea or nitrogen, unlike the high EE information. The coefficients in the third and fourth rows were insignificant, suggesting that, without EE information, participants in the control group allocated fertilizer evenly across rice plots within a household, and consequently there were no differences in outcomes between target and non-target plots.[9] The results imply that

[9] In the fourth row of the second column, the result indicated that the rice yield in the target plot of the control households whose target plot had low EE status was higher than that in their non-target plots at the 10% significance level. However, since the impact on the nitrogen use was insignificant, this positive coefficient on rice yield should be due to some other factors instead of the impact of our intervention.

Table 5 Impact of soil quality information on allocation of fertilizers within a household

Dependent variables independent variables	Nitrogen quantity[a] (kg/ha) (1)	Rice yield (kg/ha) (2)	Income (10^3MGA/ha) (3)
Treatment variables			
Treatment (high EE) (0/1)	31.89 (13.02)**	1318.03 (602.75)**	755.19 (422.97)*
Treatment (low EE) (0/1)	3.71 (3.61)	6.56 (451.60)	−30.87 (409.99)
Control (high EE) (0/1)	0.88 (6.87)	−788.56 (621.90)	−323.67 (474.76)
Control (low EE) (0/1)	1.10 (2.65)	916.54 (519.62)*	603.00 (428.51)
Plot-level covariates			
Plot size (ha)	−20.67 (10.74)*	−3897.13 (1647.50)**	−1621.34 (1034.22)
Plot size squared	13.07 (7.45)*	1389.65 (1095.94)	351.45 (663.27)
Upland rice plot (0/1)	9.57 (2.63)***	−1089.03 (408.86)***	−982.76 (372.88)**
Household fixed effect	Yes	Yes	Yes
Constant	14.75 (1.53)	4428.87 (279.91)	2360.48 (220.95)
Observations	181	181	181
Number of households[b]	55	55	55
(Adj.) R-squared	0.70	0.52	0.45
F-value	3.14	5.60	4.72

[a] The amount of nitrogen is calculated from any type of chemical fertilizer products that contain nitrogen. For calculation, urea (N46–P0–K0) and NPK (N11–P22–K16) were used as major compositions of nutrients of each fertilizer product based on our field observations

[b] The number of households is 55, which is different from the total number of participating households because 10 households that had only one rice plot and 5 households one of whose plots had extreme values for outcome variables were excluded

Robust standard errors clustered at household level are in parentheses. ***, ** and * indicate $p < 0.01$, $p < 0.05$ and $p < 0.01$, respectively

farmers do not know the effectiveness of nitrogen in their plots, and providing this information helps them optimize their decisions.

Table 6 shows the impact of the intervention on household-level outcomes using specification (3). The first column presents the results of estimating the impact of the treatment on nitrogen application rates. Columns (2) and (3) show whether and to what extent rice yields and rice income at the household level increased as a result of the intervention, regardless of the type of information. The insignificant coefficient in column (1) indicates that the intervention did not increase nitrogen application rates at the household level. It should be noted that all the households regardless of the treatment status received 5 kg of urea at the beginning of the cropping season. However, the intervention increased rice productivity at the household level by 613.94 kg/ha (column (2)). Consequently, rice income at household level was 433,760 MGA/ha higher for the treated households (column (3)). These results suggest that information provision leads farmers to achieve higher rice productivity and income not by increasing the amount of fertilizer, but by optimizing the allocation of fertilizer within the household.

Cost–benefit analysis of the intervention

To explore the financial viability of this experiment or a similar attempt in the future, Table 7 presents a cost structure based on the experience of this study. The cost of hiring an enumerator to sample soils was approximately 70,000 MGA/day, which included accommodations and other necessary items for the activity in the field. Based on the experience of this study, an enumerator could collect soil samples from an average of 3 to 4 plots per day, although various factors affected the efficiency of the work. Thus, the cost of soil sampling was approximately 20,000 MGA per plot. These samples were then taken to the Laboratoire de Radio-Isotopes, the national agricultural research institute located in the capital city of Madagascar. In this experiment, 70 soil samples were tested per day. Assuming that wage rate of a laboratory technician is the same as that of an enumerator, the cost of testing one soil sample is 1,000 MGA.[10] In addition, 5 kg of urea was provided free of charge in this experiment. At the time of the intervention, the price of urea was 1,800 MGA/kg, so the cost of 5 kg was 9000 MGA. It cost 70,000 MGA/day to rehire the enumerator to revisit the participants to deliver the urea and the soil test result. One enumerator could visit 8 households per day, so the cost was 8,750 MGA per participant. The total

[10] No chemical material was used in the analysis. We have not taken into account the depreciation of the laboratory equipment because it has multiple uses, and it is not realistic to accurately calculate the portion of depreciation that is attributable to this work.

Table 6 Impact of intervention on household-level variables

Dependent variables	Nitrogen[a] application rate (kg/ha)	Rice yield (kg/ha)	Rice income (10^3MGA/ha)
	(1)	(2)	(3)
Treatment (0/1)	9.2 (3.97)	613.94 (246.30)*	433.76 (177.39)*
Control variables			
Nitrogen application in target plot in the previous year	0.1 (0.09)		
Yield of target plot in the previous year		0.47 (0.05)***	
Total size of rice plot (ha)	−25.1(14.30)**	−2593.06 (979.98)**	−1976.32 (726.99)**
Total size of rice plot squared	5.26 (3.34)	445.99 (232.99)	334.71 (157.76)
Age of household head (years old)	−0.08 (0.16)	11.07 (9.94)	19.60 (21.21)
Years of education of household head	1.00 (0.48)*	117.06 (42.81)**	80.15 (63.82)
Village fixed effect	Yes	Yes	Yes
Constant	26.46 (5.39)	1486.41 (520.25)	1079.12 (1008.60)
(Adj.) R-square	0.43	0.55	0.15
Observations	65	65	65
F-value	50.52	25.12	8.88

[a] The amount of nitrogen is imputed from any type of chemical fertilizer products that contain nitrogen. For calculation, urea (N46–P0–K0) and NPK (N11–P22–K16) were used as major compositions of nutrients of each fertilizer product based on our field observations. The number of observations is 65 because the same households used in the column 4 of Table 4 were used here. Robust standard errors clustered at EA level before wild bootstrapping are shown in parentheses

The significance level is obtained by wild bootstrapping and indicated by ***, ** and *, which imply $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively

Table 7 Cost and benefit analysis of the intervention. Source: Author's experience in the experiment

Items	Unit Price	Rates	Costs per household[a] (MGA)	Costs per household [c] (USD)
A. Hiring an enumerator for soil sampling	70,000 MGA/day	3–4 plots/day	20,000	5.28
B. Wage for lab staff for soil examination	70,000 MGA/day	70 samples/day	1000	0.26
C. Hiring an enumerator for revisiting	70,000 MGA/day	8 households/day	8750	2.31
D. Urea	1,800 MGA/kg	5 kg/households	9000	2.38
Total cost per household (A. + B. + C. + D.)			38750	10.23
Total benefit			212542[b]	56.11

[a] These values were obtained from experience of the present study

[b] This value was obtained by multiplying the mean size of the total rice plot (0.49 ha) by the coefficients of the treatment variable in column (3) of Table 6

[c] Exchange rate as of 2020 (1USD = 3787.75MGA) was obtained from the World Bank website (https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=MG&view=chart.)

cost was 38,750 MGA for one plot per participant, which is equivalent to US$ 10.23.

As shown in Table 6, the average rice income per ha of the treated households was 433,760 MGA higher than that of the control households. Since the mean total rice plot size for a household was 0.49 ha, a typical household will receive 212,542 MGA or US$ 56.11 of benefit from the soil information of one of the household plots. This expected benefit was substantially higher than the implementation costs and would persist so even with the recent increase in international fertilizer prices.

It should be noted that the cost calculation does not include the cost of transporting a soil sample to the research institute, as the cost depends largely on the mode of transportation and the distance between the study site and the location of the institute. This may be a concern especially if a similar intervention is carried out on a larger scale. In addition, implementing similar interventions for farmers in remote areas may be more difficult because, for a developing country, the number of research institutes that can conduct soil analysis is limited and these institutes are usually located in or near urban areas. However, if the demand for soil testing increases, the number of soil samples will increase, and test laboratories can be established in many places in the country. Therefore, the transportation cost per soil sample will decrease.

Partial budget analysis

In addition, to investigate whether nitrogen application is an economically attractive option for farmers whose plot is high EE, the partial budget analysis was performed according to [34]. Table 8 compares a partial budget for nitrogen application in plots with high EE. In a partial budget analysis, the net benefits are calculated by subtracting the costs from the gross field benefits. Costs include only those that vary due to shifting from one option to the other, which in the context of this study were the cost of nitrogen and labor to apply urea.[11] Calculations of these costs are shown in Table A1. The gross field benefits are obtained by multiplying the average yield by the field price of the output, farmgate rice selling price in the context of this study.

The partial budget analysis shows that the net benefits of nitrogen application were higher than those of no nitrogen application in high-EE plots. The additional gross field benefit was 1,127,280 MGA/ha (4,935,266MGA—3,807,986MGA), while the increase in the total variable costs was 257,084 MGA per ha. Thus, for farmers whose plot was high-EE but did not receive nitrogen fertilizer, applying nitrogen at the average application rate of those who applied it would result in an additional net benefit of 870,196 MGA/ha. Furthermore, the marginal rate of return for nitrogen application was calculated by dividing the net benefit gain of 870,196 MGA/ha by the additional cost of 257,084MGA/ha, and that was 3.38. These results imply that nitrogen application is an economically attractive option in high-EE plot and highlight the importance of an intervention to make farmers aware of their soil characteristics.

Table 8 A partial budget of nitrogen application in a plot with high EE

	Without N application	With N application
Average yield (kg/ha)[a]	4459	5779
Gross field benefits (MGA/ha)[b,c]	3,807,986	4,935,266
Cost of nitrogen (MGA/ha)[d]	0	248,084
Cost of labor to nitrogen application (MGA/ha)	0	9,000
Total variable costs (MGA/ha)	0	257,084
Net benefit (MGA/ha)	3,807,986	4,678,182

[a] The average yield for each column was obtained by taking average of yields of high-EE plots according to whether urea was used regardless of the treatment assignment

[b] In the manual of partial budget analysis provided by [34], adjusted yield instead of average yield is used to calculate gross field benefits. However, we do not need adjusted yield because our data come from randomly selected farmers' plots instead of representative farmers in the study site

[c] To obtain this value, the farmgate selling price, 854MGA/kg, was used as the mean selling price among farmers whose plot was high EE

[d] Cost for transportation was not considered because all EAs are located along the national road and therefore access to fertilizer retailers did not considerably differ among participants

Limitations of the study

The limitations of this study are as follows. First, the experiment was conducted on a relatively small scale; hence, the number of observations was not so large. Considering the criticism of the external validity of many RCT studies, in addition to the small sample size, the generalization of the results of this research requires special caution. Similar interventions on a larger scale will be important to confirm the main findings of this study. Second, this study examined the impact of information only during the 2019–2020 season, which began immediately after our intervention. It would be useful to have additional data for subsequent seasons to see if the impact is sustained without the provision of free fertilizer.

Conclusion and policy implications

While the necessity of site-specific fertilizer management advice is widely recognized, the specific type of site-specific information can improve soil fertility management and increase crop yield, without resorting costly comprehensive soil analysis, was previously uncertain. To address this, we demonstrated the effectiveness of a unique binary indicator of fertilizer effectiveness based on the Pox value of the soil. This proposition has been firmly supported by agronomic evidence that P deficiency in soils is a primary limiting factor for rice response to nitrogen inputs, the main fertilizer source, in SSA provided that other observable stresses such as drought, flooding, weed, pests, and diseases are absent.

A randomized controlled trial in Madagascar showed that simple binary information contributed to effective use of nitrogen fertilizer. Farmers informed about the high EE status of their target plot applied significantly more nitrogen to these plots compared to those who did not receive EE information or plots with no information. Moreover, providing EE information helped

[11] Additional cost of seeds may have to be considered if farmers use seeds of different rice cultivar which they consider more fertilizer responsive when they choose. However, it is reported that farmers do not care about rice cultivar when they use fertilizers [27], and thus we did not include the cost of seeds in this analysis.

optimize the allocation of available fertilizers, and increasing yield and rice income at the household level.

Given the general need to increase nitrogen use in rice production in SSA, this study makes an important contribution to the discussion by showing that even simple information can enhance the effectiveness of conventional fertilizer policies such as subsidy programs, credit, and fertilizer use training for promoting fertilizer use. Additionally, the cost–benefit analyses showed that our approach is cost effective.

The use of a simple indicator of nitrogen effectiveness is unique to this study because previous studies have used many soil properties to determine the type and amount of mineral fertilizer to be applied in each plot. Nevertheless, we do not intend to oversimplify reality, and we agree with the comments of Burke et al. (2019) [35] on Marenya and Barrett (2009) [36] that crop yield response is influenced by a complex soil structure. In this regard, future studies that examine whether complex information consisting of multiple soil properties leads to greater or lesser impacts on farmers' practices than the simple information based on a single soil property used in this study, taking into account the costs of information generation, will be useful for both researchers and policy makers.

Abbreviations

ANCOVA	Analysis of covariance
CMEST	Comité Malgache d'Ethique pour les sciences et les technologies
EA	Enumeration area
EE	Expected effectiveness
IRRI	International Rice Research Institute
RCT	Randomized controlled trial
MAFF	Ministry of Agriculture, Forestry and Fisheries
MGA	Madagascar Ariary
Pox	Oxalate-extractable phosphorus
SSA	Sub-Sahara Africa
S.D.	Standard deviation
WCB	Wild cluster bootstrapping

Supplementary Information

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Additional file 1.

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Not applicable

Author contributions
RO was a major contributor in data collection, econometric analysis, and writing the manuscript. RO, YT, and TS contributed to conceptualization, design of the experiment, interpretation of data analysis, and revision of the manuscript. YT, AA, and HR contributed to acquisition of soil data and performed soil property analysis. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The activities relevant to this study were approved by the Comité Malgache d'Ethique pour les Sciences et les Technologies (CMEST) of Madagascar with the reference number of N° 014/2020—AM/CMEST/P. The purpose of the study was explained to each participating household and informed consent was obtained by interviewers before starting the interview.

Consent for publication
Not applicable.

Competing interests
There are no conflicts of interest to declare.

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