MISSPECIFIED LEARNING IN TECHNOLOGY ADOPTION: EXPERIMENTAL EVIDENCE FROM FERTILIZER USE IN CHINA*

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Abstract

This paper investigates agents' learning about multiple interacting technologies in the context of fertilizer application in China. We first present experimental evidence that farmers overuse nitrogen fertilizers and underuse phosphorus and potassium fertilizers. Our first-phase intervention provides customized fertilizer recommendations and leads to reduced use of nitrogen and increased use of phosphorus and potassium. Average yields and revenues are 5%-7% higher, while total fertilizer costs remain unchanged. Survey data suggest that farmers overestimate the return to nitrogen because it produces a salient signal of increasing greenness in crops, but they underestimate the effectiveness of phosphorus and potassium because their effects are barely observable during the growing stages. We propose a model of misspecified learning in which agents face two technologies with unknown returns. When learning about the effectiveness of these technologies, an overestimation of the return to the first causes undervaluation and underuse of the second. We further test the model, with a second-phase intervention that distributes leaf color charts to farmers to correct their overestimation of the return to greenness. Consistent with the model's prediction, the intervention not only immediately reduces farmers' nitrogen use, but also induces gradual learning about phosphorus and potassium. Both the share of farmers using phosphorus and that of potassium increase by 6 percentage points, relative to 3% and 9% in the control group.

Keywords **: Mislearning, Overestimation, Effectiveness, Undervaluation**

JEL classification: **D83, O13, O33, Q16, Q51**

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1 Introduction

Existing theoretical and empirical literature identifies and explains learning failures in technology adoption in a single domain. However, agents often need to choose multiple technologies simultaneously in reality. For example, with limited budget, agents face a trade-off problem between using antibiotics or improving hygiene conditions. Farmers face a trade-off between using pesticides or introducing bug-resistant crops. Firm owners can either choose to increase managers' hours of work or improve management practices. In these cases, the first technology is more immediately noticeable than the second, which causes agents to overuse the first, which crowds out the adoption of the second less-salient technology. Hanna, Mullainathan, and Schwartzstein (2014) begin to explore the role of selective attention in modeling learning failures along a particular input dimension. Yet little is known about how mistaken beliefs about one technology impede effective learning in other related technologies.

This paper sheds light on mislearning transmission between technologies by explicitly modeling the interactive effects that occur when agents learn about two technologies and presents novel experimental evidence from the utilization of fertilizer technology in China. We chose this context for two reasons. First, fertilizers, which consist of multiple technologies (nitrogen, phosphorus and potassium), are essential to productivity growth in most developing countries but are often underused or overused.[1] Simultaneous underuse and overuse of different fertilizers are puzzling because farmers have employed these technologies over decades, which should be a sufficient time frame for them to learn their correct usage according to learning-by-doing models. Second, the efficiency loss and greenhouse gas emissions (CO_2 and N_2O) caused by the misuse of fertilizers are especially pronounced in China,[2] which accounts for 28% of global fertilizer use.

Using administrative data from the soil analysis of millions of local plots conducted by the government, we observed that farmers simultaneously overuse nitrogen (N) fertilizer in the growing stage and underuse phosphorus (P) and potassium (K) fertilizers throughout the cropping cycle. To study whether farmers can correctly learn the effectiveness and optimal application levels of different fertilizers, we designed and implemented a two-phase randomized controlled trial (RCT) among 1,200 farmers in 200 villages. In the first phase of our experiment, we provided farmers with customized fertilizer recommendations based on the soil analysis at the plot level. We randomly varied whether farmers received only soil testing (T_1);[3] whether they received the soil analysis and customized fertilizer recommendations through a smart mobile application (T_2); whether they received the soil analysis, the mobile application, and a training session from agricultural extension specialists (T_3); or whether they served as a pure control group (C). Extension meetings for the

[1] For example, Kenyan farmers underuse fertilizers due to procrastination (Duflo, Kremer, and Robinson, 2008, 2011), Chinese farming households overuse fertilizers as a consequence of poor education (Cui et al., 2018), and Mexican maize farmers misuse different types of fertilizers because of soil heterogeneity (Corral et al., 2020).

[2] According to the International Atomic Energy Agency (IAEA), agricultural activities, mainly the use of fertilizers, contribute approximately 10-30% of global greenhouse gas emissions, driven primarily by activities in Brazil, Europe, India, the United States, and particularly China. This share varies among different countries, for example, agriculture accounts for 10% of total U.S. greenhouse gas emissions (EPA).

[3] Specifically, farmers received detailed information about the soil quality and micronutrient content of their plots.

T_3 group were conducted one-on-one in-person, and specialists showed the experimental effects of phosphorus and potassium on yields to update farmers' beliefs about the effectiveness of these fertilizers.

Results from the first-phase experiment indicate that T_2 and T_3 interventions reduced farmers' application of nitrogen fertilizer by 13.3-14.7 percent, which occurred mainly during the growing stage of rice crops. Before our intervention, the share of farmers using phosphorus fertilizer was merely 3% in the control group C, and it jumped up by 23.2-23.9 percentage points in the T_2 and T_3 groups. The proportion of farmers using potassium fertilizer was 9% in the control group, and similarly it increased substantially by 24.1-32.4 percentage points. The increase in the adoption of potassium and phosphorus fertilizers was predominantly driven by extensive margin. In contrast, soil analysis alone (T_1 vs. C) did not have any significant impacts on fertilizer use due to the failure among farmers to understand how raw soil testing data to inform their farming practices.

The cost of misuse was substantial. T_2 and T_3 increased yields and revenues significantly by 5-7% and 6.0-6.9% respectively without increasing the cost of fertilizers. These results also imply that our interventions substantially reduced the greenhouse gas (e.g. N_2O) emissions due to inefficient farmer practice.

Our survey evidence highlights the importance of salience in farmers' learning. The primary effect of nitrogen fertilizer is to immediately increase crop greenness during the growing stage. Farmers overestimate the return to nitrogen fertilizer due to the salience of greenness and the mistaken belief that excessive greenness will further boost yields. On the other hand, the effect of phosphorus and potassium fertilizers is less direct and observable. Indeed survey responses suggest that farmers often do not correctly understand the role of potassium and phosphorus, and as a result underuse them.

The wide availability of all kinds of fertilizers, coupled with the persistence of suboptimal fertilizer application suggests significant barriers that prevent farmers from Bayesian learning and updating their beliefs. Selective attention (e.g. Hanna, Mullainathan, and Schwartzstein (2014)) on the other hand, predicts that farmers will optimally use nitrogen fertilizer, which farmers pay adequate attention to. But it cannot rationalize the behavior of simultaneous overuse and underuse in this setting.

To explain these phenomena, we propose a model of misspecified learning, building on work by Heidhues, Kőszegi, and Strack (2021), in which agents face two interacting technologies and overestimate the return to the first technology. The overestimation of the return to greenness (nitrogen) distorts agents' adoption of the first technology, which influences their valuation of the effectiveness of the second technology. The difference in profits between their subjective beliefs and their observations is rationalized by their lower-than-true perceptions of the effectiveness of phosphorus and potassium. Consequently, agents overuse the first and under use the second. Our model generates three main predictions: 1) farmers are trapped in a sub-optimal equilibrium, where nitrogen is overused and phosphorus and potassium are undervalued and underused; 2) farmers' perception about the effectiveness of phosphorus and potassium moves toward the true value as

their actions in fertilizer use move to the optimal composition and level; and 3) correcting the overestimation of the return to greenness not only leads to immediate learning about nitrogen, but also induces farmers to learn more about phosphorus and potassium fertilizers.

We verify prediction (1) from the first-phase experiment. We then present evidence consistent with model prediction (2) regarding beliefs about the effectiveness of different fertilizers. Our experimental results from the first-phase show that farmers' evaluation of the effectiveness of nitrogen remained unchanged since most farmers (95.2% in the control group) already understood its effects on greenness. We then explore the T_2 intervention, which encouraged farmers to change their fertilizer applications, but didn't involve direct contact to change their beliefs. We find that 22.0, 20.8, and 17.1 percent more farmers correctly understood the relationship between P/P/K and flower timing/root length/grain density after the T_2 intervention. In the T_3 group, these effects on beliefs about the effectiveness of different fertilizers were almost doubled due to the presence of farmers' social learning from agricultural extension specialists.[4]

Can model-driven interventions help resolve learning failure in the application of different fertilizers? To test model prediction (3), in the second-phase field experiment, we randomly varied whether farmers received leaf color charts (LCCs) to help them better calibrate the optimal level of nitrogen to use on their crops. The goal of the LCC intervention was to correct farmers' overestimation of the return to greenness in the production function. By following the instructions, farmers could compare the actual leaf color of their crops with the optimal greenness on the charts to make informed decisions about optimal top-dressing nitrogen fertilizer applications.

Results from the second-phase experiment confirm our model prediction (3) that correcting misperceptions about one technology (nitrogen fertilizer) induces agents to learn about and experiment more with the second technology (phosphorus and potassium fertilizers). Specifically, the LCC intervention immediately reduced farmers' application of nitrogen fertilizer by 3.76 kg per mu—a 12.3% decrease compared with the control mean. The leaf color charts also encouraged a small proportion of farmers to experiment with using phosphorus (6.62 percentage points) and potassium (6.66 percentage points) for the first time. The results suggest that reducing farmers' misspecification in one dimension pushed them to learn about the other dimensions more effectively. We estimate that the changes in fertilizer use caused by the leaf color charts led to a 3.4% increase in average yields and a 4% increase in revenues compared with the control group.

We next discuss some issues with measurement problems and alternative theories for nitrogen overuse. One natural concern is that the self-reported inputs and outputs may affect the results. To address this concern, we collected data on fertilizer use in three different ways, the overall amount of purchase and use in a year and amount of use in different cropping stages. We find that the data are quite consistent. Another concern is that supply-side sellers and price may affect farmers' decision-making. We present direct and indirect evidence that these factors did not drive the overuse of nitrogen fertilizers. First, the farmers' bias with regard to fertilizer application

[4]In T_2, we provided only the mobile application and instructions to farmers; thus, the updating of beliefs should have come only from self-learning.

concentrated on the growing stages. Second, their decision-making is based mainly on greenness signals during the growing season. They believe the greener the better.

Taken together, the new mechanisms proposed by this paper are externally relevant in other contexts where agents learn about interacting technologies simultaneously. Our results also demonstrate that cost-effective interventions guided by theory can correct agents' sub-optimal input choices, which has important policy implications. A cost-benefit analysis indicates that the profit gains exceed the costs for the app-based interventions (T_2), the extension services intervention (T_3), and the leaf color chart intervention. However, there is a trade-off of cost versus speed of realized results for policymakers when choosing between these interventions. On the one hand, the app-based intervention (T_2) and extension services intervention (T_3) allow agents to optimize input choices immediately, but they are more costly to implement and require plot-level soil testing data. In comparison, the leaf color chart intervention is more easily scaled due to significantly lower costs, but induces slower learning. We also analyze the aggregate benefits of these interventions. A back-of-the-envelope estimate suggests that total greenhouse gas emissions would fall by 37.4 million tons per year (0.4% of China's annual CO_2 emissions), while rice farmers' revenues would increase by roughly 30 billion RMB.

Our work contributes to three main strands of the literature. Our research questions are most related to topics on technological learning and misuse of a single technology. Existing theories and empirical evidence in the field explore under-investment in agricultural technologies due to labor costs (Foster and Rosenzweig, 2010), procrastination (Duflo, Kremer, and Robinson, 2011), distance to public transport (Suri, 2011), and low attention to one particular input dimension (Hanna, Mullainathan, and Schwartzstein, 2014).[5] We complement this strand of literature in two aspects: 1) We first experimentally document the existence of simultaneous overuse and underuse of different technologies when more than one technology is at play;[6] 2) We propose a new mechanism—mislearning between different technologies. Our model and survey evidence suggest that the misperception of one technology can influence the perception of the effectiveness of other technologies.

Our methodology and results on mechanisms build on recent theoretical literature on misspecified learning (Heidhues, Kőszegi, and Strack, 2018; Fudenberg, Lanzani, and Strack, 2021; Heidhues, Kőszegi, and Strack, 2021). The key intuition of these theories is that misspecification in the production function affects agents' actions, and such distorted actions then change agents' valuation of the technology. We contribute to this work by extending the model to two interactive technologies, and studying how mistaken beliefs in one technology could affect the adoption of other

[5] Beyond the agriculture sector, recent studies have looked at the misuse of technology in other fields, such as deworming (Miguel and Kremer, 2004; Hamory et al., 2021), antibiotics (Currie, Lin, and Meng, 2014), vaccines (Karing, 2018), new health products (Dupas, 2014); management (Bloom et al., 2013) and new products in firms (Atkin et al., 2017); energy efficiency products Allcott and Taubinsky (2015) and energy-saving stoves (Berkouwer and Dean, 2019).

[6] We compare our impacts with related interventions. In terms of nitrogen-fertilizer application, Chen et al. (2014) estimate that an integrated soil–crop system management (ISSM)-based recommendation led to higher yields (18–35%) and a reduction in nitrogen usage (4–14%).

technologies. To the best of our knowledge, our paper is the first to experimentally test the theory of misspecified learning in the field. We provide evidence consistent with the model predictions and find that a theory-based intervention in our second-phase experiment can indeed resolve learning failure in fertilizer application.

Our interventions and policy implications leverage information communication technology (ICT) to improve farmers' efficiency and reduce environmental damage and greenhouse gas emissions. The role of ICT has been considered by several studies in agriculture (Casaburi et al., 2014; Casaburi, Kremer, and Ramrattan, 2019; Fabregas, Kremer, and Schilbach, 2019; Cole and Fernando, 2021), in environmental protection (Greenstone et al., 2020), and in firm and business performance (Jensen, 2007; Jensen and Miller, 2017). Our paper relates to this literature by providing farmers with customized agricultural services through a smart mobile application. This is particularly relevant in low- and middle-income countries (LMICs) since many smallholder farmers in LMICs lack access to science-based agricultural advice. In these countries, information provision to farmers is often "top-down" and not localized, which results in inadequate diagnosis of farmers' needs with respect to local agro-ecological settings and diverse farm-level characteristics. By taking advantage of administrative data on soil testing, our mobile application serves as a precise benchmark for optimal fertilizer application and thus reliably complements the service provided by extension agents. This paper also adds to the studies on greenhouse gas emissions (Gilbert, 2012; Tian et al., 2020). Fertilizer pollution in agriculture is often under-evaluated in the economics literature but has a significant impact on the global environment.

The paper proceeds as follows. Section 2 describes the setting and first-phase experimental design. Section 3 discusses results from the first-phase field experiment. Section 4 presents our theoretical framework. Section 5 details the second-phase experimental design and interprets the results. Section 6 provides some additional discussions. Section 7 concludes.

2 Setting and First-Phase Experimental Design

2.1 Fertilizer Consumption: China vs. the World

Fertilizer has been able to generate high returns for farmers and was responsible for significant growth in agricultural yields during the 20th century. In 2020, the global fertilizer market amounted to more than US$ 171 billion. With the considerable increase in fertilizer use, traditional agricultural extension programs have not always provided the most useful instructions for farmers or given them knowledge about alternative farming practices (Beaman et al., 2021), especially in less developed countries, where smallholders may be ill-informed regarding safe and sustainable fertilizer use due to a lack of extension support. China provides a perfect context for studying the inappropriate use of fertilizer technology, since 98% of farming households have a farming plot of less than 2 hectares (Wu et al., 2018).

There is a longstanding discussion on fertilizer misuse in China.[7] As the world's largest fertilizer

[7]See discussions on the relationship between excessive nitrogen use and yield by Chen et al. (2014); Zhang et al.

producer and consumer, China accounts for roughly 28.8% of global fertilizer use, while its arable land is only 7.6-9% of the world's total. Figure 1 shows the intensity of fertilizer application indexed by kilograms per hectare from 1961 to 2014 among some developed and developing countries, including Brazil, Bangladesh, China, Germany, India, Kenya, Mexico, and the United States. Starting in 1961, China's rate of fertilizer application grew rapidly, particularly after 1980 when synthetic fertilizers were introduced. Developing countries like Bangladesh, Brazil, and India, followed a similar growth pattern in fertilizer intensity as China in the earlier stage. For developed countries like Germany, fertilizer use reached a peak around 1980, and dropped dramatically after 2000,[8] when the German government started to impose restrictions limiting fertilizer application. From this cross-country comparison, we believe that it is important for the other countries to avoid following the same path of excessive fertilizer application.

Using a rich panel dataset that traces roughly 20,000 farming households from 1986 to 2015 over 360 villages, we depict the relationship between fertilizer application rate per hectare and farm scale. In Figure 2a, the top red line indicates the suggested amount of fertilizer application per hectare in western Kenya (Duflo, Kremer, and Robinson, 2008), roughly 242 kg/ha, and the bottom line shows the suggested level in India (Foster and Rosenzweig, 2010), roughly 160 kg/ha. Figure 2a highlights two important features. First, Chinese farmers tend to systematically overuse fertilizer at the intensive margin, which is consistent with the macro statistics that fertilizer intensity in China is four times the world average. Second, the downward sloping curve implies that smallholders have even higher application rates than farmers with large landholdings, suggesting poorer decision-making on fertilizer input by smallholders.

While underresearched in the economics literature, excessive use of fertilizers, especially nitrogen fertilizer, has resulted in massive emissions of greenhouse gases (CO_2, N_2O). As shown in Figure A1 in Appendix A, developed countries such as the United States, Australia, Germany, the Netherlands, and Denmark, and developing countries including India, Bangladesh,[9] and China are experiencing the same environmental concern regarding nitrogen overuse. Therefore, finding an appropriate way to improve fertilizer application can resolve the global concern for sustainable development and the fight against global warming (Tian et al., 2020).

2.2 Design of Interventions

A recent study on fertilizer application in China suggests that a reduction of 30% to 50% in the application of fertilizer would not necessarily compromise yields (Cui et al., 2018). To determine whether farmers in China apply a sub-optimal mix of fertilizers and to understand the economic consequences of such misuse, we designed and implemented two experiments consisting of two main phases: (i) change farmers' actions in choosing the level of fertilizer application by providing individual soil analysis and customized fertilizer recommendations; (ii) correct farmers' overestimation

(2015); Cui et al. (2018); Wu et al. (2018), etc.

[8] We ignore the period around 1990 since statistics might change due to reunification.

[9] See Brainerd and Menon (2014); Rahman and Zhang (2018); Islam and Beg (2021).

of the return to nitrogen and greenness by distributing leaf color charts among 1,200 farmers in 200 villages.

Universal Soil Testing Program. To provide farmers with customized recommendations, we first acquired the administrative data on the soil analysis from the universal soil testing program implemented by Hunan province. Figure 3a shows the distribution of universal soil testing program in our experimental site. Each green dot is a testing point/paddy field where an agricultural extension specialist collected a soil sample and analyzed its micronutrient components in the laboratory. Similar to the soil analysis protocol in Corral et al. (2020), the project recorded (for each green dot) soil texture (type of soil under soil taxonomy), pH levels, levels of primary macronutrients (nitrogen, phosphorus, and potassium), secondary macronutrients (calcium, magnesium, and sulfur), and level of organic matter.[10]

Our baseline survey, which was implemented in April 2020, shows that dissemination of the testing results to farmers was quite low. Less than 5% of 1,200 surveyed households reported that they had access to this information. We find two main obstacles that prevented information dissemination: 1) the soil testing results are too abstract and barely readable on farmers' side; and 2) the cost of face-to-face dissemination is high and the agricultural extension workers didn't have strong incentives to distribute the results. Furthermore, in our surveys, less than 20% of farmers had talked with or received guidance from agricultural extension workers about agricultural practices. Therefore, self-learning plays an important role in the application of different fertilizers.

Recommendations. To address obstacle (1), in addition to the soil analysis, we also randomly offer corresponding fertilizer recommendations.[11] The customized recommendations of fertilizer dosage that mix N/P/K could be generated based on three elements: a reliable production function of different fertilizers, crop-specific demand models for the micronutrients, and seasonal prices to maximize farmers' profits. The primary production function is simulated from 10,000 experimental trials in Hunan province, in which three fertilizers (nitrogen, phosphorus and potassium) were randomly adopted at four different levels, 1) *zero*, 2) *0.5 times local average recommendations*, 3) *local average recommendations*, and 4) *1.5 times local average recommendations*.[12] The crop-specific demand for the micronutrients is presented as a function of the micronutrients in the soil and targeted yields.

Tools for Intervention: A Smart Mobile Application. To address obstacle (2) and disseminate individual test results and customized fertilizer recommendations more effectively, we partnered with local governments in Hunan province and a technology company,[13] co-developing

[10] See similar protocols of soil testing in Fishman et al. (2016); Murphy et al. (2020); Harou et al. (2018), etc.

[11] The recommendations are not weather- and temperature-specific. The algorithm is under normal rain and temperature conditions.

[12] China officially called such experimentation the 3-4-14 trials. The number 3 indicates three different fertilizers, the number 4 means four different levels of the application of different fertilizers, and the number 14 indicates 14 different combinations and trials. See the official announcement by the Ministry of Agriculture and Rural Affairs of China: http://www.moa.gov.cn/govpublic/CWS/201405/t20140523_3915330.htm and http://m.ynforestry-tec.com/upload/manager/image/201908/21/201908210925215482309 38.pdf

[13] Tianjiandao technology software company. This mobile application was first developed in 2015. But our baseline survey shows that the dissemination of soil analysis data to farmers was very low in our experimental site. We joined

a mobile application that has the following appealing features: 1) It is fully endorsed by Hunan and Leiyang governments (Figure A2a) and can provide guidance for up to 15 crops (Figure A2b). It connects the farmer to the administrative dataset on universal soil testing for millions of local plots in Hunan province. Through GPS tracking (Figure A3a) or by selecting the region (Figure A3b), farmers can acquire the soil analysis results of the nearest test plot where a soil sample was collected and analyzed. 2) This smart mobile application displays the recommended and dynamic combination of different individual fertilizers (N-fertilizer, P-fertilizer, and K-fertilizer) to be used in each stage (planting and growing), as shown in Figure A4a. 3) Since most farmers use an N-P-K compound fertilizer, it also recommends the optimal mix of N-P-K compound fertilizer and individual fertilizers (N/P/K) together in the multiple cropping stages. As shown in Figure A4b in Appendix A, it displays the amount of N-P-K compound fertilizer and nitrate fertilizer (N) to be used before the planting stage (the basal fertilizer stage) and the amount of top-dressing nitrogen, phosphorus, and potassium fertilizers to be used during the growing stage (the top-dressing stage).[14]

2.3 Experimental Timeline and Framework

Randomization. We first compiled a full list of 348 villages from the Department of Agriculture in local areas, with basic information including the total land area, average pH value, average N/P/K concentration in the soil, and organic matter in the plots. In the screening of villages with sufficient numbers of rice farmers, we kept villages whose agricultural land area was more than 1000 mu (equivalent to 66.7 hectares). We listed these villages in alphabetical order and then randomly selected 200 villages with a random number generator. Afterwards, as shown in Figure 4, we randomized these 200 villages into four arms (T_1, T_2, T_3 and Control). In each village, we randomly selected six rice farming households from the list provided by the village head. To summarize:

1) T_1: ST group. In this group, 300 farming households in 50 villages were provided only with individualized soil testing analysis data. Farmers were informed of the level of micronutrients, including nitrogen, phosphorus, and potassium, in their plots.

2) T_2: App group. In this arm, 300 farming households in 50 villages were provided with the mobile application and detailed instructions in a well-designed handbook and an instructive video, as shown in Appendix C. To ensure the farmers or their household members understood the mobile application, we asked them to repeat the procedures for use during the visit. Enumerators recorded the whole process in the survey.

3) T_3: App + In-person agricultural extension agents' training (AEA's training). In

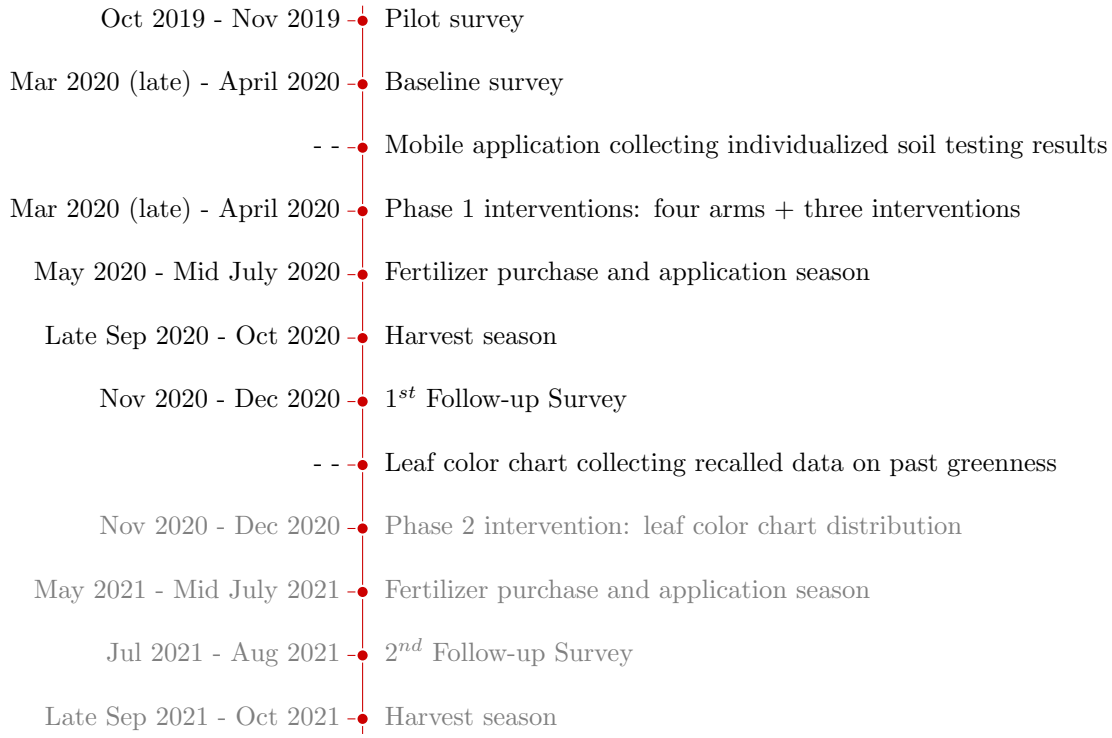
in 2019 to improve the algorithms, profit generation, and fertilizer recommendations. The latest updated version was on 08/27/2020.

[14]The application is also friendly to non-smart-phone users. There is a function called "send a message about the testing results and recommendations". A non-smart-phone user can use another person's smart phone to get the test result, and then send the test result and recommendations to her own phone as a message.

this group, 300 farmers were not only offered the smart mobile application, but also given agricultural extension services. During the visits, the agricultural extension agents held an in-person and one-to one training session, showing the experimental relationship between phosphorus/ potassium and yields (as well as profits) to update farmers' beliefs about the effectiveness of these two fertilizers. This intervention builds on Hanna, Mullainathan, and Schwartzstein (2014), who presented farmers with a summary of the trials' findings that pod size is important to yields, and found evidence of improving farmers' learning.

4) Control group: 300 farming households in 50 villages received no intervention but only surveys.

We list the timeline of the data collection activities and the implementation of the first-phase experiment as follows,[15]



We randomly assigned the 200 villages in our sample to four different arms (T_1, T_2, T_3 and Control) in late March 2020, when China's economy was fully reopened.[16] Data collection activities lasted for two years: we surveyed farmers in late March 2020 before the season of fertilizer

[15] Activities for the second-phase experiment are in gray and will be introduced later.

[16] China's economy was gradually reopened in March 2020 after coronavirus shutdowns and recovered fully in late March. Our experimental site, Leiyang, had very few identified cases and was in the first batch of reopening. The number of existing confirmed cases went down to zero by 02/28/2020 and Leiyang city has recorded no cases from 02/28 to date.

application (baseline), in November 2020 after the harvest season (first follow-up survey), and in summer 2021 after the second season-year of fertilizer application. In our surveys, we collected information including (i) input and output, such as yields, profit, land area, and other variables; (ii) the purchase and use of different fertilizers in various stages of the cropping cycle; (iii) the results on individual soil quality from the nearest test plot, distance from the farmer's plot to the test plot, fertilizer recommendations predicted by the soil testing, and gaps in fertilizer use between farmers' actual practice and the recommended use; and (iv) farmers' beliefs about the returns to greenness, and effectiveness of nitrogen, phosphorus, and potassium fertilizers.

The first-phase experiment was conducted in April 2020. We did several things to ensure the implementation of the design. For the T_3 group (App + in-person training by AEA), in December 2019, we organized two training sessions for all the agricultural extension agents in Leiyang, Hunan province, helping them to prepare for the incoming interventions in the T3 group. Two weeks before the survey, we started to provide comprehensive training to the enumerators, who were recruited from local colleges and could speak the local dialect. During the survey itself, we also sent several independent monitor teams to proctor the interview process to control the quality of the questionnaire.

2.4 Data and Balance Test

Table 1 shows basic summary statistics from the baseline survey. The first four columns report the means for T_1, T_2, T_3, and control farmers; the last three columns report the difference between T_1 and control, T_2 and control, and T_3 and control, respectively. Panel A on farm characteristics shows that in 2020, the average yield was about 460-470 kilograms per mu, with a revenue of 1096-1120 RMB per mu. On average, for each mu of land, farmers applied 36 kilograms of N-P-K compound fertilizers and 20 kilograms of nitrogen fertilizers. The adoption rate of top-dressing phosphorus and potassium fertilizers was quite low; most farmers (97% for phosphorus and 91% for potassium) didn't apply any top-dressing phosphorus or potassium in the growing stage. The application intensity for phosphorus and potassium fertilizers, on average, was only 0.84/2.16 kilograms per mu.

Panel B presents the soil testing results and predicted fertilizer recommendations. We are able to link the vast majority of farmers to a test plot within 0.2 kilometers ($> 50\%$). One-third of households had a distance less than 0.1 kilometers. Panel C demonstrates farmers' perception of the return to greenness, beliefs about the effectiveness of potassium fertilizers,[17] and attrition. We present the results for two related questions.

To measure farmers' beliefs about the return to greenness:

[17] Unfortunately, we had data only for farmers' beliefs about the effectiveness of potassium in the baseline, but no data for farmers' beliefs about the effectiveness of phosphorus fertilizers.

What is the relationship between greenness and yield?
1) The greener the leaves are, the better the yield is;
2) No strong relationship;
3) Inverted U-shape, yield first increases as the level of greenness goes up, and then decreases when greenness passes a certain threshold.

Among these options, 3) is well-documented in scientific and agronomic studies. The relationship between greenness and yield is an inverted-U shape. Panel C shows that only a small proportion (7%) of farmers gave the correct response to this question.

To measure farmers' beliefs about the effectiveness of potassium, we asked the following question,

Which of the following micronutrients affects grain density?
(1=N, 2=P, ***3=K****, 4=don't know)*

The correct answer is 3 = K. Survey data show that most farmers (98%) didn't realize that potassium is effective in increasing grain density.

Overall, we do not find a systematically significant difference between each of the treatment arms and the control farmers in any of the outcomes, except for two variables that are statistically different at the 10% level. The first comes from the recommended N-P-K compound fertilizer between the T_3 group ($App + Visit$) and the control group. The second imbalance appears in the attrition rate between T_2 and control farmers. However, the overall attrition is quite low: roughly only 3-8 farmers in each treatment arm opt out of our study. Therefore, such an imbalance should not cause any major concerns.

3 First-phase Experiment Results

In this section, we establish several stylized facts that farmers simultaneously overuse nitrogen fertilizer and underuse phosphorus/potassium fertilizers. Our experiment shows that such a sub-optimal input choice can be corrected by cost-effective interventions. We demonstrate that the provision of customized fertilizer recommendations through a mobile application improves farmers efficiency, and induces lower nitrogen application and increased phosphorus/potassium use. We then study mechanisms and design a theory-based intervention to test the predictions of our model.

3.1 Actual Use Deviates from Recommended Use

We begin the analysis with graphical evidence that highlights several main features in the data. Figure A5 presents the number of households (y-axis) against the extent of deviation (x-axis) in fertilizer application between farmers' actual use and recommended use.[18] The green bar and red bar suggest the simultaneous overuse of nitrogen and underuse of phosphorus and potassium,

[18] Deviation ratio = (Actual use - recommended use)/recommended use.

respectively. The degree of deviation in fertilizer use is present in a large domain, which indicates a 30-150% overuse of nitrogen fertilizer and 10-70% underuse of phosphorus/potassium fertilizers. The magnitude of the excessive use of nitrogen fertilizer is consistent with the conclusions in Wu et al. (2018), but we also find new evidence of phosphorus/potassium underuse.

In Figures A6a, A7a, and A8a, we provide more detailed evidence about farmers' deviation in the use of nitrogen fertilizer across multiple cropping stages. Figure A7a shows that the average use of nitrogen fertilizer (blue line) overlaps the mean recommendation (red line) in the planting stage, suggesting that in the planting stage, the use of nitrogen fertilizer barely deviated from the recommendations. Figure A8a presents the fact that overuse of nitrogen was driven mainly by the farmers' practice in the growing stage (use was much greater than recommended).The underuse of phosphorus (the use level was much lower than recommended) appeared in both the planting stage (Figure A10a in Appendix A) and the growing stage (Figure A11a in Appendix A). The application of potassium fertilizers followed a similar pattern to that of phosphorus fertilizer: we observe underuse of potassium fertilizer in both the planting (Figure A13a in Appendix A) and growing stage (Figure A14a in Appendix A).

3.2 Main Specification

To quantify the efficiency loss from simultaneous overuse and underuse of different fertilizers, we employ the following regression specification,

$$\mathrm{Y}_{iv} = \beta_0 + \beta_1 * T1_v + \beta_2 * T2_v + \beta_3 * T3_v + \eta_{iv}$$

where Y_{iv} is the outcome of interest for household i in village v in the post-treatment period, including 1) the use of different fertilizers; 2) the revenue, profits, fertilizer cost and other input costs; 3) farmers' evaluation of the effectiveness of different fertilizers. T_1, T_2, and T_3 are indicators for the corresponding treatment arms, which equal one if the village is assigned to the soil-testing group, mobile application group, and App plus training group, respectively. For inference, we cluster standard errors at the village level to reduce any correlated noise within the same village. Our coefficients of interest are β_1, β_2, and β_3, which measure the intention-to-treat effects of these three treatments.

3.3 Results

Table 2 presents the regression results for the utilization of four different fertilizers (N, P, K, and N-P-K- compound fertilizers) as the outcomes. In columns (1)-(3), we compute the total use of individual nitrogen, phosphorus/potassium fertilizers by converting compound fertilizer (use N:P:K = 15:15:15) into individual fertilizers.[19] We find that our recommendations were followed by farmers in the T_2 and the T_3 groups. In column (1) the outcome is the total utilization of nitrogen

[19]Total N = (Urea *46% + Compound fertilizer* 15%)/(46%).
Total P = (Calcium superphosphate * 39% + Compound fertilizer* 15%)/(39%).
Total K = (KCL *45% + Compound fertilizer* 15%)/(45%).
where Urea is the most widely used nitrogen fertilizer, containing 46% nitrogen. Calcium superphosphate is the main

fertilizer (after conversion). While the average intensity of nitrogen use by farming households in the control group was 30.84 kg/mu (equivalent to 462.6 kg per hectare), the usage in the T_2 (mobile application) group declined dramatically, by 3.92 kg/mu ($p < 0.05$), corresponding to a treatment effect of 12.17%. In addition, the use of nitrogen fertilizer in the T_3 group (mobile application + training visit) dropped by 4.42 kg/mu($p < 0.01$), corresponding to a treatment effect of 14.33%.

For phosphorus, column (2) shows that, compared with an average use of 14.74 kg/mu (equivalent to 221.1 kg per hectare) in the control group, the T_2 and T_3 interventions increased households' phosphorus use by 2.34 kg/mu ($p < 0.01$) and 2.72 kg/mu ($p < 0.01$), respectively. Likewise, column (3) suggests that, the T_2 and T_3 interventions increased the use of potassium by 1.37 kg/mu ($p < 0.1$) and 2.89 kg/mu ($p < 0.01$), relative to the mean use of 13.31 kg/mu (equivalent to 221.1 kg per hectare) in the control group. As expected, we do not detect any significant change in the adoption of nitrogen/phosphorus/potassium for farmers in the T_1 group, since it's difficult for farmers to read and interpret the soil analysis results by themselves.

The remaining columns demonstrate the treatment effects at the extensive and intensive margins across different cropping stages. Column (4) presents the treatment effects in the planting stage, showing that the use of a compound fertilizer increased in the T_2 and T_3 groups, which contributed to the reduction in nitrogen fertilizer reported in column (1) and the increase of total phosphorus/potassium fertilizers reported in columns (2) and (3). Columns (5)-(9) present the treatment effects of adopting top-dressing phosphorus/potassium in the growing stage. While columns (6) and (8) report the rise in top-dressing with phosphorus/potassium fertilizers per unit of land, columns (7) and (9) focus on the extensive margin — the proportion of households that used phosphorus/potassium as top-dressing fertilizers. Although only 3% of farmers applied top-dressing phosphorus fertilizer during the growing stage prior to treatment, the T_2 and T_3 interventions significantly increased the share using phosphorus fertilizer by 23.9 and 23.2 percentage points ($p < 0.01$). In parallel, the treatment effects of T_2 and T_3 are 24.1 and 32.4 percentage points ($p < 0.01$) for the proportion of farmers using potassium fertilizer, compared with the mean of 9% in the control group. Altogether, we conclude that Table 2 shows that our interventions led to reduced nitrogen application at the intensive margin and increased use of phosphorus/potassium both at the intensive and extensive margins.

Closing the yield gap. Table 3 explores the treatment effects on agricultural outcomes as farmers optimized the mix of different fertilizers after our interventions. Columns (1) and (2) suggest significant treatment effects on crop yields in the T_2 and T_3 groups. Addressing the issues of nitrogen overuse and phosphorus/potassium underuse led to a 22.74 kg/mu and 31.65 kg/mu increase in yields for households in the T_2 and T_3 groups, relative to an average yield of 465.6 kg/mu in the control group. Column (2) shows that the treatment effect corresponds to increases of 5.4% ($p < 0.1$) and 6.7% ($p < 0.05$) increases in the yields of farmers in the T_2 and T_3 groups. Column (3) demonstrates that farmers in the T_2 and T_3 groups had a higher profit than those in

phosphorus fertilizer used, containing roughly 18%-20% P_2O_5, and hence 39% phosphorus. Potassium chloride (KCL) is the most widely used potassium fertilizer, containing 45% potassium. The most widely used compound fertilizer contains 15% nitrogen, 15% phosphorus, and 15% potassium.

the control group, driven by increased revenues and unchanged costs. As shown in column (4), the total revenues of farmers in the T_2 and T_3 groups rose by 68.57 Yuan/mu and 78.79 Yuan/mu, respectively, accounting for a 6% ($p < 0.1$) and a 6.9% ($p < 0.05$) growth. While column (5) shows that fertilizer costs didn't experience significant change, column (6) suggests that the costs of other inputs, including labor, energy consumption, irrigation, and insurance stayed at the same level.

In summary, we find that interventions T_2 and T_3 both effectively helped farmers optimize fertilizer inputs and improve yields and profits.[20] The treatment effects are not statistically different between T_2 and T_3.

3.4 How Large Was the Inefficiency?

To capture the efficiency loss, we first compare our treatment effects with other interventions related to fertilizer use. First, in terms of nitrogen-fertilizer application, Chen et al. (2014) estimate that recommendations based on integrated soil–crop system management (ISSM) resulted in higher yields (18–35%) and a reduction in nitrogen usage (4–14%). Similarly, Cui et al. (2018) show that the rollout of the ISSM program in China induced a reduction in the use of nitrogen of 14.7–18.1%, an overall yield improvement of 10.8–11.5% and a reduction in greenhouse gas emissions by 4.6–13.2%. We find smaller effects in the reduction of nitrogen (14%) and improvement in yields (5%-7%), but our intervention appears to be less costly and is cost-effective. Second, with regard to other fertilizers, Duflo, Kremer, and Robinson (2011) suggest that offering free fertilizer delivery immediately increased the proportion of farmers using fertilizer by 33%, and using $\frac{1}{2}$ teaspoon of top-dressing fertilizers per hole increased farmers' income by 15%. Our intervention also increased the proportion of farmers using phosphorus/potassium by 19.1/22.5 percentage points, as well as increasing their revenue by roughly 7%.

Our treatment effects lie between these studies, suggesting that policy-makers can find a unified solution to resolve simultaneous overuse and underuse. We also quantify the efficiency loss from incorrectly using fertilizers by the profits lost from misuse. The estimate suggests that, if all 440 million mu of rice plots[21] experienced the same level of fertilizer adoption, then their total revenues could rise by 30 billion RMB without increasing costs – not to mention the benefits to other crops and the environment.

We also compare our impacts with the research on Information and Communications Technology (ICT) and agricultural development. Cole and Fernando (2021) estimate the return of a mobile-phone-based agricultural advice service provided to farmers in India, suggesting that it increased yields of cumin by 28% and cotton by 8.6%. We find smaller effects of 5-7% yield increases, perhaps because our mobile application focuses only on the optimization of fertilizer application, while theirs also directly delivered time-sensitive information, such as weather forecasts and pest planning strategies to farmers. There is longstanding concern that traditional agricultural exten-

[20] We also summarize these results in Figures A6b for nitrogen fertilizers, A9c for phosphorus fertilizers, A12c for potassium fertilizers and A15b for yields.

[21] 1.8 billion mu arable land in total for different kinds of crops in China.

sion has not always provided the most useful information for farmers or given them knowledge about alternative farming practices (Beaman et al., 2021). This is especially the case for farmers in less-developed countries, especially smallholders, who may be ill-informed about sustainable fertilizer practices. Our interventions can serve as both a complement to and a substitute for the traditional agricultural extension service by using the smart mobile application, which apparently reduced administrative costs and agents' travel costs, but led to a similar growth in yields.[22]

4 Theoretical Framework

It's particularly puzzling that fertilizers are simultaneously underused and overused because farmers have been working with these technologies for decades. In addition, as rational farmers, they should be able to carry out their own experimentation to find the optimal mix of different fertilizers since land and fertilizers are divisible. Despite this availability, the prevalence of misuse suggests that there is a clear cognitive barrier in learning and belief formation that prevents them from choosing the optimal application. Thus, understanding what exactly the cognitive barrier is and to what extent farmers can benefit from overcoming it, could help farmers go beyond merely adopting the technology, but using it efficiently. In this section, we explore the mechanisms behind such misuse of technologies.

4.1 Stylized Facts and Survey Evidence

Why did farmers overuse nitrogen but underuse phosphorus and potassium fertilizers? To answer this question, we dig deeply into the functions of different fertilizers. Fertilizers contain three vital dimensions —nitrogen (N), phosphorus (P), and potassium (K) — among which nitrogen produces salient signals by increasing the greenness of crops in the growing stage, while the effects of phosphorus and potassium do not generate such signals. Specifically, phosphorus can boost root length and change the timing of flowering, while potassium can enhance the density of rice grains, all of which are barely observable.

In Figure 5a, we present the recommended practice suggested by specialists for optimal fertilizer application in different cropping stages. The crop cycle can be divided into three stages, as shown from left to right: 1) transplanting/planting stage, in which the basal fertilizer is applied; 2) growing stage, in which top-dressing fertilizers are strongly recommended; and 3) ripening and harvest stage, in which no fertilizer is needed. In the transplanting stage, farmers are advised to apply N-P-K compound fertilizer as the basal fertilizer, while extra top-dressing with nitrogen and phosphorus/potassium fertilizers is recommended during the growing stage. Meanwhile, farmers receive signals through the greenness of crops in the growing stage.

Figure 5b shows farmers' actual fertilizer application in the baseline, with the share of households that adopted different fertilizers on the y-axis and timing on the x-axis. Consistent with

[22] Yield effects of T_2 and T_3 are quite close.

the recommended practice, the red bar suggests that, almost all the 1,200 farmers applied N-P-K compound fertilizer as the basal fertilizer in the planting stage. However, the green, orange, and blue bars demonstrate the inconsistency between farmers' actual use and the recommended practice in the growing stage. We observe that during the growing stage (after the second week), farmers applied and adjusted only nitrate fertilizer but did not add any phosphorus and potassium fertilizers in the same period.

Combined with the findings presented in Table 2 that overuse of nitrogen occurred mainly in the growing stage, we hypothesize that, because farmers can observe the greenness signals that reflect the effectiveness of nitrogen during the growing stage, they will only adjust the use of nitrogen fertilizer. Since they barely observe any salient feedback from applying phosphorus and potassium fertilizers, they cannot learn about the effectiveness of these two fertilizers and thus underuse them.

To verify this, we further elicited farmers' beliefs about the relationship between yield and greenness. The following question was presented,

> *What is the relationship between greenness and yield?*
> *1) The greener the leaves are, the better the yield is;*
> *2) No strong relationship;*
> *3) Inverted U-shape, yield increases first as greenness increases, and then decreases when greenness passes a certain threshold.*

Figure 6 plots farmers' beliefs about the relationship between greenness and yields. Most farmers believed that greenness is always positively correlated with yields (option 1). Only a small proportion of farmers (less than 7%) understood the true production function between greenness and yields — an inverted U-shape relationship (option 3), which is well documented in agriculture literature. Given this incorrect prior and the salient signals from nitrogen, farmers persistently over-applied nitrogen because of their overestimation of the return to greenness (misspecified production function).

Based on these stylized facts, we leverage recent theory in behavioral economics on misspecified learning (Heidhues, Kőszegi, and Strack, 2021) to develop our conceptual framework. We display the basic model intuition in Figure 7. First, the salient feature of nitrogen induces farmers' overoptimism about the return of nitrogen fertilizers. This exogenous overestimation then endogenously causes farmers to overuse nitrogen fertilizer and expect a great yield. At the end of each period, farmers observe that yields are lower than expected. They rationalize such lower-than-expected yield to the lower-than-true-perception of the effectiveness of phosphorus and potassium, which endogenously leads to underuse of phosphorus and potassium.

We outline farmers' decision-making problem as a farmer that faces two technologies (different fertilizers in this context), in which her overestimation of one technology leads to overuse, and then such overuse in turn affects the farmer's beliefs about the effectiveness of the other technology and causes underuse. We also demonstrate how farmers' actions and beliefs evolve over time and converge to a sub-optimal equilibrium.

4.2 Setup

The objective environment: In each period $t \in \{1, 2, 3, \ldots\}$, a representative farmer produces observable profit (via output) $\pi_t \in \mathbb{R}$ according to the twice differentiable profit function $\Pi(a_t, b_t)$ which depends on her action $a_t \in (\underline{a}, \bar{a}) = A$ and on an external state $b_t \in \mathbb{R}$ beyond her control. Similar to Hanna, Mullainathan, and Schwartzstein (2014), to capture the idea that farmers have to learn about two types of fertilizers at the same time — nitrogen (N) and phosphorus (P)/potassium (K) — her production function has two dimensions that separately contribute to profit:

$$\Pi(a_{Nt}, b_{Nt}, a_{Kt}, b_{Kt}) = f_1(a_{Nt}) \exp(b_{Nt}) - c_N a_{Nt} + f_2(a_{Kt}) \exp(b_{Kt}) - c_K a_{Kt}, \tag{1}$$

Where the functions f_1 and f_2 are production function of nitrogen (N) and phosphorus (P)/potassium (K) and are both concave, with $f_i > 0, \lim_{a\to\infty} f_i'(a) = 0$. $a_{Nt}, a_{Kt} > 0$ is the amount of N-fertilizer and P/K-fertilizer that farmers use at t, c_{Nt} and c_{Kt} are the normalized unit costs of N-fertilizer and P/K-fertilizer, respectively. Without loss of generality, we assume that land area is fixed in a certain period and do not include labor in this production function. Parameters $\exp(b_{Nt})$ and $\exp(b_{Kt})$ represent external states as a productivity shiftier, which influence the marginal product of a_{Nt} and a_{Kt}, and are correlated across time. In this context, we can interpret $\exp(b_{Nt})$ and $\exp(b_{Kt})$ as the realized effectiveness of N and P/K fertilizers.

We further assume that

$$b_{Nt} = \Theta_N + \epsilon_{Nt}, b_{Kt} = \Theta_K + \epsilon_{Kt}$$

where $\Theta_N, \Theta_K \in \mathbb{R}$ are the underlying fixed fundamentals and ϵ_{Nt} and ϵ_{Kt} are independently normally distributed random variables with mean zero and variance σ_N^2, σ_K^2. Θ_N and Θ_K can be interpreted as **the average effectiveness** of nitrogen fertilizer and phosphorus/potassium fertilizers. The farmer needs to learn about these two parameters as a Bayesian learner. b_{Nt}, which measures the effectiveness of nitrogen fertilizer, can also be observed by the farmer through greenness.

Farmer's subjective beliefs. The farmer's prior is that Θ_N and Θ_K are normally distributed with means θ_{N0} and θ_{K0}, and with variances v_{N0} and v_{K0}, respectively. Motivated by the stylized facts in Section 4.1, while the farmer understands the general form of the profit function, she misunderstands the specification of the production function of nitrogen fertilizer f_1 as follows:

$$\tilde{\Pi}\left(a_{Nt}, b_{Nt}, a_{Kt}, \tilde{b}_{Kt}\right) = \tilde{f}_1(a_{Nt}) \exp(b_{Nt}) - c_N a_{Nt} + f_2(a_{Kt}) \exp\left(\tilde{b}_{Kt}\right) - c_K a_{Kt}, \tag{2}$$

where $\tilde{f}_1(\cdot)$ indicates the exogenous misspecification in the production function of nitrogen fertilizers. $\tilde{b}_{Kt}$ captures the farmer's subjective belief about the effectiveness of phosphorus/potassium fertilizers, which deviates from the true effectiveness status b_{Kt}.

To be specific and without loss of generality, we define $\tilde{f}_1(\cdot) = \lambda f_1(\cdot)$. The famer form the

belief about the profit function as:

$$\tilde{\Pi}\left(a_{Nt}, b_{Nt}, a_{Kt}, \tilde{b}_{Kt}\right) = \lambda f_1\left(a_{Nt}\right) \exp\left(b_{Nt}\right) - c_N a_{Nt} + f_2\left(a_{Kt}\right) \exp\left(\tilde{b}_{Kt}\right) - c_K a_{Kt}, \tag{3}$$

where λ represents the degree of overestimation in the production function due to her misperception about the return to nitrogen. Given her model, the farmer updates her beliefs about the fundamental in a Bayesian way and chooses her action in each period to maximize her perceived discounted expected profit $\tilde{\Pi}\left(a_{Nt}, b_{Nt}, a_{Kt}, \tilde{b}_{Kt}\right)$.

To solve for the equilibrium, we then impose three assumptions.

Assumption 1. $\lambda > 1$. *The farmer's misspecification in the production function of nitrogen is greater than one.*

Consistent with our survey evidence in Figure 6, this assumption is the core exogenous misunderstanding from the farmer. One possible explanation is that the use of nitrogen fertilizer has increased across time (as shown in Figure 1). Farmers would have formed the belief that more greenness leads to greater yields since they have spent most of their time observing the upward-sloping part of the inverted-U shape relationship curve. The mechanism here is similar to that "what you see is all there is" by Enke (2020).

Assumption 2. *The farmer may misunderstand the effectiveness of P/K fertilizers b_{Kt} as $\tilde{b}_{Kt}$, since the effects of P/K-fertilizers are barely observable during the growing stage.*

The farmer can learn about the effectiveness of nitrogen fertilizers, b_{Nt} through greenness. In our sample, 93.8% of farmers understand that nitrogen enhances greenness, while only 4.4% and 2.5% of farmers know about the effect of phosphorus on root development and the impact of potassium on the grain density.

Assumption 3. *For any input level a_{Nt} $a_{Kt} \in \mathbb{R}$, and any level of effectiveness $b_{Nt}, b_{Kt} \in \mathbb{R}$, there exists a farmer's belief $\tilde{b}_{Kt}$ such that the farmer's perceived profits equal the realized profits, $\tilde{\Pi}(a_N, a_K, b_N, \tilde{b}_K) = \Pi(a_N, a_K, b_N, b_K)$.*

Thus, Bayes' rule can specify beliefs.[23]

Belief updating. The farmer chooses the input level of these two fertilizers (a_N and a_K) in each period to maximize her expected profit ($\tilde{\Pi}$) in that period. As the farmer's priors (Θ_N, Θ_K) are normally distributed with mean ($\theta_{N0}, \tilde{\theta}_{K0}$) and variance ($v_{N0}$, v_{K0}), and her beliefs b_N and $\tilde{b}_K$ are independent and identically distributed (i.i.d.) with $\mathcal{N}\left(\Theta_N, \sigma_N^2\right)$ and $\mathcal{N}\left(\Theta_K, \sigma_K^2\right)$, respectively, the Bayes' updating rule is presented as follows.

For nitrogen, we assume that farmers have learned about its effectiveness through the observation of greenness. Another noteworthy stylized fact is that Chinese farmers started to use nitrogen fertilizer in the 1940s, but only used phosphorus/potassium on a large scale in the 1990s. The long duration between 1940 and 1990 should be a sufficient time frame for farmers to learn

[23] We also impose some weak technical assumptions. See detailed proofs in Appendix B for reference.

about the effectiveness of nitrogen. So time period 0 indicates when farmers started to learn about phosphorus/potassium, and we treat b_N as a constant and true value. Therefore, the key learning is concentrated on phosphorus/potassium.

Updating Rule of $\tilde{\theta}_K$. At the end of period $t \geq 1$, her posterior belief about phosphorus/potassium is that $\tilde{\Theta}_K$ is normally distributed with mean:

$$\tilde{\theta}_{Kt} = \frac{\frac{\sigma_K^2}{v_{K0}}\tilde{\theta}_{K0} + \Sigma_{s=1}^{t}\tilde{b}_{Ks}}{\frac{\sigma_K^2}{v_{K0}} + t}$$

and variance:

$$v_{Kt} = \frac{1}{v_{K0}^{-1} + t\sigma_K^{-2}}$$

Where $\tilde{\theta}_{K0}$ is the initial prior of the effectiveness of phosphorus/potassium.

4.3 Predictions and Simulations:

After observing the profit at the end of period t generated by the realized states b_N and b_K, the farmer believes that the effectiveness of nitrogen fertilizer b_{Nt} and of phosphorus/potassium fertilizer $\tilde{b}_{Kt}$ satisfies:

$$\tilde{\Pi}\left(a_{Nt}, a_{Kt}, b_{Nt}, \tilde{b}_{Kt}\right) = \pi_t = \Pi\left(a_{Nt}, a_{Kt}, b_{Nt}, b_{Kt}\right) \tag{4}$$

where π_t is the realized profits observed by the farmer at the end of t. We then derive the subjective belief about the effectiveness of phosphorus/potassium $\tilde{b}_K$ as follows,

$$\tilde{b}_K\left(a_N, a_K, b_K\right) = \tilde{b}_K\left(a_K, b_K\right) = \log\left(C + f_2\left(a_K\right)\exp\left(b_K\right)\right) - \log\left(f_2\left(a_K\right)\right) \tag{5}$$

Where $C = (1-\lambda)\, f_1\left(a_N\right)\exp\left(b_N\right)$.

The interpretation of equation (5) is that the farmer believes that whatever action she chooses, she can infer a unique signal $\tilde{b}_K$ about Θ_K to equalize her belief and her real profit.

We then summarize and present the key predictions as follows. If a farmer overestimates the return to greenness ($\lambda > 1$), then:

Prediction 1. *The **exogenous** misspecification in the production function for nitrogen induces farmers to overuse nitrogen fertilizer and **endogenously** undervalue the effectiveness of P/K fertilizers, and then under-invest in phosphorus/potassium fertilizers. Consequently, farmers will be trapped in a sub-optimal equilibrium with lower profits. They could become better off by optimizing the mix of different fertilizers.*

Prediction 2. *If farmers are nudged to adopt less nitrogen fertilizer and more P/K fertilizers in the current period, then their belief, $\tilde{b}_K$, about the effectiveness of P/K will move toward the true effectiveness. Thus, farmers' undervaluation of P/K will decrease. See the details in Appendix B for the derivation of this prediction.*

Prediction 3. *Correcting farmers' overestimation/misspecification of the return to nitrogen fertilizer leads to lower nitrogen fertilizer application, and higher use of P/K fertilizers. Their belief about the effectiveness of P/K could also converge to the true effectiveness. Specifically, revising farmers' overestimation reduces their nitrogen application immediately (within the same period), but also induces gradual learning about phosphorus and potassium fertilizers.*

Prediction (1) is verified by the point estimates in Tables 2 and 3. We present the simulations in Figure 8, showing convergence of the beliefs about the effectiveness of nitrogen and phosphorus/potassium fertilizers. Consistent with our theoretical predictions and survey evidence, farmers' belief about the effectiveness of P/K slowly converges to an equilibrium that is below the true value, as shown in Figure 8c, while Figure 8b shows that learning about nitrogen is much faster.

5 Test of Predictions and Second-phase Experiment

In this section, we first run additional regressions to test model prediction (2) that farmers will place more value on phosphorus and potassium if their misuse behavior is corrected. We then design and implement a second-phase experiment to test model prediction (3) and finally discuss the results from the second-phase experiment.

5.1 Test of Prediction 2

We present the results for prediction 2) in Table 4 using regression specification (1) in Section 3.2 from the first-phase interventions. In column (1), the outcome variable is a binary dummy variable equal to 1 if farmers understand the relationship between greenness and yield correctly (inverted U-shape). Farmers in the T_2 and T_3 groups in the post-treatment period show highly improved understanding of this relationship. While only 6% of farmers gave the right response to this question in the control group, T_2 and T_3 interventions increased the share by 15 ($p < 0.01$) and 31 percentage points ($p < 0.01$), respectively. The impact in T_2 solely reflects the effect of individual learning. The effect in T3 — double that in T_2 — suggests the presence of simultaneous individual learning and social learning due to farmers' interactions with the agricultural extension specialists.

In columns (2)-(5), we proxy farmers' beliefs about the effectiveness of different fertilizers with farmers' responses to the following questions. The correct response to each question is in bold type.

*a. Which of the following micronutrients is the main determinant of crop's greenness? (**1=N**, 2=P, 3=K, 4=don't know)*
*b. Which of the following micronutrients is the main determinant of the flowering timing? (1=N, **2=P**, 3=K, 4=don't know)*
*c. Which of the following micronutrients is the main determinant of root length? (1=N, **2=P**, 3=K, 4=don't know)*
*d. Which of the following micronutrients is the main determinant of grain density? (1=N, 2=P, **3=K**, 4=don't know)*

In Table 4, the outcome variables in columns (2)-(5) are binary variables that take the value of 1 if farmers gave the correct response to the corresponding questions. Column (2) shows that farmers' understanding of the effectiveness of nitrogen on greenness in the T_1, T_2, and T_3 villages is not significantly different from that of the control group, because 95% of farmers already understood it correctly. Column (3) presents the treatment effects of farmers' learning about the effectiveness of phosphorus on flowering time in the growing stage. Relative to the average value of 13 percentage points in the control group, farmers in T_2 and T_3 improved their understanding of the effectiveness of phosphorus by 22 percentage points ($p < 0.01$) and 34 percentage points ($p < 0.01$). Similarly, column (4) reports the treatment effects of farmers' learning about the effectiveness of phosphorus on root length, which shows the same direction as column (3). Column (5) focuses on farmers' understanding of the effectiveness of potassium. Again, our interventions in T_2 and T_3 increased farmers' understanding of potassium by 17.1 and 36.8 percentage points, compared with only 2.8% of farmers in the control group that understood the effect of potassium.

In summary, Table 4 provides direct evidence of model prediction (2) that farmers' undervaluation of the effectiveness of phosphorus/potassium will decrease if their underuse behavior is corrected, but their valuation of the effectiveness of nitrogen remains unchanged. Furthermore, we find a large difference in the treatment effects between T_2 and T_3, which might be driven by social learning. Farmers in the T_2 group must determine the effectiveness of phosphorus and potassium by themselves (individual learning). In the T_3 group, farmers also have focused interactions with agricultural extension agents, which can boost their learning (social learning).[24]

5.2 Second-phase Intervention

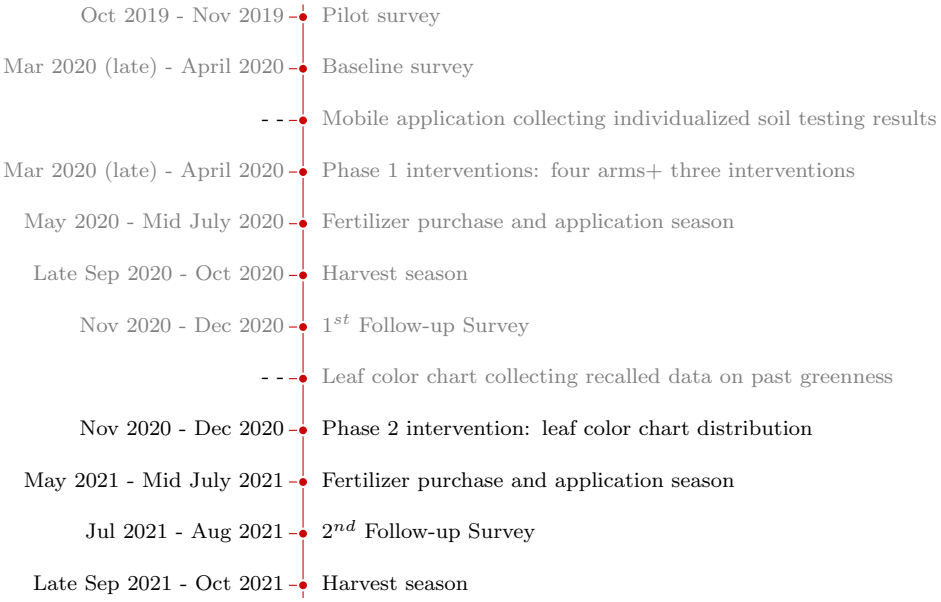
To test model prediction (3) in Section 4, we design and implement a second-phase experiment by introducing the leaf color chart, aiming to correct farmers' overestimation of the return to greenness (aligning λ to 1).

Leaf Color Chart (LCC). The leaf color chart, developed by the International Rice Research Institute (IRRI), contains six panels of different shades of green, which match the green colors to the reflecting spectral signature of rice leaves. It is a cost-effective tool (US$4-US$8) for

[24]Prior to our interventions, only 20% of farmers had ever been instructed by the agricultural extension agents.

the management of real-time nitrogen use, which can facilitate farmers' learning about optimal greenness.[25] According to the IRRI's simulations and recommendation, the optimal greenness in two main growing stages — peak tiller formation (20-30 days after the transplanting) and spike differentiation (40-50 days after the transplanting) — should be around panel 3 or slightly above panel 3.[26] We also prepared a brochure with detailed instructions, showing farmers the correct timing, position, and method of using the LCCs. Our enumerators stayed with farmers for an average of 30 minutes to demonstrate the correct use of the charts.

As shown in Figure 10, to improve farmers' learning and correct their overestimation, we distributed LCCs among the 150 villages selected in the first-phase interventions (T_1, T_2, and T_3).[27] Table A1 shows the results of an additional balance test conducted between farmers in the T_1 group and the control group. We do not find any significant difference between these two groups before the second-phase intervention. The timeline of the data collection activities and the implementation of second-phase experiment is as follows.



The second-phase intervention was implemented in December 2020, right after the first follow-up survey conducted in November 2020. In August 2021, we conducted a second follow-up survey to explore the treatment effects of the LCC intervention on fertilizer use and farmers' beliefs about the effectiveness of different fertilizers. If our model and prediction (3) is correct, then we should

[25] Similarly, Islam and Beg (2021) conducted a field experiment in Bangladesh, and found that LCC intervention reduced nitrogen fertilizer use by 8% and increased yields by 7%. According to a back-of-the-envelope estimate, the cost-benefit ratio is about 1:9.

[26] See details in Appendix C, which demonstrates the full guidance and application process.

[27] Ideally, the cross-randomization could help us better identify the pure effect of LCC intervention. However, there are two concerns that prevent us from conducting cross-randomization. First, our partners, the local governments, hoped we could keep the experimental structure as simple as possible. Our survey activities could not go smoothly without their coordination. Second, because we have only 50 villages in each treatment arm and the regressions are clustered at the village level, such a design could help us keep statistical power when exploiting the combined effects of LLC, LCC + App, and LCC + App + Training Visit.

be able to see that the LCC effectively corrects farmers' overestimation of the return on greenness, and simultaneously accelerates their learning about the use of phosphorus and potassium.

5.3 Results from the Second-phase Intervention

Table 5 reports the regression results using the regression specification in Section 3.2. We start the analysis with farmers in T_1. The coefficient in column (1) suggests that LCC intervention leads to an immediate drop in aggregate nitrogen use by 3.76 kg per mu ($p < 0.05$), which is consistent with our model prediction (3) that learning about nitrogen is fast. As for phosphorus and potassium fertilizers, the positive coefficients in columns (2) and (3) for T_1, while not significant, suggest that, on average, the LCC intervention may increase the aggregate adoption of top-dressing with phosphorus and potassium in the growing stage. Perhaps the large variation in the outcome variables results in the insignificance.

To further explore the potential effect of LCC on the adoption of phosphorus and potassium fertilizers, we decompose fertilizer applications into two stages: the planting stage and the growing stage. Column (4) reports the application of N-P-K compound fertilizer, which is used in the planting stage. Since LCC can be used only in the growing stage, we do not observe any significant change in the use of compound fertilizer during planting. However, we do find encouraging results in columns (7) and (9), which report the proportion of farmers using phosphorus and potassium fertilizers in the growing stage. The positive and significant coefficients in columns (7) and (9) suggest that, the LCC intervention led to a 6 percentage point increase in the proportion of farmers using top-dressing phosphorus and potassium fertilizers in the growing stage ($p < 0.01$ and $p < 0.1$).

As suggested in Hanna, Mullainathan, and Schwartzstein (2014), while the dimensions of technology are large, agents' attention is limited. An agent can learn only about the dimensions that she pays attention to. In our context, our treatment effects indicate that some farmers were starting to conduct their own experimentation with phosphorus and potassium fertilizers (columns (7) and (9)), perhaps because their binding attention on nitrogen was relaxed due to the help of LCC. Thus, they were getting more confident about conducting experiments with phosphorus and potassium fertilizers. Combining the results in columns (1), (2), (3), (7) and (9), we find that, consistent with model prediction (3), correcting farmers' overestimation of the return to greenness via LCC not only immediately improved their learning about nitrogen, but also simultaneously induced their gradual learning about phosphorus and potassium.

For farmers in the T_2 group (App + LCC) and the T_3 group (App + LCC + training by AEA), columns (1), (2), and (3) show that the LCC did not significantly enhance the pre-existing treatment effects of the first-phase experiment on the aggregate use of nitrogen, phosphorus and potassium, since many farmers in these two groups had already learned to optimize fertilizer inputs in the first-phase experiment. The LCCs did not alter the existing treatment effects of the first-phase experiment in either the planting stage (column (4)) or the growing stage (columns (5)-(9)). Since soil testing and customized fertilizer recommendations had already provided farmers with precise guidance, it is quite plausible to see that the LCC intervention had no add-on effect.

Table A2 presents the effects of the LCC intervention on farmers' perceptions of the return to greenness and their beliefs about the effectiveness of different fertilizers. Column (1) reports farmers' beliefs about the relationship between greenness and yield, while column (2) reports farmers' understanding about the effect of nitrogen on greenness. Columns (3) and (4) present farmers' understanding of the effects of phosphorus on flowering time and root length, and column (5) shows farmers' understanding of the effects of potassium on grain density. Consistent with the results in Table 4, farmers in the T_2 and T_3 groups, reduced their overestimation of the return to greenness (column (1)), retained high understanding of the effectiveness of nitrogen, and better understood the effectiveness of phosphorus and potassium (columns (3)- (5)).

For farmers in the T_1 group who received only the LCC treatment, column (1) shows that their overestimation of the return to greenness declined, reflected by the point estimate that the share of farmers that chose the inverted U-shape relationship between greenness and yield increased by 27 percentage points ($p < 0.01$). This sole influence of the LCC is very close to the effects of the customized fertilizer recommendations in the T_2 and T_3 groups (31.0 percentage points). While farmers' understanding of the effectiveness of nitrogen on greenness did not change, since 95% of them already knew this, we also do not see any increase in their understanding of the effectiveness of phosphorus and potassium in the current period. This is because farmers did not update their beliefs or recognize the effectiveness of phosphorus and potassium, because they had not yet observed the new yields and learned under Bayesian rule.[28] We expect to see an updating of beliefs after farmers produce and observe the new yields and profits in the next period, which inspires our future follow-up survey and research design.

Overall, compared with customized fertilizer recommendations, we find that the second-phase intervention using the LCCs also effectively corrected farmers' overestimation of the return on greenness and improved their learning about nitrogen, phosphorus and potassium. But such learning is dependent on self-learning, which requires a longer learning period to converge. All of these results are summarized in Figures A6, A7, and A8, as well as in Figures A9, A10, A11, A12, A13 and A14 in Appendix A. Nitrogen fertilizers were overused only in the growing stage, while phosphorus and potassium fertilizers were underused throughout the cropping cycle (both planting stage and growing stage). From the perspective of policy design, policymakers face a trade-off between choosing customized recommendation or the LCC intervention. The former is more effective immediately but is costly, while the latter is more scalable but less immediate. Policymakers should balance this trade-off based on budget and time constraints.

5.4 IV Strategy: Deviation in Fertilizer Application and Yields

In this subsection, we examine the yield response to deviations between actual fertilizer application and the benchmark recommendations based on soil testing. We first present evidence that our first- and second-phase interventions significantly reduced the deviation in fertilizer use between actual and recommended fertilizer use. In Table 6, columns (1), (2) and (3) present the treatment effects

[28] Our third-round survey was conducted in August 2021, while the harvest season was in October.

of the first-phase interventions on the difference between actual application and recommended use. The outcome variables in columns (1), (2), and (3) are the nitrogen use gap [used - recommended], the phosphorus use gap [used - recommended], and the potassium use gap [used - recommended], respectively. In the first phase, interventions T_2 and T_3 dramatically reduced the nitrogen gap by 3.6 kg/mu and 4.7 kg/mu, corresponding to a 50% decline in the average gap in the control group. Similarly, the interventions also effectively closed the phosphorus gap and the potassium gap by roughly 50%.

Columns (4), (5) and (6) present the treatment effects of the second-phase interventions on the gap between actual application and recommended use. Again, we find very similar effects from the LCC intervention on closing the gaps in fertilizer application. Since the soil testing data were acquired through GPS tracking, in Table A3 in Appendix A we show that the gaps are not statistically correlated with the distance between a farmer's plot and the nearest soil testing plot, in either the first- or second-phase experiment.

We then use the following IV strategy to estimate the causal impact of loss in yields due to misuse of fertilizer.

(1) Sample Selection. We limit the regression sample to those who simultaneously overuse nitrogen fertilizer and underuse phosphorus/potassium fertilizers so that the underlying relationship between fertilizer gaps and yields is clearly defined. The overuse of nitrogen and underuse of phosphorus/potassium lead directly to lower yields. In Table A7 and A8 in appendix A, we relax this restriction and the results are still consistent and robust.

(2) Main Outcomes. We calculate the gaps for each type of fertilizer use by aggregating them across different stages, N_Gap, P_Gap, and K_Gap as the main outcomes, where N_Gap=(total nitrogen used - recommended), P_Gap=(total phosphorus used - recommended), and K_Gap=(total potassium used - recommended).

(3) Identification. In Table 6, we show that the T_2 (App) and T_3 (App + Training) interventions effectively reduced the nitrogen/phosphorus/potassium gaps, suggesting that T_2 and T_3 can serve as valid instruments for the fertilizer gaps. But this also raises the issue of under-identification: we have three endogenous variables (N_Gap, P_GaP, and K_Gap) but only two instruments (T_2 and T_3). To address the under-identification constraint, we construct a new variable, Gap^2, which measures the Euclidean distance between the actual fertilizer application and the recommendations:

$$Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$$

Then we take the log of Gap^2 and instrument $logGap^2$ with T_2 and T_3 with the two-stage least squares (2SLS) regression.

The following equation (6) characterizes the causal effect of T_2 and T_3 interventions on Gap^2.

$$logGap_i^2 = \alpha' + \beta_1' T_{2i} + \beta_2' T_{3i} + \epsilon_i' \tag{6}$$

Equation (7) captures the effects of deviation in fertilizer application measured by Gap^2 on yield.

$$Yield_i = \lambda + \delta \widehat{logGap_i^2} + \epsilon_i'' \tag{7}$$

where $Yield_i$ indexes yields (or $logyield$) of farmer i in the second round of the survey (after the first-phase interventions). Our coefficient of interest, δ, measures the effect of deviation in fertilizer application on yields.

Table 7 reports the point estimates of regressions (6) and (7). Column (1) presents the coefficients β_1' and β_2' in the first-stage regression, which again suggests that interventions T_2 and T_3 effectively reduced the natural log of Gap^2 by roughly one unit. The second-stage regression estimate in column (2) suggests that, if the natural log of Gap^2 increases by one unit, then yields will decline by 336.39 kg/mu. In column (3) for robustness purposes, we replace yields with the natural log of yields and find that a 10% drop in Gap^2 will boost yields by 0.77%. To make the magnitude more intuitive and straightforward, our T_1 and T_2 interventions in the first phase reduced the outcome Gap^2 by 100% (column (1)), corresponding to a 7.7% increase in yields, which is consistent with our reduced form regression result of 7% in Table 3.

To check the validity of using T_2 and T_3 as instrumental variables, in Table A4 we replicate the IV-2sls regression using the baseline data and employing equations (6) and (7). We do not find any significance in either the first-stage or second-stage regressions since T_2 and T_3 did not affect the fertilizer applications and yields in the baseline, which further confirms the validity of the instrumental variables.[29]

Back-of-the-Envelope Estimation for the Second-Phase Intervention. To predict the yield response to the LCC intervention, we take coefficients in Table 5: 3.76 from column (1), 0.48 from column (2), and 0.173 from column (3). Then we obtain ΔGap^2 as:

$$\Delta Gap^2 = (N - 3.76 - \bar{N})^2 + (P - 0.48 - \bar{P})^2 + (K - 0.13 - \bar{K})^2$$

The naive estimation suggests that the LCCs reduced the log of Gap^2 by 0.44 points, indicating a 44% decline in Gap^2. This decrease corresponds to an underlying gain in yields of 3.4% or 16 kg/mu. In Table A5, we additionally present the effects of the deviation in fertilizer application on revenues, fertilizer costs, and other costs using regression equations (6) and (7). Column (2) suggests that a 10% drop in Gap^2 will increase revenues by 9.82 RMB per mu.[30] By plugging in

[29] In Table A6, we conduct another type of IV regression. In columns (1), (2) and (3), we estimate the effects of each gap on yields separately by instrumenting the gap in nitrogen use [used - recommended], the gap in phosphorus use, and the gap in potassium use separately with the T_2 and T_3 indicators. The results are still consistent with that of the IV regression presented in Table 7.

[30] We do not find significant impacts of Gap^2 on fertilizer costs and other input costs, which are consistent with previous findings presented in Section 3.3.

the value of 44% decline in the Gap^2 , we estimate that farmers' revenues would be increased by 43.21 RMB per mu, corresponding to a 4% increase in revenues per unit of land without changing the costs. These results are similar and robust when we employ the full sample from the second follow-up survey.

In summary, based on the back-of-the-envelope estimation, our second-phase intervention that provided LCCs led to an increase in yields of roughly 3.4% and in revenues of 4%.

6 Additional Discussions

In this section, we discuss some general applications, issues related to identification and interpretation, as well as some potential alternative explanations for nitrogen overuse.

Applications in Other Fields. Although this paper focuses on agricultural farming, our finding that the misperception of one technology could affect the assessment of the effectiveness of other technologies has more general implications. For example, in the field of health studies in less-developed areas, there is a trade-off problem between taking antibiotics and improving hygiene conditions. Since the effects of antibiotics are immediate and easily observed, while the health effects of improving hygiene are less salient, we can see why antibiotics are often abused. Likewise, farmers are going to overuse pesticides if they face a trade-off between using pesticides or planting bug-resistant crops, since pesticides generate more salient feedback. School administrators will spend more money on building better facilities than on improving teachers' qualities due to the immediate impact of better facilities.

Measurement Error in Self-Reporting. A natural concern about our data is that our main outcomes of interest, such as yields and inputs, are self-reported, which raises the possibility that measurement errors and the effects of experimenter's demand may affect the results. First, we argue that farmers have no incentive to misreport their use of different fertilizers or their yields, since our interventions are very likely to influence the use of different fertilizers in different directions. Second, we mitigate this concern by collecting farmers' responses based on three different question modules regarding fertilizer use: 1) the total use of different fertilizers; 2) the total purchase of different fertilizers; 3) fertilizer application in different growing stages and aggregate level of multiple stages. We find that data in these questions are quite consistent, which makes misreporting issues unlikely.

Other Learning Models. The existing leading learning models cannot explain both overuse and underuse; for example, in the model of learning-by-doing, farmers should be able to learn the value of different technologies with a lot of experience and exposure to natural variation. In the model of learning through noticing (Hanna, Mullainathan, and Schwartzstein, 2014), the selective attention mechanism induces farmers to either pay attention to and correctly use one input dimension or ignore and underuse that input dimension. However, these models cannot predict simultaneous overuse and underuse. Likewise, the procrastination cited in Duflo, Kremer, and Robinson (2011) and social learning in Wolitzky (2018) can only partially explain underuse.

Supply Side Actions. Another question is why sellers aren't stepping in to correct farm-

ers' beliefs about the effectiveness of different fertilizers, especially phosphorus and potassium. To answer this question, we first present survey evidence that 1) farmers did not lack access to phosphorus and potassium, as shown in Figure 11a; and 2) only a small proportion (2.43%) of them took the advice from fertilizer sellers seriously and followed their recommendations as in Figure 11b. One plausible explanation is that sellers, unlike us, didn't have science-based knowledge on the soil quality of individual plots, and therefore were able to provide only average recommendations, which are less convincing. Besides, by correcting farmers' beliefs to induce them to use more phosphorus and potassium and less nitrogen, fertilizer traders would lose profits if farmers used less nitrogen.

Furthermore, the majority of misapplication took place during the growing stage, when farmers added additional top-dressing nitrogen, where they could have instead (or also) bought phosphorus and potassium, which does not cost any more than their current regime (applying nitrogen only). Figures 11c and 11d also show that farmers' application decisions were not driven by learning from others or by low-quality of fertilizers. The former argument is consistent with the "learning from others" literature of Wolitzky (2018), which shows that input information is much more difficult to learn from neighbors than output data. The latter argument is consistent with the fact that fertilizer quality was high in our experimental site.[31]

Price Difference and Budget Constraints. 1) Farmers may use more nitrogen because it has a relatively lower price than the other two fertilizers. We directly elicit farmers' decision-making in terms of nitrogen use. In Figure A16a, contradicting the low-price explanation, survey evidence shows that farmers applied a given amount of nitrogen fertilizer, not because of low price, but directly because of greenness signals (Figure A16b). 2) Farmers use nitrogen more than the other two fertilizers because it is cheaper than the other two fertilizers. Contradicting this explanation, we find that farmers only deviated nitrogen fertilizer use during the growing stage when they received signals from crops (Figures A6, A7, and A8), but still used compound fertilizers (more expensive) during the planting stage.

Based on the above arguments, we believe that these plausible alternative explanations are unlikely to affect our main results that overestimation of the return to greenness indeed induces undervaluation and underuse of phosphorus and potassium.

7 Conclusions

In this paper, we used a two-phase RCT to investigate the simultaneous overuse and underuse of different fertilizers in China and to understand the mechanisms behind this sub-optimal equilibrium. Farmers underuse phosphorus and potassium due to an overestimation of the return on greenness, which reflects the primary effect of nitrogen. In their subjective beliefs, the lower-than-expected output is rationalized by a lower-than-true-perception of the effectiveness of phosphorus/potassium fertilizers. Our interventions, which included the provision of customized fertilizer recommendations

[31] See the official announcement: http://www.hunan.gov.cn/hnszf/hnyw/bmdt/201403/t20140314_4808623.html. On average, qualified fertilizers accounted for 93% of the total fertilizers sold in 2014 based on an inspection of 226 batches of fertilizer samples.

through a mobile application and leaf color charts, effectively reduced nitrogen fertilizer application, increased the use of phosphorus/potassium fertilizers, and increased yields and profits by 5-7%. We find direct and indirect evidence of two essential mechanisms: 1) the salient feature of the technology leads to an overestimation of the return on that technology, resulting in its overuse, and 2) the overestimation of the return on the salient technology leads to undervaluation and underuse of the technologies with low salience. Our interventions significantly improved farmers' learning about the effectiveness of different fertilizers.

We now discuss the external validity, scalability, and policy implications of these results. We begin with a cost-benefit analysis. Based on the parameters from Cui et al. (2018), a back-of-the-envelope estimate suggests that, if all rice farmers in China, for a total of 440 million mu of paddy fields, adopt either the mobile application that provides customized fertilizer recommendations or the leaf color chart, then the total use of nitrogen fertilizer would be reduced by 1.76 million tons (related to N_2O emissions reduction), CO_2-equivalent emissions could be reduced by 37.4 million tons, and yield would rise by 11 million tons (equivalent to 22 billion Chinese Yuan or US$3.4 billion). In addition, the mobile application is applicable to up to 15 types of crops. The average cost of soil testing is about 100-150 RMB per plot (equivalent to US$15.6 – US$23.4). For the mobile application, the one-time cost for programming is roughly 30,000 RMB, and the annual cost of server maintenance is roughly 10,000 RMB. The leaf color charts cost only 8-30 RMB each. If we apply the soil testing and mobile application intervention to every 4-5 mu of land, then the average annual benefit will be more than twice the estimated cost. If we apply the leaf color charts to all rice farmers, then for an average farmer with land of 7.5 mu the benefits would be more than 10 times as large as the cost.

Given these results, a natural question is why farmers overestimate the return to greenness. There are several possible answers. First, consistent with the argument of Enke (2020) that what you see is all there is, fertilizer use has increased across time (see Figure 1), and it is plausible that people believe that more greenness is equivalent to greater yields, because they have spent most of their time on the upward-sloping part of the fertilizer application curve. Second, path dependence may play an important role in nitrogen overuse. In the 1990s, many farmers just followed the advice of extension agents. However, it's very likely that the extension agents recommended an application level under output maximization to follow the national food security strategy proposed by the central government. Under such a food production target, smallholders might respond only to the average return of fertilizers, rather than to the marginal return. In this case, it becomes more difficult for them to reach the optimum because they cannot continuously vary fertilizer input and observe the corresponding outcomes. This argument is supported by the findings in Ito (2014) that, in the electricity market, consumers responded to the average price rather than the marginal or expected marginal price. Other remaining questions include, 1) why don't farmers perform their own experiments and 2) how does the social network affect the overuse and underuse of different fertilizers? These questions deserve a systematic investigation to help other developing countries avoid following the same path of fertilizer misuse.

Understanding the case of fertilizer misuse in China also has general implications for other parts of the world. For instance, underuse of fertilizers is prevalent in developing countries and overuse of nitrogen is common in developed countries. We hope these results can shed light on future interventions and scalable solutions in the fight against low productivity in agriculture and global greenhouse gas emissions.

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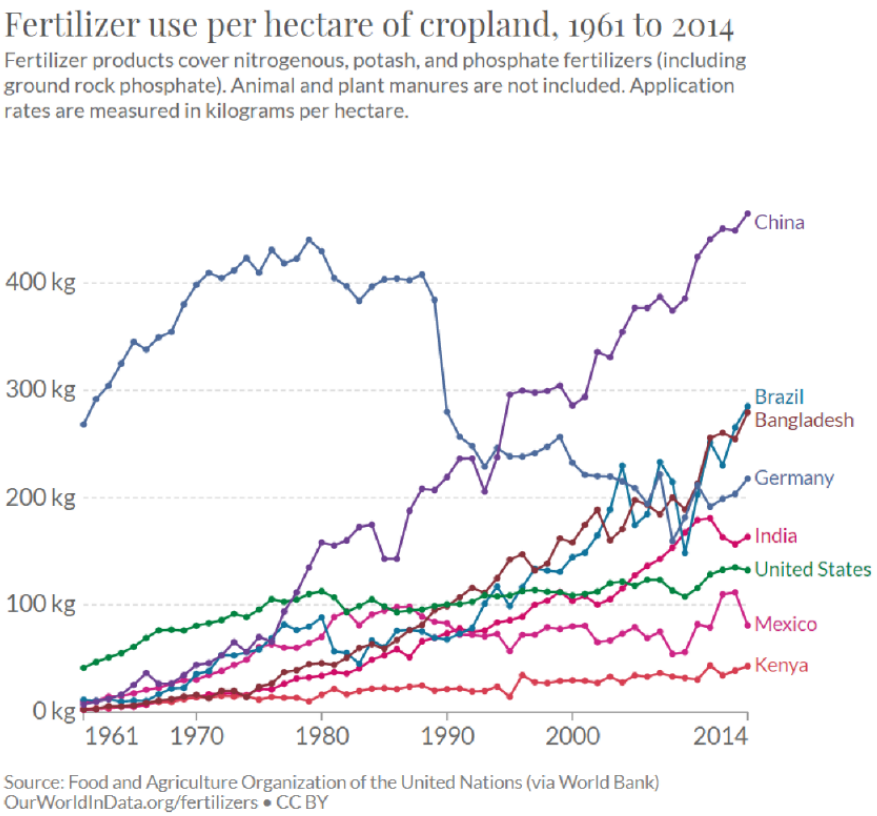
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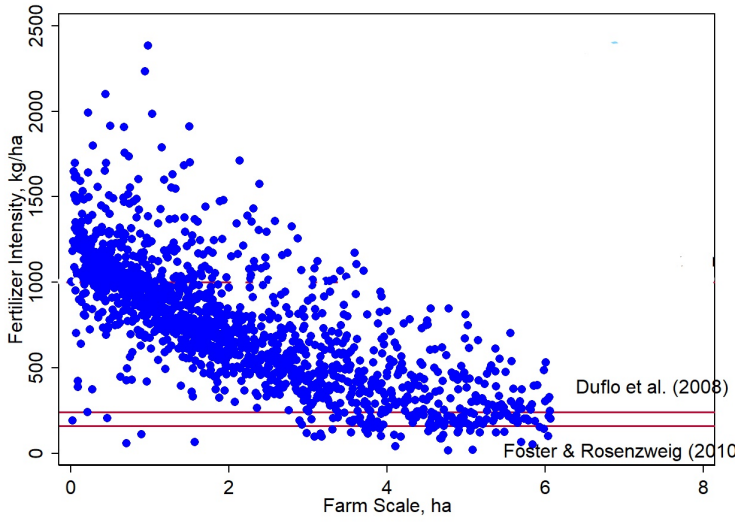
Figure 1: Cross-Country Fertilizer Intensity, kg/ha



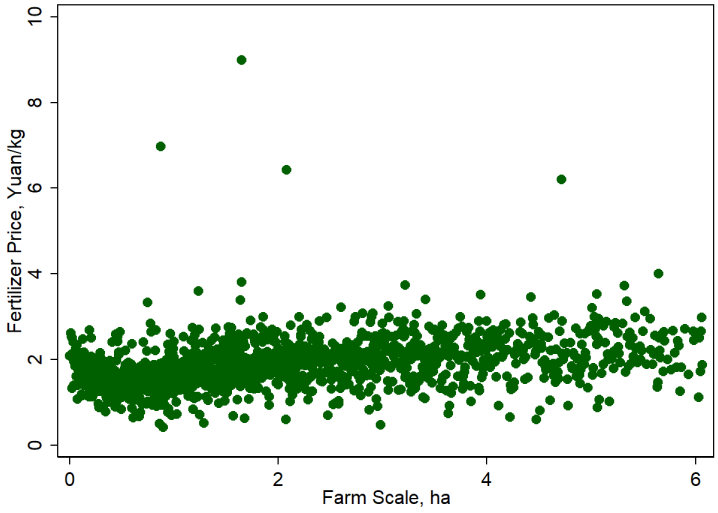
Note: This figure presents the pattern of cross-country fertilizer use per hectare from 1961 to 2014. The selected countries, in terms of fertilizer intensity in 2014, from top to bottom are China, Brazil, Bangladesh, Germany, India, the United States, Mexico and Kenya. Most developing countries are on the upward-sloping part of the curve.

Figure 2: Fertilizer Intensity (kg/ha) and Price by Farm Scale

(a) Fertilizer Intensity (kg/ha) by Farm Scale



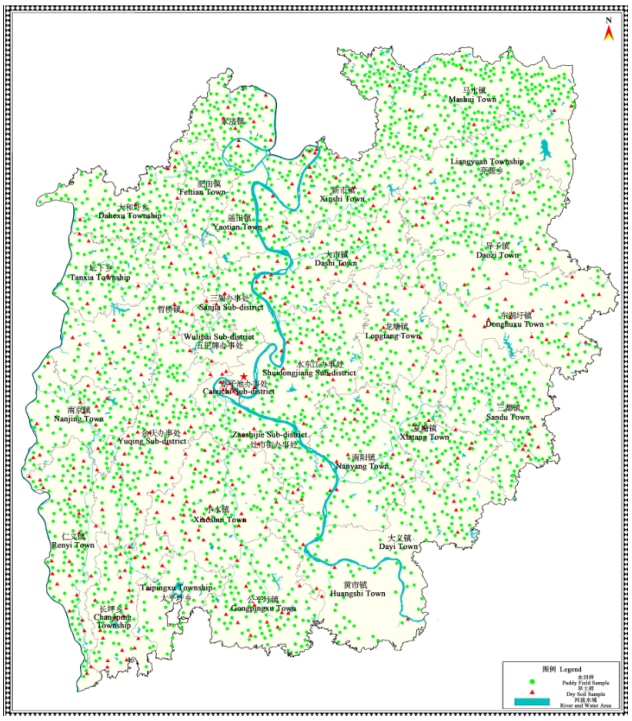
(b) Fertilizer Price by Farm Scale



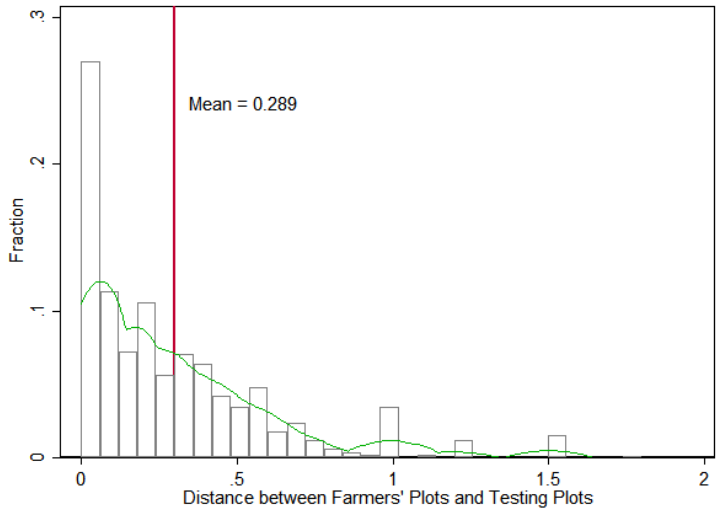
Note: The top panel of this figure depicts the relationship between fertilizer use per hectare (kg/ha, vertical axis) by farm-scale (horizontal axis) using a rich panel dataset that traces roughly 20,000 farming households in China from 1986 to 2015. The top red line indicates the optimal level of fertilizer use in western Kenya in Duflo, Kremer, and Robinson (2008), roughly 242 kg/ha, and the bottom line shows the optimal level in India by Foster and Rosenzweig (2010).
The bottom panel shows the distribution of fertilizer price by farm scale.

Figure 3: Link Farmers to the Universal Soil Analysis Points

(a) Universal Soil Testing Program in Leiyang, Hunan
(Green Dots as Testing Plots for Paddy Fields)

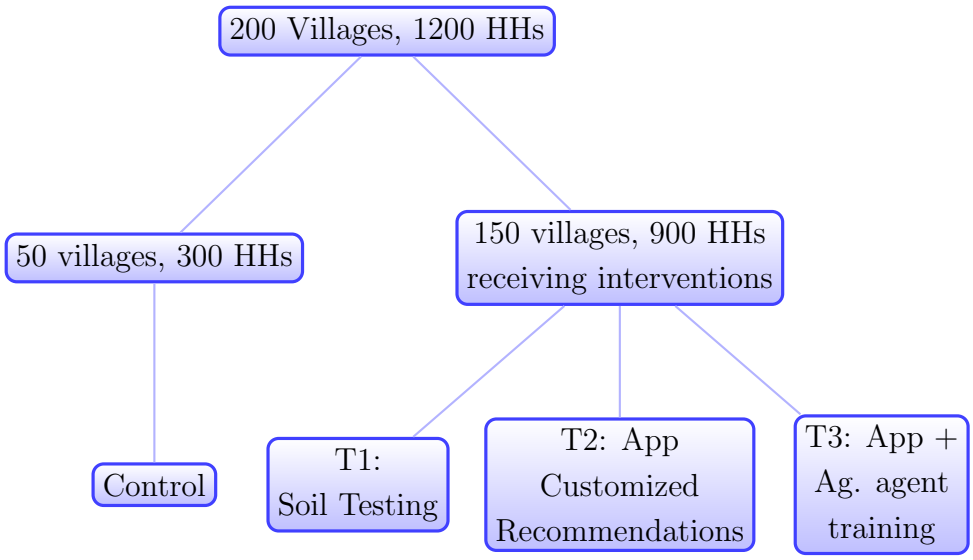


(b) Distance between Farmers' Plots and Nearest Testing Plots



Note: This figure presents (a) the universal soil analysis in Leiyang, Hunan and (b) the distribution of distance between farmers' plots and the nearest testing point. In Figure 3a, each green dot is a testing point where a soil sample was collected and analyzed in the lab for micronutrients by agricultural extension specialists. We linked each farmer in the survey to the nearest testing plot (green dot), collected individual soil analysis results, and then generated customized fertilizer recommendations. Figure 3b presents the distribution of distance between a farmer's plot and the nearest soil testing point. On average, the distance was around 0.289, while the majority of distances were no more than 0.2km, and nearly 1/3 of households had a distance lower than 0.1 km.

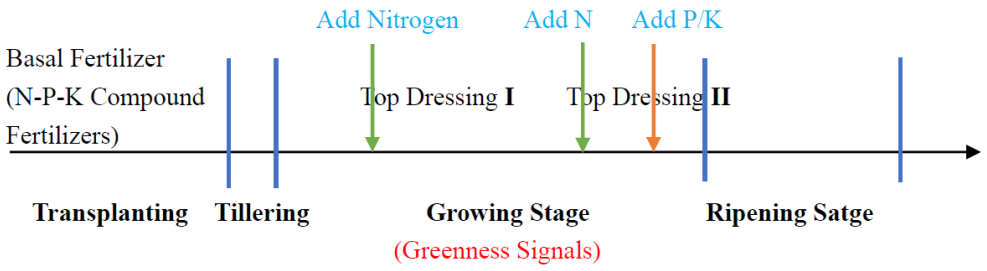
Figure 4: First-Phase Experimental Design



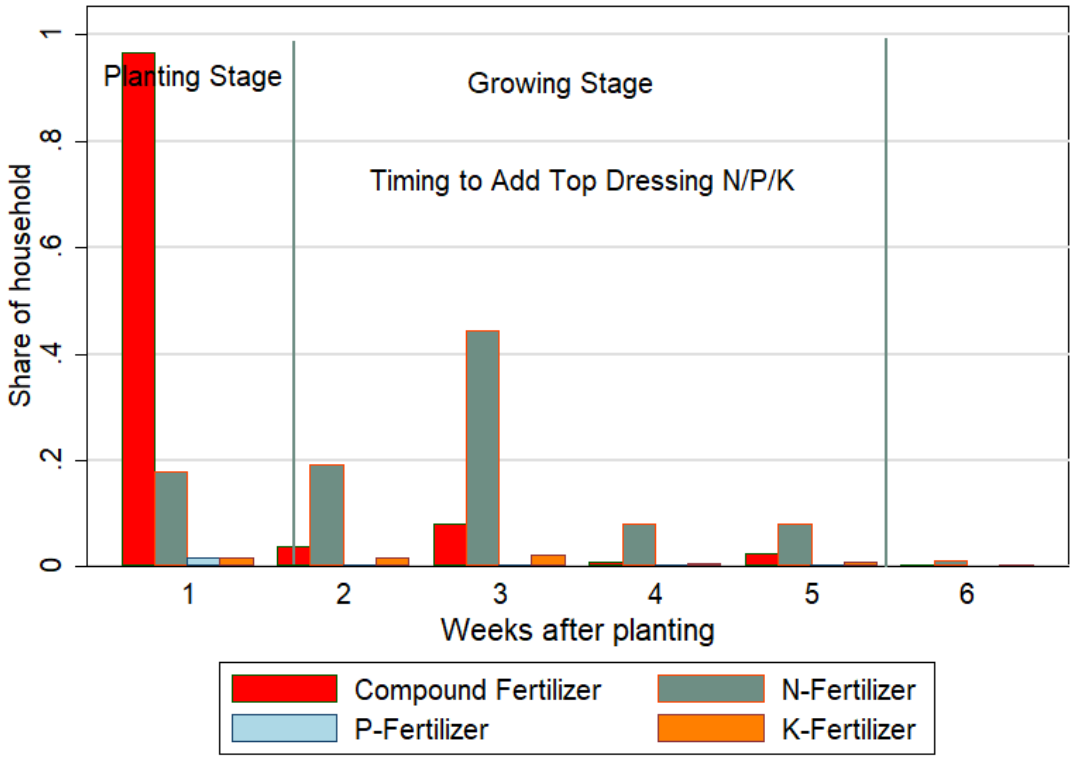
Note: This figure presents the design and randomization for the first-phase experiment on 1,200 households in 200 villages. We randomly assigned 200 villages into four arms. In the T_1 group, farmers were provided with only soil analysis information (levels of micronutrients in their plots). In the T_2 group, farmers received access to and training on our mobile application, which not only displayed the soil analysis results, but also offered customized dynamic-fertilizer-application recommendations based on the soil analysis. In the T_3 group, in addition to receiving the mobile application, farmers also received a training session with agricultural extension agents, showing experimental evidence on the relationship between phosphorus/potassium and yields, to increase their understandings on the effectiveness of phosphorus/potassium fertilizers. The first-phase experiment was conducted in April 2020, prior to the season for purchase and application of fertilizers.

Figure 5: Actual Application Deviates from Recommended Practice in the Growing Stage

(a) Recommended Practice by Time



(b) Actual Practice by Time



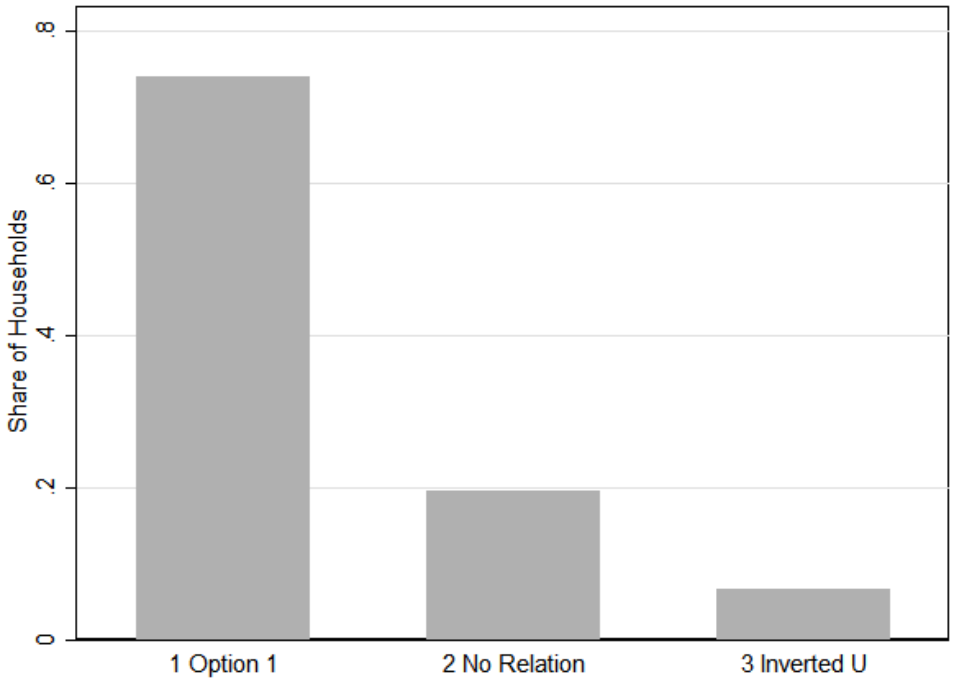
Note: These figures present how actual fertilizer use from survey deviates from recommended practice. Figure 5a shows the recommended fertilizer application, divided into two main stages. During the transplanting stage, farmers are advised to apply N-P-K compound fertilizer as the basal fertilizer, while during the growing stage, top-dressing nitrogen and phosphorus/potassium fertilizers are recommended. In Figure 5b, the y-axis indexes the proportion of households applying different fertilizers, and the x-axis indexes different time. The left panel of Figure 5b is consistent with the recommended practice as shown in Figure 5a that almost all of the farmers were applying N-P-K compound fertilizer in the planting stage. However, the middle panel of Figure 5b shows that farmers only adjusted nitrogen use, but never added any phosphorus and potassium, which deviates from the recommended practice.

Figure 6: Overestimation of the Return to Greenness

Option 1: The greener, the higher the yields are

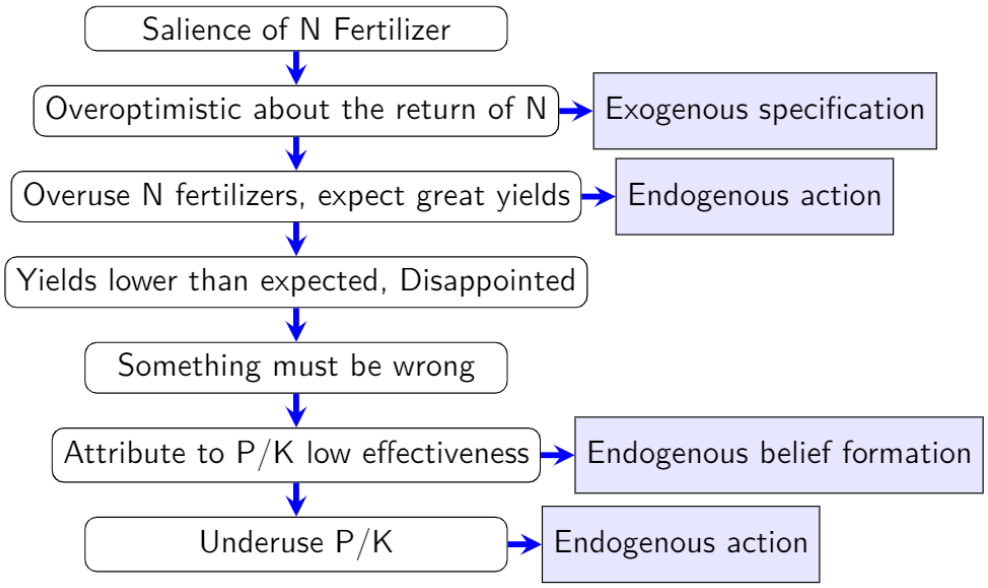
Option 2: No strong Relationship

Option 3: Inverted-U Shape [✓]



Note: This figure presents the farmers' beliefs about the relationship between greenness and yields. The y-axis indexes the proportion of households, while x-axis lists three different options. We find that most of the surveyed farmers, believed that the greener the leaves are, the higher the yields are, suggesting an overestimation of the return to greenness.

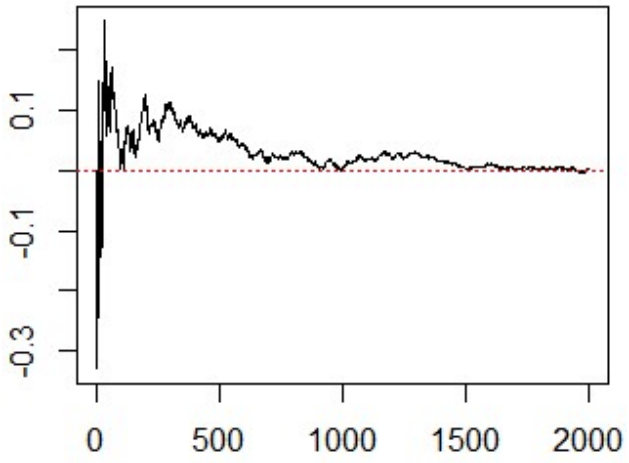
Figure 7: Model Intuition: Misspecified Learning Process



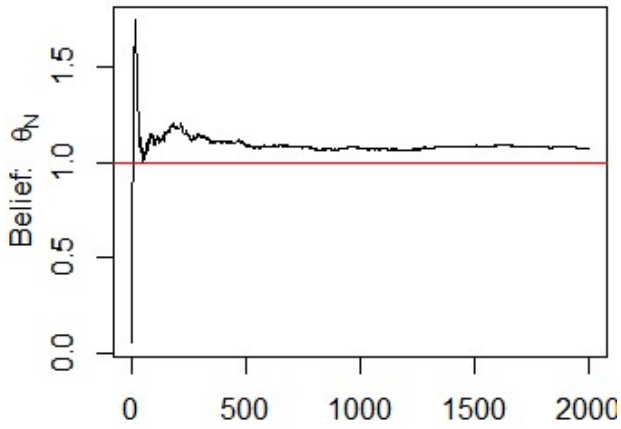
Note: This figure presents the basic logic of our model intuition.

Figure 8: Convergence of Beliefs about the Effectiveness of Different Fertilizers

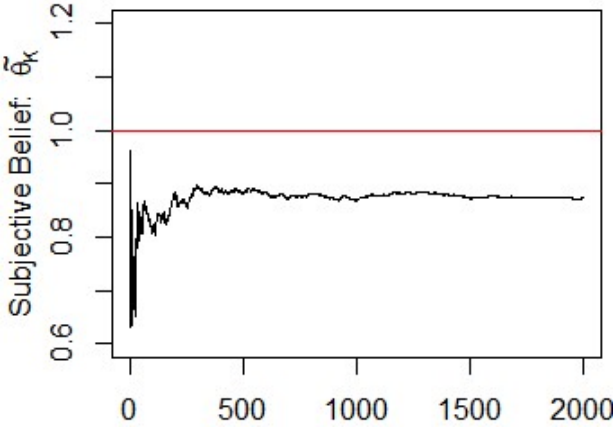
(a) Convergence of g Function ($g = 0 \Rightarrow$Equilibrium)



(b) Learning Effectiveness of Nitrogen

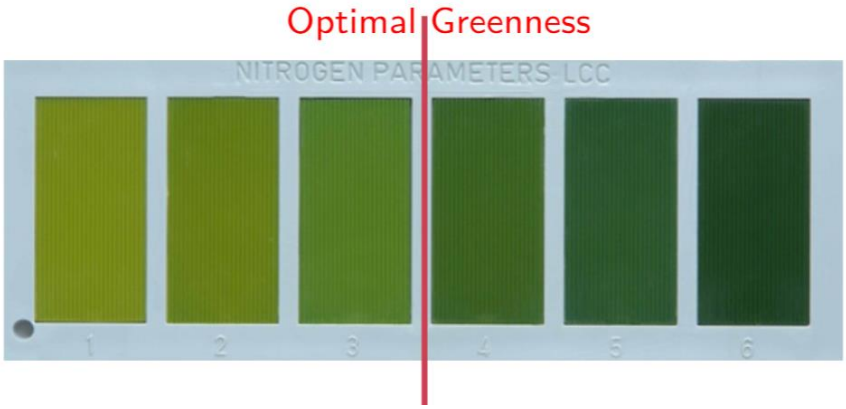


(c) Learning Effectiveness of Phosphorus/Potassium



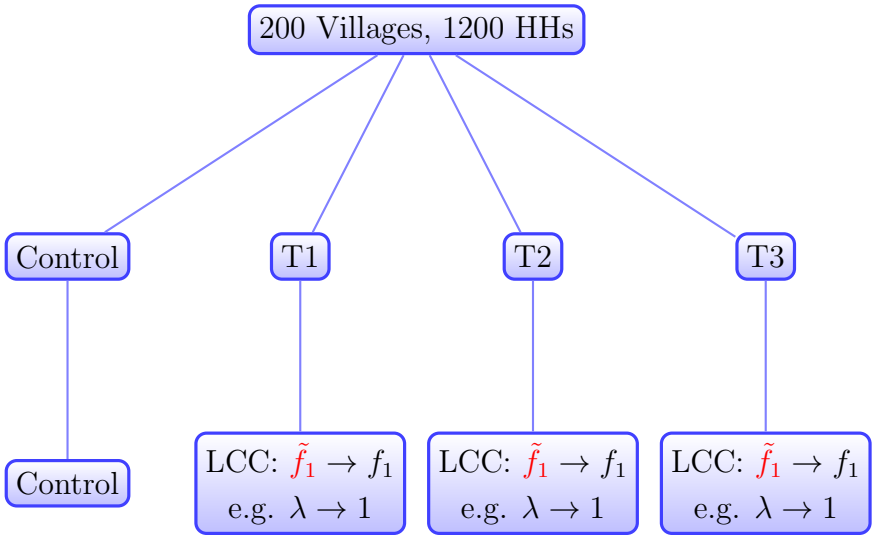
Note: This figure presents simulations about farmers' Bayesian learning about the effectiveness of nitrogen- v.s. phosphorus/potassium fertilizers. The top panel shows the convergence of the g function, indicating the new equilibrium. Figure 8b displays farmers' belief about the effectiveness of nitrogen fertilizer compared to a true value of 1. Figure 8c depicts farmers' belief about the effectiveness of phosphorus/potassium fertilizer relative to a true value of 1, which is slower and undervalued.

Figure 9: Sample of a Leaf Color Chart



Note: The figure presents the six-color leaf color chart and the suggested optimal greenness.

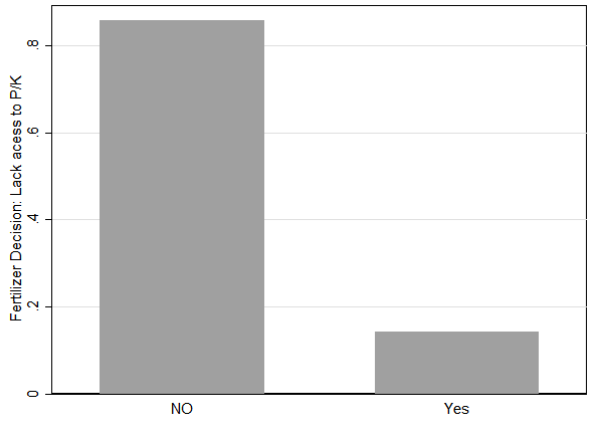
Figure 10: Second-phase Experimental Design: Correcting Overestimation



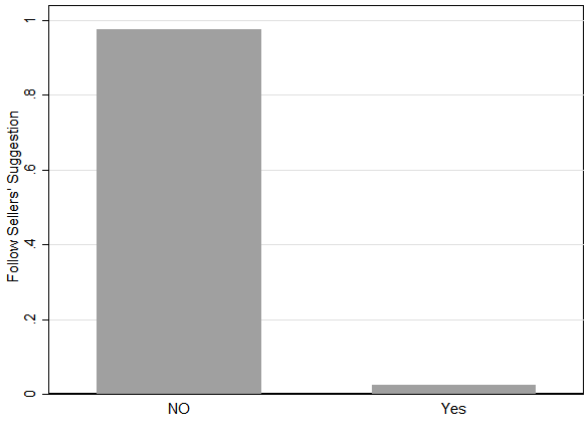
Note: The figure presents the design and randomization for the second-phase experiment on 1,200 households in 200 villages. Farmers in the existing treatment groups, T_1, T_2, and T_3, all received the leaf color chart intervention. The target is to test model prediction (3) by changing farmers' overestimation of the return to greenness and comparing the effects on T_1 and the control. The intervention was conducted in December 2020, after the harvest season and before the next fertilizer application season.

Figure 11: Supply Side-factors of Fertilizer Use

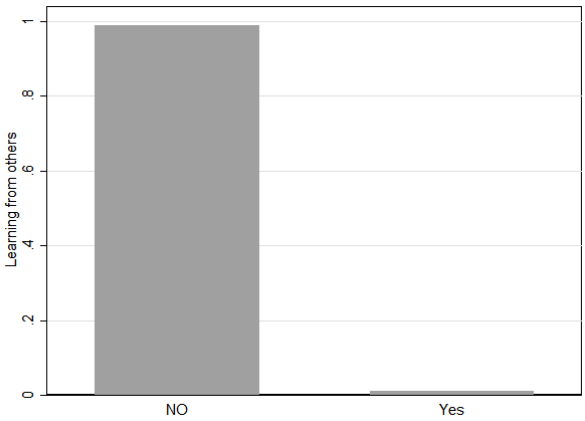
(a) Lack Access to P/K



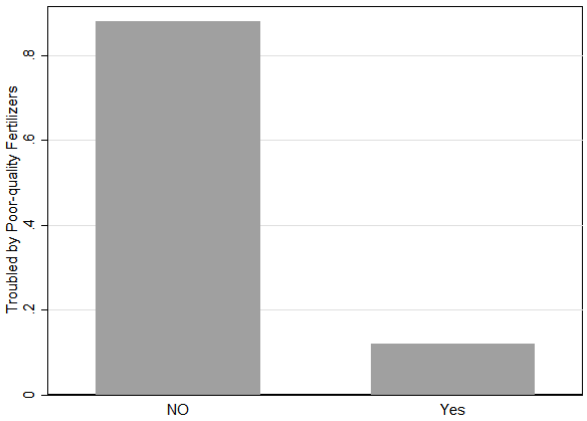
(b) Take Sellers' Suggestions



(c) Learning from Others (AEAs/Neighbors)



(d) Troubled by Poor-Quality Fertilizers



Note: The figure presents supply-side alternative explanations that might affect fertilizer use. Figure 11a shows that farmers were not subject to the supply constraints on phosphorus and potassium. Figure 11b rejects the hypothesis that fertilizer sellers influenced farmers' choice of different fertilizers. Less than 3% farmers followed the recommendations from sellers. Figure 11c suggests no evidence of learning from others, while Figure 11d shows direct evidence that quality was not a concern for farmers' choice.

Table 1: Household Characteristics, Fertilizer Recommendations, and Beliefs

	(1) T_1: ST	(2) T_2: App	(3) T_3: App+ training	(4) Control	(5) T_1-C	(6) T_2-C	(7) T_3-C
Panel A: Agricultural production							
Yield (kg/mu)	456.198	462.524	470.740	461.719	-5.522	0.805	9.020
	(108.445)	(109.091)	(104.811)	(107.706)	(8.824)	(8.851)	(8.677)
Area of plot (mu)	24.073	30.212	30.721	26.479	-2.405	3.733	4.242
	(69.053)	(88.619)	(91.842)	(74.921)	(5.883)	(6.700)	(6.843)
Revenue (RMB/mu)	1,095.754	1,095.747	1,121.603	1,120.591	-24.837	-24.844	1.012
	(391.229)	(382.665)	(428.841)	(421.841)	(33.217)	(32.883)	(34.730)
Profits (RMB/mu)	522.997	530.837	553.506	556.142	-33.145	-25.305	-2.636
	(473.205)	(472.774)	(545.048)	(493.563)	(39.477)	(39.460)	(42.453)
Compound fertilizer used (kg/mu)	37.140	36.032	35.636	35.748	1.392	0.284	-0.112
	(16.520)	(15.573)	(16.755)	(16.670)	(1.355)	(1.317)	(1.365)
Nitrogen fertilizer used (kg/mu)	19.676	20.774	22.256	21.177	-1.501	-0.404	1.079
	(14.000)	(14.700)	(15.158)	(13.936)	(1.140)	(1.169)	(1.189)
Phosphorus fertilizer used (kg/mu)	0.820	0.846	0.869	0.841	-0.021	0.005	0.027
	(5.561)	(6.098)	(6.771)	(5.779)	(0.463)	(0.485)	(0.514)
Share of HH using phosphorus fertilizer	0.027	0.027	0.023	0.023	0.003	0.003	-0.000
	(0.161)	(0.161)	(0.151)	(0.151)	(0.013)	(0.013)	(0.012)
Potassium fertilizer used (kg/mu)	1.235	1.230	1.263	1.236	-0.001	-0.005	0.027
	(4.945)	(6.593)	(5.996)	(4.966)	(0.405)	(0.477)	(0.450)
Share of HH using potassium fertilizer	0.090	0.090	0.090	0.087	0.003	0.003	0.003
	(0.287)	(0.287)	(0.287)	(0.282)	(0.023)	(0.023)	(0.023)
Total nitrogen used (kg/mu)	31.787	32.523	33.876	32.834	-1.047	-0.311	1.042
	(15.301)	(17.050)	(17.589)	(16.145)	(1.284)	(1.356)	(1.378)
Total phosphorus used (kg/mu)	15.105	14.704	14.575	14.590	0.515	0.114	-0.016
	(8.470)	(8.622)	(8.163)	(8.471)	(0.692)	(0.698)	(0.679)
Total potassium used (kg/mu)	13.615	13.241	13.141	13.151	0.463	0.090	-0.010
	(7.423)	(9.123)	(7.400)	(7.244)	(0.599)	(0.673)	(0.598)
Panel B: Recommendations based on soil testing							
Distance to the nearest testing plot (km)	0.276	0.301	0.266	0.315	-0.039	-0.014	-0.049*
	(0.305)	(0.283)	(0.314)	(0.351)	(0.027)	(0.026)	(0.027)
Compound fertilizer recommendations	43.050	42.319	44.273	43.150	-0.101	-0.831	1.122*
(kg/mu)	(8.441)	(8.609)	(8.381)	(8.182)	(0.679)	(0.686)	(0.676)
Nitrogen fertilizer recommendations	11.440	11.572	11.215	11.398	0.042	0.174	-0.184
(kg/mu)	(3.691)	(3.668)	(2.938)	(3.049)	(0.276)	(0.275)	(0.244)
Phosphorus fertilizer recommendations	2.976	3.115	2.588	2.991	-0.016	0.124	-0.403
(kg/mu)	(4.892)	(4.997)	(4.299)	(5.990)	(0.447)	(0.450)	(0.426)
Potassium fertilizer recommendations	2.070	2.007	2.073	2.257	-0.187	-0.250	-0.184
(kg/mu)	(2.569)	(2.963)	(2.889)	(3.533)	(0.252)	(0.266)	(0.263)
Panel C: Beliefs							
Correct belief: greenness and yield	0.070	0.073	0.057	0.063	0.007	0.010	-0.007
	(0.256)	(0.261)	(0.232)	(0.244)	(0.020)	(0.021)	(0.019)
Correct belief: potassium and grain's density	0.020	0.017	0.017	0.017	0.003	0.000	-0.000
	(0.140)	(0.128)	(0.128)	(0.128)	(0.011)	(0.010)	(0.010)
Attrition rate	0.013	0.010	0.023	0.030	-0.017	-0.020*	-0.007
	(0.115)	(0.100)	(0.151)	(0.171)	(0.012)	(0.011)	(0.013)
Observations	300	300	300	300	600	600	600

Notes: Columns (5), (6), and (7) report the difference in characteristics between the treatment arms T_1, T_2, T_3 and the control groups, respectively. Standard deviations in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effects of Different Treatment Arms on Fertilizer Use by Timing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Aggregate Usage: (1)-(3)			**Planting Stage: (4)**		**Fertilizer Use in Growing Stage: (5)-(9)**			
Dept. Vars.	Total N	Total P	Total K	Compound Fertilizer	N-Fertilizer	P-Fertilizer	Share of HH Using P	K-Fertilizer	Share of HH Using K
T_1: Soil Testing	-0.913	-0.259	-0.231	-0.705	-0.684	0.012	-0.004	0.004	-0.002
	(1.733)	(0.791)	(0.736)	(1.657)	(1.612)	(0.489)	(0.014)	(0.510)	(0.034)
T_2: App	-3.924**	2.344***	1.374**	1.699	-4.478***	1.691***	0.239***	0.808*	0.241***
	(1.662)	(0.716)	(0.686)	(1.513)	(1.445)	(0.514)	(0.023)	(0.477)	(0.039)
T_3: App +	-4.426***	2.721***	2.888***	2.457*	-5.227***	1.776**	0.232***	2.069***	0.324***
Training	(1.541)	(0.855)	(0.835)	(1.436)	(1.381)	(0.694)	(0.029)	(0.674)	(0.043)
Control Mean	30.84	14.74	13.31	36.16	19.05	0.833	0.0275	1.259	0.0893
Control SD	18.96	7.737	7.627	15.29	16.88	5.257	0.164	5.371	0.286
Clusters	200	200	200	200	200	200	200	200	200
Observations	1177	1177	1177	1177	1177	1177	1177	1177	1177

Note: This table presents the treatment effect of the first-phase interventions on the application of different fertilizers in multiple stages. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating provision of soil testing results, soil testing + customized fertilizer recommendations through an app, and soil testing + customized fertilizer recommendations through an app + training by agricultural extension agents, respectively. Columns (1), (2), and (3) present treatment effects for the aggregate fertilizer application across all timings. Column (4) presents the treatment effect for N-P-K compound fertilizer use in the planting stage. Columns (5), (6) and (8) present treatment effects for the application of top-dressing nitrogen-, phosphorus-, and potassium fertilizers in the growing stage. And columns (7) and (9) report the treatment effects for the proportion of households using phosphorus- and potassium fertilizers. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table 3: Effects of First-Phase Interventions on Yields, Profits, and Costs

	(1)	(2)	(3)	(4)	(5)	(6)
	First-phase Interventions					
Dept. Vars.	Yield	Log Yield	Profit	Revenue	Fertilizer	Other
VARIABLES	kg/mu		Yuan/mu	Yuan/mu	Cost	Cost
T_1: Soil Testing	-7.523	-0.007	-1.244	-10.683	-6.286	-3.153
	(13.931)	(0.031)	(43.049)	(39.117)	(7.866)	(20.347)
T_2: App	22.737*	0.054*	87.249**	68.569*	-7.048	-11.632
	(12.435)	(0.028)	(40.191)	(37.219)	(7.689)	(18.439)
T_3: App + Training	31.647**	0.067**	82.420**	78.786**	3.452	-7.086
	(12.369)	(0.028)	(39.073)	(34.584)	(7.606)	(19.766)
Control Mean	465.6	6.117	520.7	1142	164.1	457.4
Control SD	106.9	0.262	360.8	298.2	83.48	168
Clusters	200	200	200	200	200	200
Observations	1177	1173	1177	1177	1177	1177

Note: This table presents the treatment effect of the first-phase interventions on secondary outcomes. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating provision of soil testing results, soil testing + customized fertilizer recommendations through an app, and soil testing + customized fertilizer recommendations through an app + training by agricultural extension agents, respectively. Columns (1), (2), (3), and (4) present treatment effects for yields, log yields, profits, and revenues. Columns (5) and (6) present the treatment effect for the costs of fertilizers and other inputs, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table 4: Effects of First-Phase Interventions on Beliefs about Effectiveness

	(1)	(2)	(3)	(4)	(5)
	Beliefs about the effect of N/P/P/K: Correct = 1 (2)-(5)				
Dept. Vars.	Greenness & Yield	Nitrogen & Greenness	Phosphorus & Flowering Time	Phosphorus & Root Length	Potassium & Grain Density
T_1: Soil Testing	0.006	-0.016	0.005	0.003	-0.004
	(0.021)	(0.021)	(0.035)	(0.019)	(0.016)
T_2: App	0.150***	-0.033	0.220***	0.208***	0.171***
	(0.033)	(0.023)	(0.035)	(0.029)	(0.032)
T_3: App + Training	0.310***	-0.024	0.340***	0.338***	0.368***
	(0.040)	(0.022)	(0.042)	(0.037)	(0.034)
Control Mean	0.0584	0.952	0.131	0.0412	0.0275
Control SD	0.235	0.214	0.338	0.199	0.164
Clusters	200	200	200	200	200
Observations	1177	1177	1177	1177	1177
R squared	0.111	0.00231	0.0999	0.134	0.172

Note: This table presents the treatment effects of the first-phase interventions on farmers' beliefs. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating the provision of soil testing results, soil testing + customized fertilizer recommendations through an app, and soil testing + customized fertilizer recommendations through an app + training by agricultural extension agents, respectively. Column (1) shows farmers' understanding of the relationship between greenness and yields. The outcome variable is a dummy for whether a farmer understood the relationship correctly (option 3, inverted-U shape relationship). Column (2) shows whether they understood the effects of nitrogen on greenness correctly. The outcome variables in columns (3), (4), and (5) are a set of dummies for whether farmers correctly understood the effects of phosphorus on flowering time, of phosphorus on root length, and the effects of potassium on grain density, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table 5: Effects of Leaf Color Charts on Fertilizer Usage in Different Stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Aggregate Usage: (1)-(3)			**Planting Stage: (4)**	**Fertilizer Use in Growing Stage: (5)-(9)**				
Dept. Vars.	Total N	Total P	Total K	Compound Fertilizer	N-Fertilizer	P-Fertilizer	Share of HH Using P	K-Fertilizer	Share of HH Using K
Panel A: Phase 2 Interventions for comparison									
T_1: LCC	-3.757**	0.482	0.173	0.223	-3.829**	0.396	0.062***	0.098	0.066*
	(1.662)	(0.828)	(0.745)	(1.750)	(1.519)	(0.521)	(0.021)	(0.560)	(0.040)
T_2: App + LCC	-4.865***	2.187***	1.898**	1.891	-5.482***	1.459***	0.206***	1.267*	0.247***
	(1.631)	(0.815)	(0.865)	(1.564)	(1.410)	(0.523)	(0.025)	(0.690)	(0.038)
T_3: App +	-4.809***	2.917***	3.143***	2.951**	-5.771***	1.782**	0.246***	2.159***	0.316***
Training + LCC	(1.620)	(0.914)	(0.851)	(1.465)	(1.466)	(0.737)	(0.033)	(0.687)	(0.045)
Control Mean	30.48	14.42	13.18	35.07	19.04	0.928	0.0418	1.488	0.0941
Control SD	19.27	8.347	8.337	15.72	17.12	5.799	0.201	6.080	0.292
Clusters	199	199	199	199	199	199	199	199	199
Observations	1153	1153	1153	1153	1153	1153	1153	1153	1153
Panel B: Recap of Phase 1 Interventions									
T_1: Soil Testing	-0.913	-0.259	-0.231	-0.705	-0.684	0.012	-0.004	0.004	-0.002
	(1.733)	(0.791)	(0.736)	(1.657)	(1.612)	(0.489)	(0.014)	(0.510)	(0.034)
T_2: App	-3.924**	2.344***	1.374**	1.699	-4.478***	1.691***	0.239***	0.808*	0.241***
	(1.662)	(0.716)	(0.686)	(1.513)	(1.445)	(0.514)	(0.023)	(0.477)	(0.039)
T_3: App + Training	-4.426***	2.721***	2.888***	2.457*	-5.227***	1.776**	0.232***	2.069***	0.324***
	(1.541)	(0.855)	(0.835)	(1.436)	(1.381)	(0.694)	(0.029)	(0.674)	(0.043)

Note: Panel A presents the treatment effects of the second-phase intervention intertwined with the first-phase interventions on the application of different fertilizers in multiple stages. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating leaf color charts, customized fertilizer recommendations through an app + leaf color charts, and customized fertilizer recommendations through an app + training by agricultural extension agents + leaf color charts, respectively. Columns (1), (2), and (3) present treatment effects on the application of aggregate fertilizer across all stages. Column (4) presents the treatment effect on the use of N-P-K compound fertilizer in the planting stage. Columns (5), (6) and (8) presents treatment effects on the application of top-dressing nitrogen-, phosphorus-, and potassium fertilizers in the growing stage. And columns (7) and (9) report the treatment effects for the proportion of households using phosphorus- and potassium fertilizers.
For panel B, we replicate the treatment effects of the first-phase interventions on the application of different fertilizers in multiple stages. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating the provision of soil testing result, soil testing + customized fertilizer recommendations through the app, and soil testing + customized fertilizer recommendations through an app + training by agricultural extension agents, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table 6: Effects of Two-Phase Interventions on Gap between Applications and Recommendations

	(1)	(2)	(3)	(4)	(5)	(6)
	First-Phase Intervention (1) - (3)			***Second-Phase Intervention (4) - (6)***		
Dept. Vars.	Nitrogen Gap	Phosphorus Gap	Potassium Gap	Nitrogen Gap	Phosphorus Gap	Potassium Gap
	[Gap = the Used - the Recommended]					
T_1: Soil Testing/LCC	-0.740	-0.197	-0.019	-3.581**	0.560	0.388
	(1.797)	(0.990)	(0.784)	(1.724)	(1.018)	(0.788)
T_2: App/LCC + App	-3.614**	2.212**	1.815**	-4.500***	2.375**	2.401***
	(1.690)	(0.965)	(0.742)	(1.648)	(0.997)	(0.859)
T_3: App + Training/App + Training + LCC	-4.661***	2.936***	2.688***	-5.109***	3.070***	2.913***
	(1.615)	(1.018)	(0.913)	(1.710)	(1.098)	(0.918)
Observations	1177	1177	1177	1153	1153	1153
Control Mean	7.637	-4.866	-3.339	7.269	-5.205	-3.465
Control SD	19.34	10.13	8.559	19.63	10.45	9.160
Clusters	200	200	200	199	199	199
R-squared	0.0167	0.0180	0.0186	0.0175	0.0141	0.0182

Note: Columns (1), (2) and (3) present the treatment effects of the first-phase interventions on the gap in fertilizer use between actual application and recommended use. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating the provision of soil testing results, soil testing + customized fertilizer recommendations through an app, and soil testing + customized fertilizer recommendations through an app + training by agricultural extension, respectively. The outcome variables in column (1), (2), and (3) are nitrogen use gap [used - recommended], phosphorus use gap [used - recommended], and potassium use gap [used - recommended], respectively.

Columns (4), (5) and (6) present the treatment effects of the second-phase interventions on the gap in fertilizer use between actual application and recommended use. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating leaf color charts, customized fertilizer recommendations through the app + leaf color charts, and customized fertilizer recommendations through the app + training by agricultural extension agents + leaf color charts, respectively. The outcome variables in columns (4), (5), and (6) are nitrogen use gap [used - recommended], phosphorus use gap [used - recommended], and potassium use gap [used - recommended] in the second follow-up survey, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table 7: IV Estimation: Deviation in Fertilizer Application and Yields

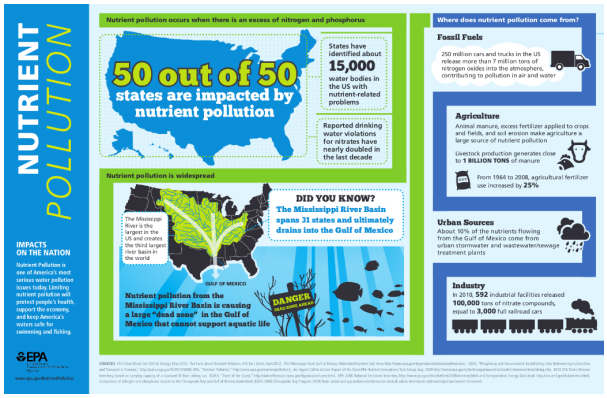
	(1) IV-First Stage $logGap^2$	(2) 2SLS Yields	(3) 2SLS Log Yields
T_2 (App)	-1.029***		
	(0.191)		
T_3 (App + Training by AEA)	-1.134***		
	(0.223)		
$LogGap^2$		-36.39***	-0.0775**
		(10.86)	(0.0246)
Observations	465	465	462
R-squared	0.124		
Control Mean	5.27	466.58	6.13
F-statistic	23.48		

Note: In this table, we employ the IV-2sls regression strategy using data from the second round of surveys to estimate the impact on yields of deviations in fertilizer application compared with the recommended use. In the IV-2sls regression, we use T_2 and T_3 indicators as the instrumental variables to run equations (6) and (7). We also limit the regression samples to those who overuse nitrogen fertilizers and underuse phosphorus/potassium fertilizers so that the underlying relationships between fertilizer gaps and yields are clearly defined. The overuse of nitrogen and underuse of phosphorus/potassium lead directly to lower yields. Column (1) reports the first-stage regression and the outcome variable is the log of Gap^2, defined as $Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$. The outcome variables in columns (2) and (3) are yields and the log of yields. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Appendices

Appendix A: Supplementary Tables and Figures

Figure A1: Nitrogen Abuse in Developed Countries



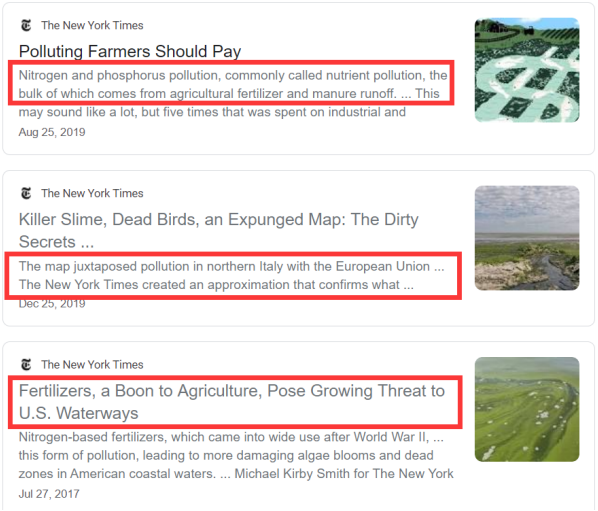


With Too Much of a Good Thing, Europe Tackles Excess Nitrogen

In Germany, the Netherlands, Denmark and other countries, European governments are beginning to push farmers, industry, and municipalities to cut back on fertilizers and other sources of nitrogen that are causing serious environmental harm.

BY CHRISTIAN SCHWÄGERL · APRIL 14, 2015

Only seconds after Claudia Wiedner drops the metallic rod into the gray waters of Lake Scharmützel, 30 miles southeast of Berlin, the probe starts sending signals back to her computer. On a cold, foggy day in March, Wiedner, a limnologist at the Brandenburg University of Cottbus-Senftenburg, and a research technician are out on the water in their small vessel to investigate nitrogen pollution.



The New York Times

Polluting Farmers Should Pay

Nitrogen and phosphorus pollution, commonly called nutrient pollution, the bulk of which comes from agricultural fertilizer and manure runoff. ... This may sound like a lot, but five times that was spent on industrial and

Aug 25, 2019

The New York Times

Killer Slime, Dead Birds, an Expunged Map: The Dirty Secrets ...

The map juxtaposed pollution in northern Italy with the European Union ... The New York Times created an approximation that confirms what ...

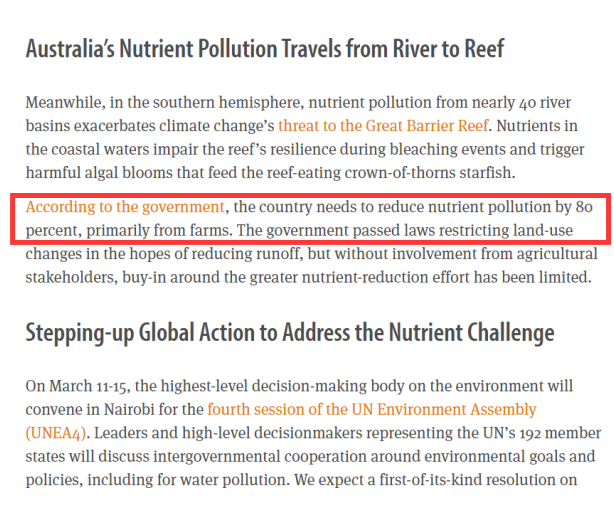
Dec 25, 2019

The New York Times

Fertilizers, a Boon to Agriculture, Pose Growing Threat to U.S. Waterways

Nitrogen-based fertilizers, which came into wide use after World War II, ... this form of pollution, leading to more damaging algae blooms and dead zones in American coastal waters. ... Michael Kirby Smith for The New York

Jul 27, 2017



Australia's Nutrient Pollution Travels from River to Reef

Meanwhile, in the southern hemisphere, nutrient pollution from nearly 40 river basins exacerbates climate change's threat to the Great Barrier Reef. Nutrients in the coastal waters impair the reef's resilience during bleaching events and trigger harmful algal blooms that feed the reef-eating crown-of-thorns starfish.

According to the government, the country needs to reduce nutrient pollution by 80 percent, primarily from farms. The government passed laws restricting land-use changes in the hopes of reducing runoff, but without involvement from agricultural stakeholders, buy-in around the greater nutrient-reduction effort has been limited.

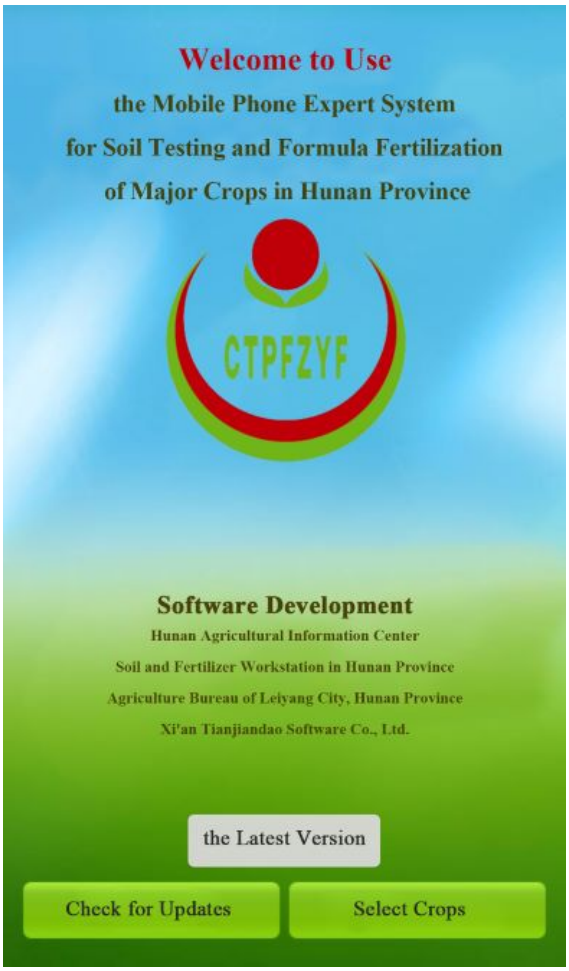
Stepping-up Global Action to Address the Nutrient Challenge

On March 11-15, the highest-level decision-making body on the environment will convene in Nairobi for the fourth session of the UN Environment Assembly (UNEA4). Leaders and high-level decisionmakers representing the UN's 192 member states will discuss intergovernmental cooperation around environmental goals and policies, including for water pollution. We expect a first-of-its-kind resolution on

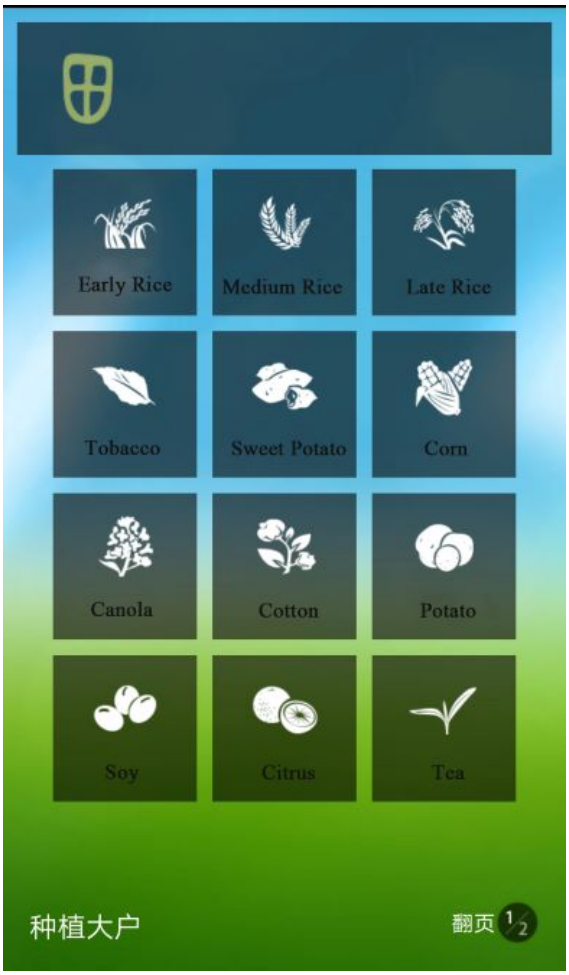
Note: Agricultural nitrogen fertilizer use has become one of the major sources for N_2O pollution.

Figure A2: The First Two Interfaces of the Mobile Application

(a) Endorsed by Hunan Government



(b) Scalable to Up to 15 Crops



Note: The left panel shows that the mobile application is endorsed by Hunan government. The right panel asks farmers to choose crops to get fertilizer recommendations.

Figure A3: The Second Two Pages of the Mobile Application

(a) Acquire Soil Analysis by GPS Tracking



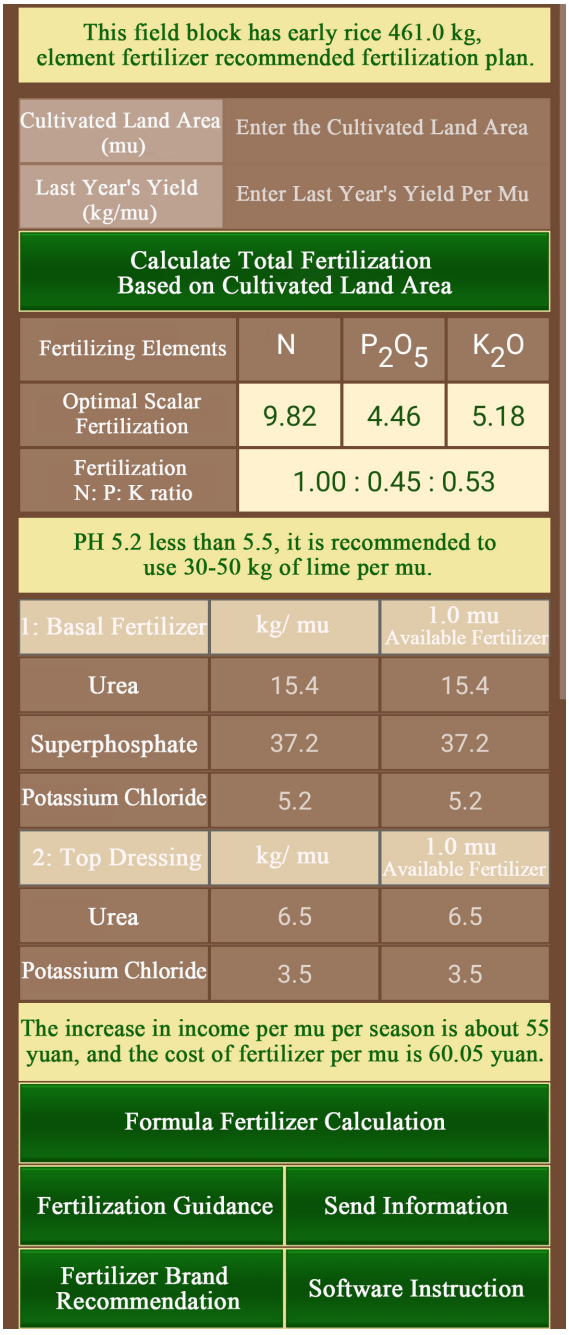
(b) Acquire Soil Analysis by Selecting Places



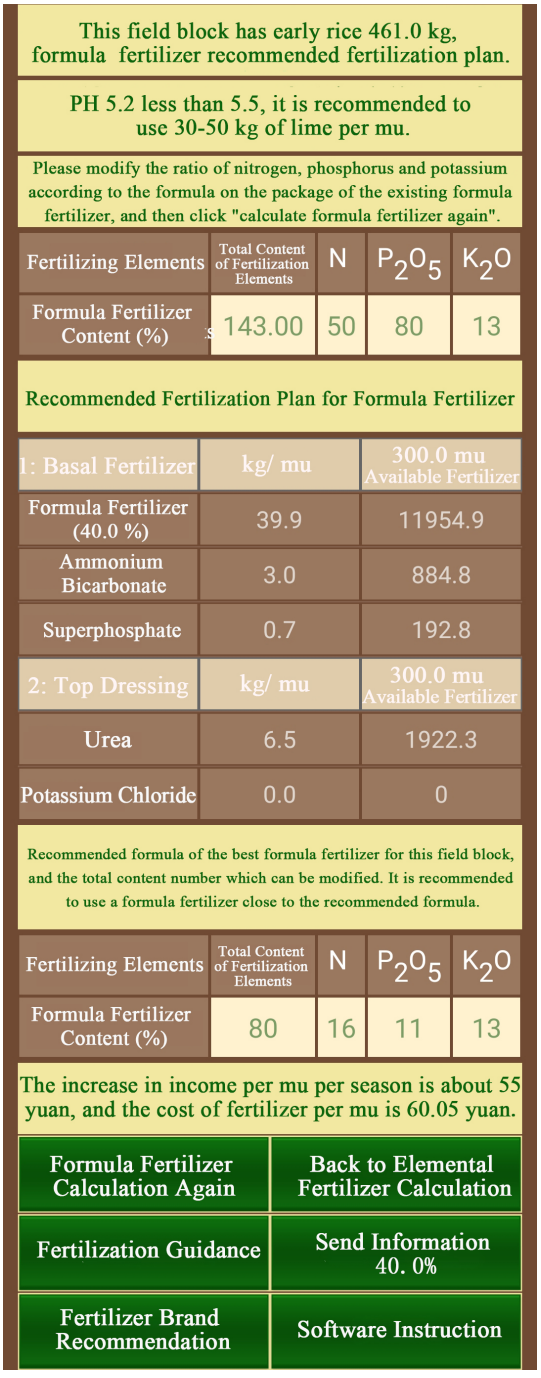
Note: The left panel shows that farmers can acquire soil testing data by GPS tracking or by choosing a location. The app then displays the pH value, and the amount of organic matter, nitrogen, phosphorus, and potassium in farmers' plots. The right panel shows a set of locations that farmers can select from.

Figure A4: Dynamic Fertilizer Recommendations

(a) Combination of Different Individual Fertilizers

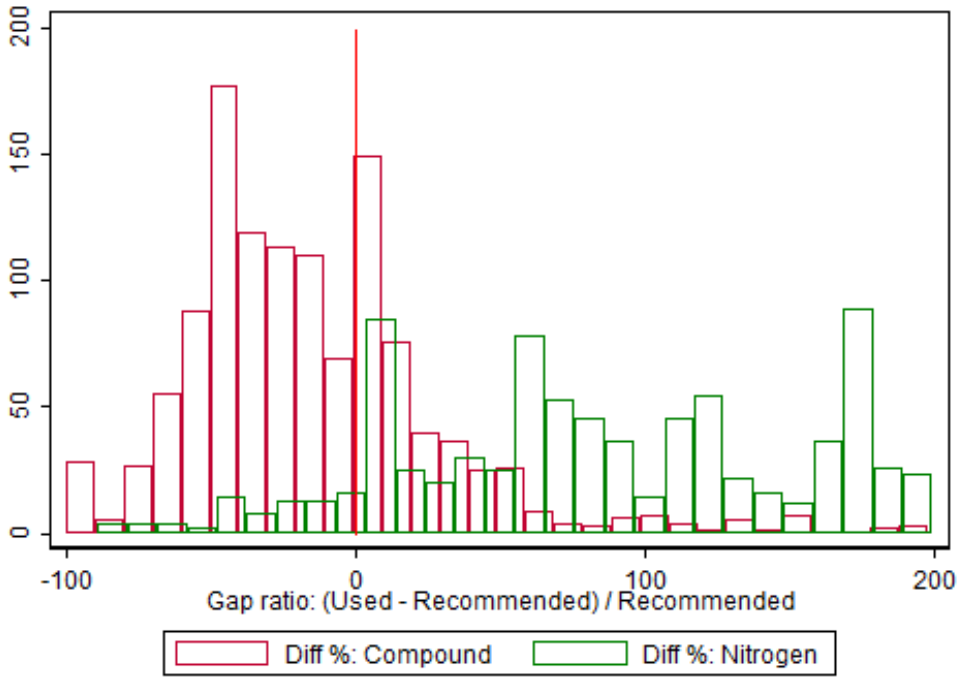


(b) Combination of Compound + Other Individual Fertilizers



Note: The left panel shows that the app can display customized recommendations for different individual fertilizers at different times based on personalized soil testing. Since most farmers are using the compound fertilizers, the right panel shows that the app can display customized recommendations for the combination of compound fertilizers and individual fertilizers at different times based on personalized soil testing.

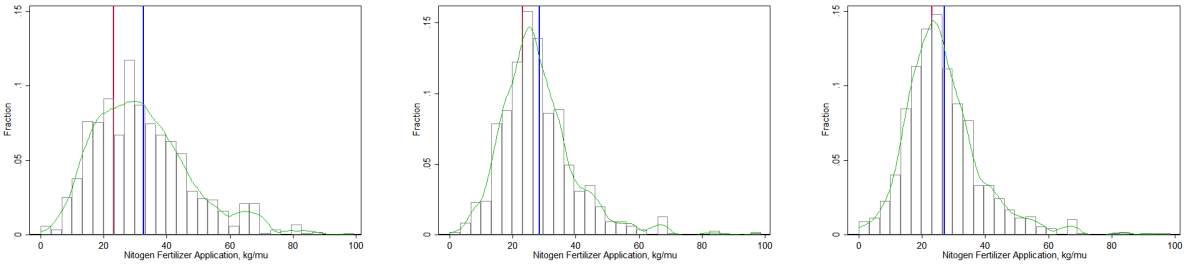
Figure A5: Gap in Fertilizer Application: (Used- Recommended)/Recommended



Note: This figure demonstrates the Gap in the use of different fertilizers between the actual use and the recommended use based on soil analysis. The y-axis indexes the number of households, and the x-axis indexes the percentage point deviation, which equals (actual Use - recommended)/recommended. The green bar and red bar indicate the deviation percentages for nitrogen and compound fertilizers, respectively.

Figure A6: Total Nitrogen Application [Used >> Recommended]

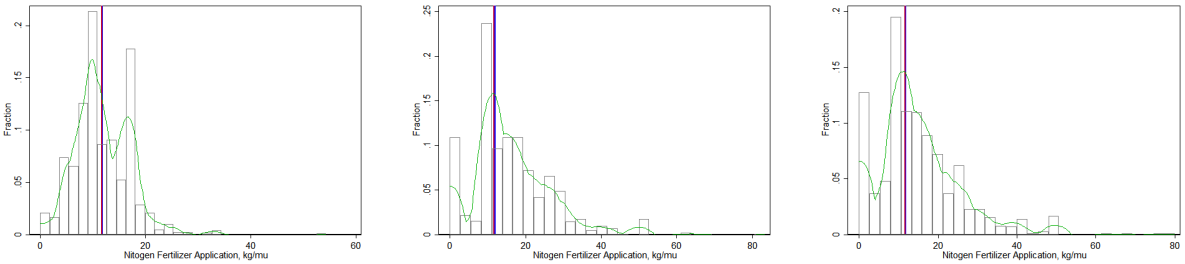
(a) Before Interventions, 2019 (b) After Phase 1 Intervention, 2020 (c) After Phase 2 Intervention, 2021



Note: This figure shows the distribution of total nitrogen fertilizer application (kg/mu) in the baseline (2019 season), after the first-phase interventions (2020 season), and after the second-phase intervention (2021 season). The red line indicates the mean of nitrogen recommendations, while the blue line shows the mean of actual use. The figure clearly shows that deviation in total nitrogen application decreases following our interventions.

Figure A7: Nitrogen Application in the Planting Stage [Used ≈ Recommended]

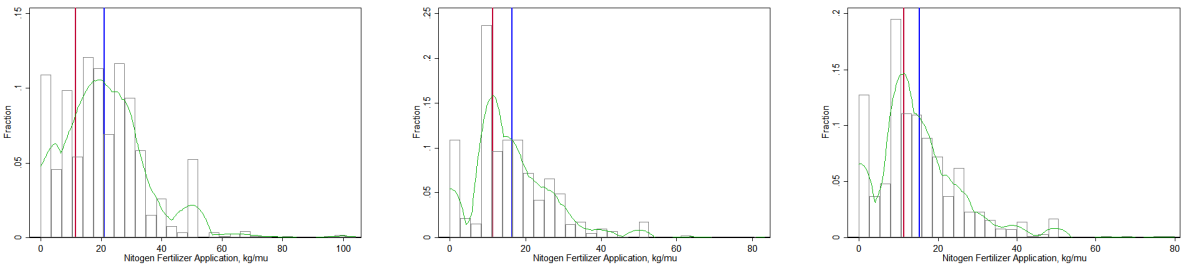
(a) Before Interventions, 2019 (b) After Phase 1 Intervention, 2020 (c) After Phase 2 Intervention, 2021



Note: This figure shows the distribution of nitrogen fertilizer application (kg/mu) in the planting stage. The red line indicates the mean of nitrogen recommendations, while the blue line shows the mean of actual use. The figure clearly shows that there is no systematic difference in the planting stage.

Figure A8: Top-Dressing Nitrogen Application in the Growing Stage [Used >> Recommended]

(a) Before Interventions, 2019 (b) After Phase 1 Intervention, 2020 (c) After Phase 2 Intervention, 2021

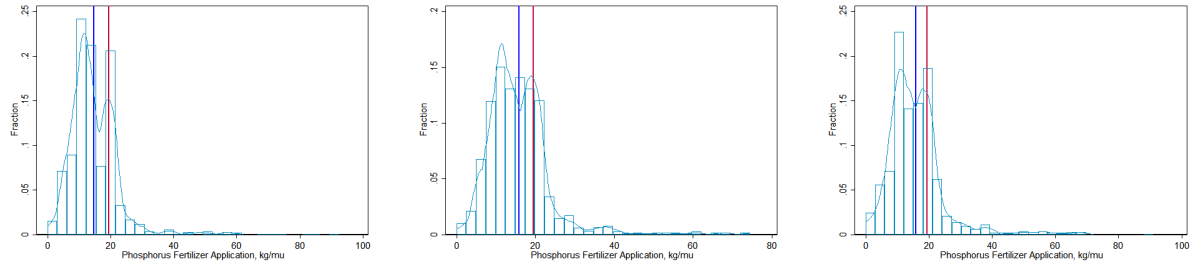


Note: This figure shows the distribution of nitrogen fertilizer application (kg/mu) in the growing stage. The red line indicates the mean of nitrogen recommendations, while the blue line shows the mean of actual use. The figure clearly shows that nitrogen fertilizers are over-applied during the growing stage.

Figure A9: Total Phosphorus Application [Used < Recommended]

(Red = Mean Recommendations, blue = Mean Application)

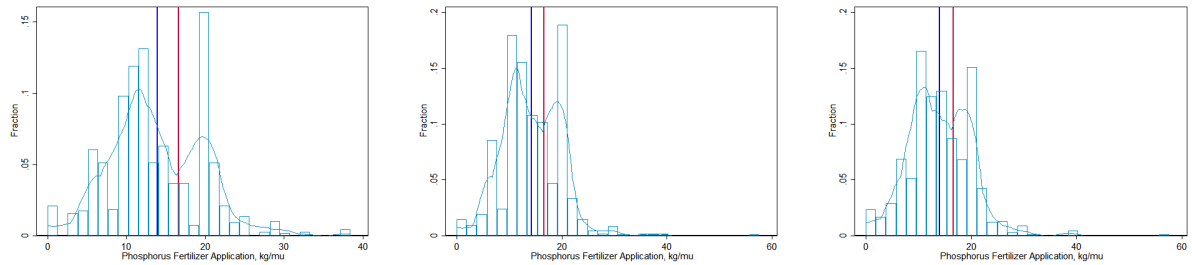
Before Interventions 2019 | After Phase 1 Intervention, 2020 | After Phase 2 Intervention, 2021



Note: This figure shows the distribution of total phosphorus fertilizer application (kg/mu) throughout the cropping cycle. The red line indicates the mean of phosphorus recommendations, while the blue line shows the mean of actual use. The figure suggests a clear pattern of phosphorus underuse and that our interventions reduced this gap.

Figure A10: Phosphorus Application in the Planting Stage [Used < Recommended]

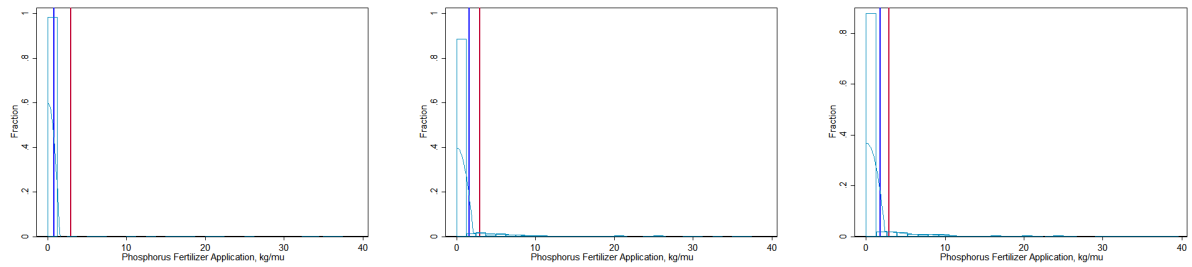
(a) Before Interventions, 2019 | (b) After Phase 1 Intervention, 2020 | (c) After Phase 2 Intervention, 2021



Note: This figure shows the distribution of top-dressing phosphorus fertilizer application (kg/mu) in the planting stage. The red line indicates the mean of phosphorus recommendations, while the blue line shows the mean of actual use. The figure suggests a clear pattern of phosphorus underuse during the planting stage.

Figure A11: Top-Dressing Phosphorus Application in the Growing Stage [Used < Recommended]

(a) Before Interventions, 2019 | (b) After Phase 1 Intervention, 2020 | (c) After Phase 2 Intervention, 2021

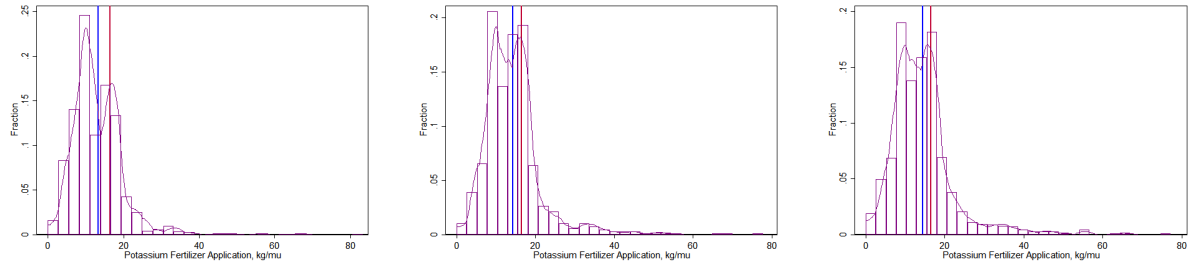


Note: This figure shows the distribution of phosphorus fertilizer application (kg/mu) in the growing stages. The red line indicates the mean of phosphorus recommendations, while the blue line shows the mean of actual use. The figure suggests underuse of phosphorus in the growing stage, and that our interventions reduced this gap.

Figure A12: Total Potassium Application [Used < Recommended]

(Red = Mean Recommendations, blue = Mean Application)

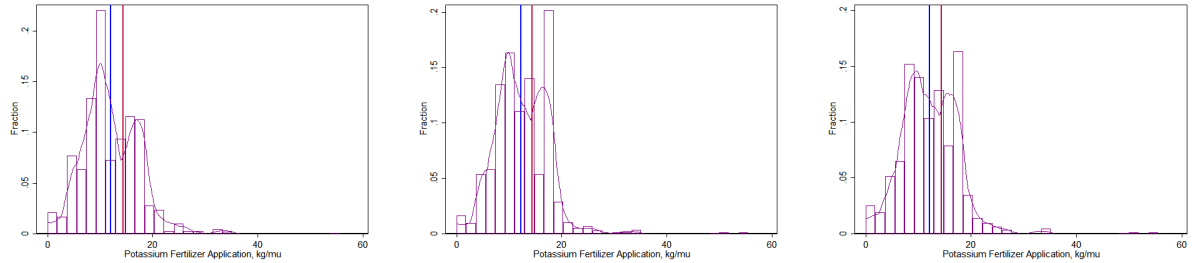
Before Interventions 2019 | After Phase 1 Intervention, 2020 | After Phase 2 Intervention, 2021



Note: This figure shows the distribution of total potassium fertilizer application (kg/mu) throughout the cropping cycle. The red line indicates the mean of potassium recommendations, while the blue line shows the mean of actual use. The figure suggests a clear pattern of potassium underuse and that our interventions reduced this gap.

Figure A13: Potassium Application in the Planting Stage [Used < Recommended]

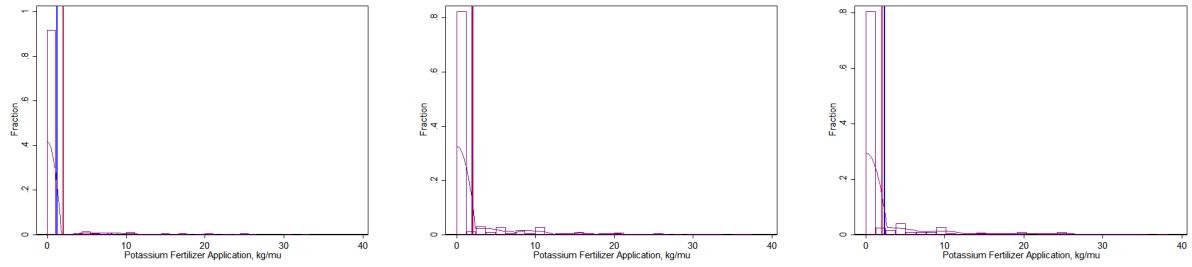
(a) Before Interventions 2019 | (b) After Phase 1 Intervention, 2020 | (c) After Phase 2 Intervention, 2021



Note: This figure shows the distribution of potassium fertilizer application (kg/mu) in the planting stage. The red line indicates the mean of potassium recommendations, while the blue line shows the mean of actual use. The figure suggests underuse of potassium in the planting stage.

Figure A14: Top-Dressing Potassium Application in the Growing Stage [Used < Recommended]

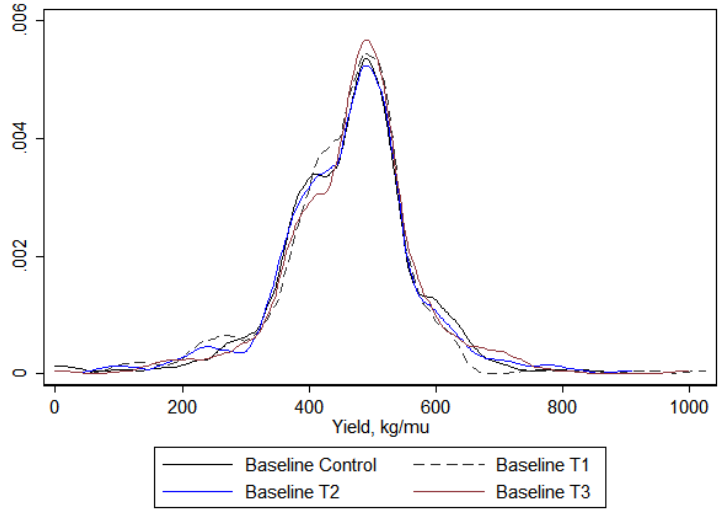
(a) Before Interventions 2019 | (b) After Phase 1 Intervention, 2020 | (c) After Phase 2 Intervention, 2021



Note: This figure shows the distribution of potassium fertilizer application (kg/mu) in the growing stage. The red line indicates the mean of potassium recommendations, while the blue line shows the mean of actual use. The figure suggests underuse of potassium in the growing stage, and that our interventions reduced this gap.

Figure A15: Yields Before/After First-Phase Interventions

(a) Yields at Baseline (kg/mu)



(b) Yields after First-Phase Interventions (kg/mu)

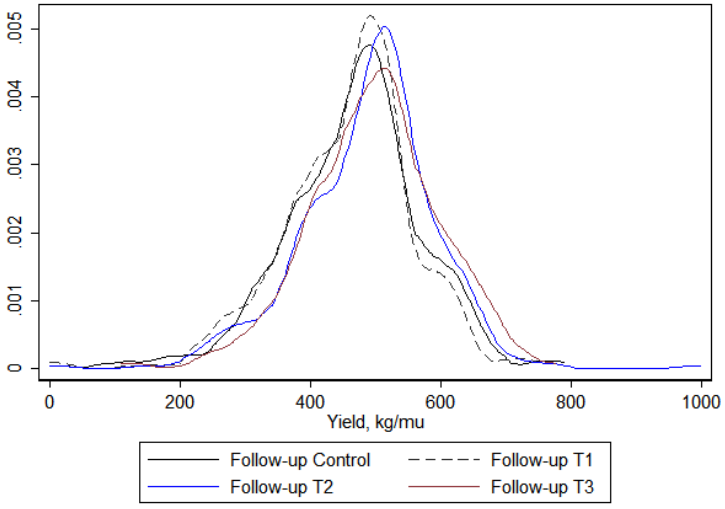
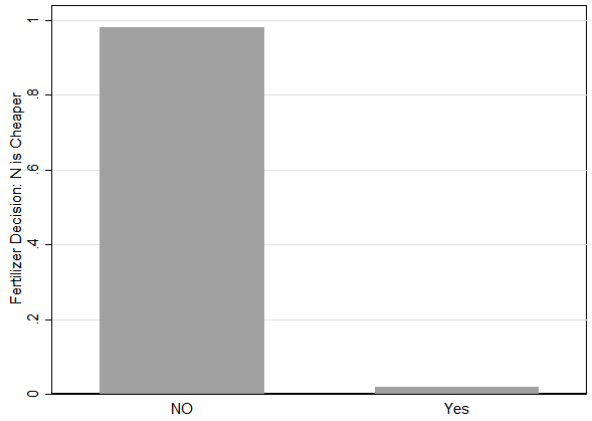
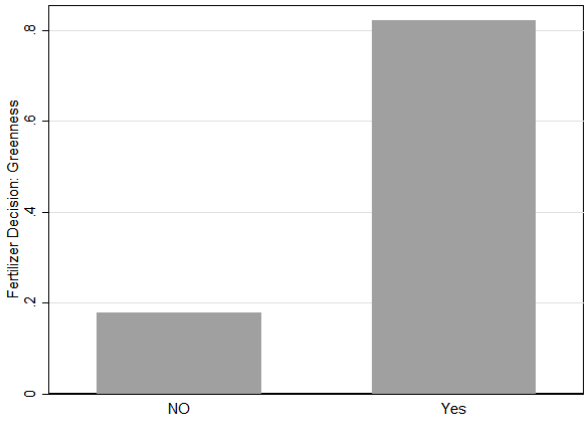


Figure A16: Top-Dressing Nitrogen Decision-Making during the Growing Stage

(a) N Is Cheaper than P/K



(b) Greenness in Growing Stage



Note: The figure presents the fact that farmers' current amount of nitrogen application is not due to the lower price of nitrogen (Figure A16a). Figure A16b shows direct evidence of farmers' decision-making during the growing stage—based on greenness signals.

Table A1: Second-Phase Intervention: Balance between T_1 and Control Group

	(1) Control	(2) T_1: ST	(3) T_1-C
Panel A: Agricultural production			
Yield (kg/mu)	465.554	458.031	-7.523
	(106.881)	(101.737)	(8.612)
Area of plot (mu)	27.290	26.263	-1.027
	(76.492)	(81.930)	(6.545)
Revenue (RMB/mu)	1,142.195	1,130.676	-11.519
	(298.177)	(285.161)	(24.079)
Profits (RMB/mu)	520.648	519.422	-1.225
	(360.765)	(352.065)	(29.422)
Compound fertilizer used (kg/mu)	36.157	35.451	-0.706
	(15.281)	(14.850)	(1.244)
Nitrogen fertilizer used (kg/mu)	19.051	18.368	-0.684
	(16.878)	(12.937)	(1.240)
Phosphorus fertilizer used (kg/mu)	0.833	0.845	0.012
	(5.257)	(5.727)	(0.454)
Proportion of HH using phosphorus fertilizer	0.027	0.024	-0.004
	(0.164)	(0.152)	(0.013)
Potassium fertilizer used (kg/mu)	1.260	1.262	0.002
	(5.373)	(4.834)	(0.422)
Proportion of HH using potassium fertilizer	0.089	0.088	-0.002
	(0.286)	(0.284)	(0.023)
Total nitrogen used (kg/mu)	30.842	29.928	-0.914
	(18.960)	(13.765)	(1.366)
Total phosphorus used (kg/mu)	14.739	14.480	-0.259
	(7.736)	(7.581)	(0.632)
Total potassium used (kg/mu)	13.313	13.079	-0.233
	(7.626)	(6.461)	(0.583)
Panel B: Recommendations based on soil testing			
Distance to the nearest testing plot (km)	0.312	0.278	-0.033
	(0.352)	(0.306)	(0.027)
Compound recommendations (kg/mu)	43.148	43.115	-0.033
	(8.119)	(8.354)	(0.680)
Nitrogen fertilizer recommendations (kg/mu)	11.381	11.404	0.023
	(2.954)	(3.621)	(0.273)
Phosphorus fertilizer recommendations (kg/mu)	3.009	2.960	-0.049
	(6.052)	(4.899)	(0.454)
Potassium fertilizer recommendations (kg/mu)	2.269	2.065	-0.204
	(3.557)	(2.567)	(0.256)
Panel C: Beliefs			
Correct belief: greenness and yield	0.058	0.064	0.006
	(0.235)	(0.246)	(0.020)
Correct belief: nitrogen and greenness	0.952	0.936	-0.016
	(0.214)	(0.246)	(0.019)
Correct belief: phosphorus and flowering time	0.131	0.135	0.005
	(0.338)	(0.342)	(0.028)
Correct belief: phosphorus and root length	0.041	0.044	0.003
	(0.199)	(0.205)	(0.017)
Correct belief: potassium and grain density	0.027	0.024	-0.004
	(0.164)	(0.152)	(0.013)
Attrition rate (second-follow-up survey)	0.014	0.027	0.013
	(0.117)	(0.162)	(0.012)
Observations	291	296	587

Notes: Standard deviations in parentheses for all the columns. Column (3) reports the difference in characteristics between treatment arm T_1 and control groups using the data from the first follow-up survey in November 2020.

Table A2: Effects of Second-Phase Interventions on Beliefs about Effectiveness

	(1)	(2)	(3)	(4)	(5)
	Beliefs about the effect of N/P/P/K: Correct = 1 (2)-(5)				
Dept. Vars.	Greenness & Yield	Nitrogen & Greenness	Phosphorus & Flowering Time	Phosphorus & Root Length	Potassium & Grain Density
T_1: LCC	0.271***	-0.010	0.038	0.031	0.031
	(0.038)	(0.021)	(0.033)	(0.020)	(0.024)
T_2: App + LCC	0.375***	-0.031	0.247***	0.224***	0.203***
	(0.040)	(0.023)	(0.034)	(0.030)	(0.035)
T_3: App + Training + LCC	0.444***	-0.028	0.350***	0.340***	0.354***
	(0.040)	(0.023)	(0.041)	(0.037)	(0.034)
Control Mean	0.0627	0.951	0.115	0.0383	0.0383
Control SD	0.243	0.216	0.320	0.192	0.192
Clusters	199	199	199	199	199
Observations	1153	1153	1153	1153	1153
R squared	0.128	0.002	0.106	0.128	0.134

Note: This table presents the treatment effects of the second-phase interventions on farmers' beliefs. T_1, T_2, and T_3 are indicators for three different treatment arms, indicating leaf color charts, customized fertilizer recommendations through an app + leaf color charts, and customized fertilizer recommendations through an app + training by agricultural extension agents + leaf color charts, respectively. Column (1) shows farmers' understanding of the relationship between greenness and yields. The outcome variable is a dummy for whether a farmer understood the relationship correctly (option 3, inverted-U shape relationship). Column (2) shows whether they understood the effects of nitrogen on greenness correctly. The outcome variables in columns (3), (4), and (5) are a set of dummies for whether farmers correctly understood the effects of phosphorus on flowering time, of phosphorus on root length, and the effects of potassium on grain density, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A3: Distance and Fertilizer Gap between Applications and Recommendations

	(1)	(2)	(3)	(4)	(5)	6
	Baseline (1) - (3)			***First Follow-Up (4) - (6)***		
Dept. Vars.	Nitrogen Gap	Phosphorus Gap	Potassium Gap	Nitrogen Gap	Phosphorus Gap	Potassium Gap
	[Gap = the Used - the Recommended]					
Distance to the Nearest Testing Point	0.992	0.088	0.297	1.951	-0.103	0.222
	(1.335)	(1.198)	(0.819)	(1.307)	(0.961)	(0.882)
Observations	1200	1200	1200	1177	1177	1177
Control Mean	9.632	-4.997	-3.489	7.637	-4.866	-3.339
Control SD	16.46	9.762	8.192	19.34	10.13	8.559
Clusters	200	200	200	200	200	200
R squared	0.000344	7.46e-06	0.000122	0.00163	9.77e-06	6.42e-05

Note: Columns (1), (2) and (3) present the relationship between the distance to the nearest soil testing plots and the gap in fertilizer use between actual application and recommended use using baseline data. The outcome variables in columns (1), (2), and (3) are nitrogen use gap [used - recommended], phosphorus use gap [used - recommended], and potassium use gap [used - recommended], respectively.

Columns (4), (5) and (6) present the relationship between the distance to the nearest soil testing plots and the gap in fertilizer use between actual application and recommended use using the first follow-up data. The outcome variables in columns (4), (5), and (6) are nitrogen use gap [used - recommended], phosphorus use gap [used - recommended], and potassium use gap [used - recommended] in the second follow-up survey, respectively. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A4: Validity of IVs: Using T2 and T3 Indicators Before Interventions

	(1) IV-First Stage (1) $logGap^2$	(2) 2SLS (2) Yields	(3) 2SLS (3) Log Yields
T_2 (App)	-0.0716		
	(0.104)		
T_3 (App + AEA's Training)	-0.00594		
	(0.106)		
$LogGap^2$		-79.60	-0.0655
		(189.1)	(0.402)
Observations	568	568	564
R-squared	0.000853	.	.
Control Mean	5.66	460.03	6.11
F-statistic	0.252		

Note: In this table, we replicate the IV-2sls regression using T_2 and T_3 indicators in the baseline data and employing equations (6) and (7). We also limit the regression samples to those who overuse nitrogen fertilizers and underuse phosphorus/potassium fertilizers so that the underlying relationships between fertilizer gaps and yields are clearly defined. The overuse of nitrogen and underuse of phosphorus/potassium lead directly to lower yields. Column (1) reports the first-stage regression and the outcome variable is the log of Gap^2, defined as $Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$. The outcome variables in columns (2) and (3) are yields and the log of yields. We do not find any significance either in the first-stage or second-stage regressions since T_2 and T_3 did not affect fertilizer applications and yields in the baseline data. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A5: IV Estimation: Deviation in Fertilizer Application and Revenues/Costs

	(1) IV-First Stage $logGap^2$	(2) 2SLS Revenues	(3) 2SLS Fertilizer Cost	(4) 2SLS Other Cost
T_2 (App)	-1.029***			
	(0.191)			
T_3 (App + Training by AEA)	-1.134***			
	(0.223)			
$LogGap^2$		-98.20**	3.251	-24.16
		(33.81)	(4.992)	(17.26)
Observations	465	465	465	465
R-squared	0.124			
Control Mean	5.27	1147.15	162.84	480.76
F-statistic	23.48			

Note: In this table, we employ the IV-2sls regression strategy using data from the second round of surveys to estimate the impact on revenues, fertilizer costs, and other costs of deviation in fertilizer application compared with the recommended use. In the IV-2sls regression, we use T_2 and T_3 indicators as the instrumental variables to run equations (6) and (7). We also limit the regression samples to those who overuse nitrogen fertilizers and underuse phosphorus/potassium fertilizers so that the underlying relationships between fertilizer gaps and these outcome variables are clearly defined. The overuse of nitrogen and underuse of phosphorus/potassium lead directly to lower revenues. Column (1) reports the first-stage regression and the outcome variable is the log of Gap^2, defined as $Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$. The outcome variables in columns (2), (3) and (4) are revenues, fertilizer costs, and other costs. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A6: IV Estimation II: Using T_2 and T_3 Indicators as IVs for Each Fertilizer Gap

Dept. Vars.	(1) Yields	(2) Yields	(3) Yields	(4) Yields	(5) Yields	(6) Yields
Nitrogen Gap	-8.243***					
	(2.942)					
Phosphorus Gap		11.615***				
		(4.237)				
Potassium Gap			13.466***			
			(5.007)			
Nitrogen Gap Ratio				-1.906***		
				(0.726)		
Phosphorus Gap Ratio					2.362**	
					(0.947)	
Potassium Gap Ratio						2.108***
						(0.776)
Observations	1,177	1,177	1,177	1,177	1,177	1,177

Note: In this table, we conduct another type of IV regression. In columns (1), (2) and (3), we instrument the gap in nitrogen use [Used - Recommended], gap in phosphorus use, and gap in potassium use separately with the $T2$ and $T3$ indicators. We then present the second-stage estimation of the effects of gap on yields separately in these columns.

In columns (4), (5) and (6), we instrument the gap ratio in nitrogen use [(Used - Recommended)/Recommended], gap ratio in phosphorus use, and gap ratio in potassium use separately with the T_2 and T_3 indicators. We then present the second-stage estimation of the effects of gap on yields separately in these columns. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A7: IV Estimation: Deviation in Fertilizer Application and Yields

	(1) IV-First Stage $logGap^2$	(2) 2SLS Yields	(3) 2SLS Log Yields
T_2 (App)	-0.664***		
	(0.149)		
T_3 (App + Training by AEA)	-0.739***		
	(0.155)		
$LogGap^2$		-44.57**	-0.0934**
		(13.87)	(0.0309)
Observations	1177	1177	1173
R-squared	0.0498		
Control Mean	5.41	465.55	6.12
F-statistic	17.88		

Note: In this table, we employ the IV-2sls regression strategy using data from the second round of surveys to estimate the impact on yields of deviation in fertilizer application compared with the recommended use. Different from Table 7, we use all the observations from the second follow-up survey here. In the IV-2sls regression, we use $T2$ and $T3$ indicators as the instrumental variables to run the equations (6) and (7). Column (1) reports the first-stage regression and the outcome variable is the log of Gap^2, defined as $Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$. The outcome variables in columns (2) and (3) are yields and the log of yields. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Table A8: IV Estimation: Deviation in Fertilizer Application and Revenues/Costs

	(1) IV-First Stage $logGap^2$	(2) 2SLS Revenues	(3) 2SLS Fertilizer Cost	(4) 2SLS Other Cost
T_2 (App)	-0.664***			
	(0.149)			
T_3 (App + Training by AEA)	-0.739***			
	(0.155)			
$LogGap^2$		-112.8**	-1.562	10.69
		(38.15)	(7.621)	(20.83)
Observations	1177	1177	1177	1177
R-squared	0.0498			
Control Mean	5.41	1142.20	164.17	457.37
F-statistic	17.88			

Note: In this table, we employ the IV-2sls regression strategy using data from the second round of surveys to estimate the impact on revenues, fertilizer costs, and other costs of deviation in fertilizer application compared with the recommended use. Different from Table A5, we use all the observations from the second follow-up survey here. In the IV-2sls regression, we use T_2 and T_3 indicators as the instrumental variables to run equations (6) and (7). The overuse of nitrogen and underuse of phosphorus/potassium lead directly to lower revenues. Column (1) reports the first-stage regression and the outcome variable is the log of Gap^2, defined as $Gap^2 = (N_Gap)^2 + (P_Gap)^2 + (K_Gap)^2$. The outcome variables in columns (2), (3) and (4) are revenues, fertilizer costs, and other costs. Robust standard errors clustered at the village level are reported in brackets. *** indicates 1% significance; ** 5%; and * 10%.

Appendix B: Proofs.

In this section we detail the derivation described in Section 4.3. We begin with equation (4).

After observing the profit π_t generated by the realized states b_{Nt} and b_{Kt}, the farmer believes that the effectiveness of nitrogen fertilizer is b_{Nt} and the effectiveness of phosphorus (P)/potassium (K) fertilizers is $\tilde{b}_{Kt}$, which satisfies:

$$\tilde{\Pi}\left(a_{Nt}, a_{Kt}, b_{Nt}, \tilde{b}_{Kt}\right) = \pi_t = \Pi\left(a_{Nt}, a_{Kt}, b_{Nt}, b_{Kt}\right)$$

$$\lambda f_1\left(a_N\right)\exp\left(b_N\right) + f_2\left(a_K\right)\exp\left(\tilde{b}_K\right) = f_1\left(a_N\right)\exp\left(b_N\right) + f_2\left(a_K\right)\exp\left(b_K\right)$$

$$\left(1-\lambda\right) f_1\left(a_N\right)\exp\left(b_N\right) + f_2\left(a_K\right)\exp\left(b_K\right) = f_2\left(a_K\right)\exp\left(\tilde{b}_K\right)$$

The interpretation for this equation is that the farmer believes that whatever action she chooses, she can infer a unique signal $\tilde{b}_K$ about Θ_K to equalize her belief and the real profit. At $\Pi = \tilde{\Pi}$, we could derive the distorted $\tilde{b}_K$ as:

$$\tilde{b}_K\left(a_N, a_K, b_K\right) = \tilde{b}_K\left(a_K, b_K\right) = \log\left(C + f_2\left(a_K\right)\exp\left(b_K\right)\right) - \log\left(f_2\left(a_K\right)\right) \tag{8}$$

where $C = \left(1-\lambda\right) f_1\left(a_N\right)\exp\left(b_N\right)$.

Turning back to the true profit function in Equation (1), we define a_K^* as the optimal phosphorus (P)/potassium (K) fertilizer input. By taking the partial derivative of the true profit function in Equation (1) w.r.t. a_K, a_K^* then satisfies: $f_2'\left(a_K^*\right)\exp\left(\theta_K + \sigma_K^2/2\right) = c_K$. By taking logs on both sides and rearranging terms, we could obtain $\log\left(f_2'\left(a_K^*\right)\right) = \log\left(c_K\right) - \theta_K - \sigma_K^2/2$, that is,

$$\theta_K = \log\left(c_K\right) - \log\left(f_2'\left(a_K^*\right)\right) - \sigma_K^2/2 \tag{9}$$

Similarly, for the the misspecified model of the profit function in Equation (3), we take the derivative of the misspecified profit function w.r.t. $\tilde{a}_K$ and obtain the following relationship:

$$\log\left(f_2'\left(\tilde{a}_K^*\right)\right) = \log\left(c_K\right) - \tilde{\theta}_K - \sigma_K^2/2 \tag{10}$$

where $\tilde{a}_K^*$ is the the optimal phosphorus (P)/potassium (K) fertilizer input under the misspeciied profit function. In Equation (8) that $\tilde{b}_K\left(a_K, b_K\right) = \log\left(C + f_2\left(a_K\right)\exp\left(b_K\right)\right) - \log\left(f_2\left(a_K\right)\right)$, we have $C < 0$ because $\lambda > 1$ and $f_1\left(a_N\right) > 0$. Thus then we can always find a negative number $A \in \mathbb{R}^-$ to ensure the following replacement,

$$\log\left(C + f_2\left(a_K\right)\exp\left(b_K\right)\right) = A + \log\left(f_2\left(a_K\right)\exp\left(b_K\right)\right)$$

Then we get

$$\begin{aligned}\tilde{b}_K\left(a_K, b_K\right) &= \log\left(C + f_2\left(a_K\right)\exp\left(b_K\right)\right) - \log f_2\left(a_K\right) \\ &= A + \log\left(f_2\left(a_K\right)\exp\left(b_K\right)\right) - \log f_2\left(a_K\right) = A + b_K\end{aligned} \tag{11}$$

Convergence of farmer's beliefs. Heidhues, Kőszegi, and Strack (2021) define the function $g : \mathbb{N} \times \mathbb{R} \to \mathbb{R}$ as the objective expectation of $\tilde{b}_{t+1} - \tilde{\theta}_t$:

$$g(t, x) = \mathbb{E}\left[\tilde{b}\left(b_{t+1}, a^*(t+1, x)\right)\right] - x$$

where b_{t+1} is the effectiveness of fertilizer at time $t+1$. The above expectation is that of an outside observer who knows the true fundamental Θ and the agent's subjective belief $\tilde{b}$, so that, being able to deduce the fertilizer input $a^*(t+1, \tilde{\theta}_t)$, she knows the distribution of $\tilde{b}_{t+1}$.The function can be thought of as the agent's mean surprise regarding the fundamental. We then redefine how the farmer's subjective beliefs are updated in the limit as:

$$g_K(x) = \lim_{t\to\infty} g_K(t, x) = \mathbb{E}\left[\tilde{b}_K\left(b_{K,t+1}, a_K^*(x)\right)\right] - x$$

In our context, farmers need to learn about phosphorus (P)/potassium (K) fertilizer. According to this expectation of the updating convergence function, we obtain:

$$g_K(\tilde{\theta}_K) = \lim_{t\to\infty} E\left(\tilde{b}_K\left(b_K, a_K^*(\tilde{\theta}_K)\right)\right) - \tilde{\theta}_K \tag{12}$$

Since $\tilde{b}_K\left(a_K, b_K\right) = A + b_K$ in Equation (11), as $t \to \infty$, $g_K(\tilde{\theta}_K) = A + E\left(b_K\right) - \tilde{\theta}_K$, and from Equation (10) above, we also have that

$$\tilde{\theta}_K = \log\left(c_K\right) - \log\left(f_2'\left(\tilde{a}_K^*\right)\right) - \sigma_K^2/2$$

Substitute it into the g_K function in Equation (12), and solve $g_K(\tilde{\theta}_K) = 0$, and we acquire:

$$A + \theta_K - \tilde{\theta}_K = 0$$

where θ_K is defined as the mean of b_K in Section 4.2. Therefore, we have:

$$A + \theta_K - \left(\log\left(c_K\right) - \log\left(f_2'\left(\tilde{a}_K^*\right)\right) - \sigma_K^2/2\right) = 0$$

Based on Equation (9) that $\theta_K = \log\left(c_K\right) - \log\left(f_2'\left(a_K^*\right)\right) - \sigma_K^2/2$, we obtain:

$$\log\left(f_2'\left(\tilde{a}_K^*\right)\right) = \log\left(c_K\right) - \theta_K - A - \sigma_K^2/2 = \log\left(f_2'\left(a_K^*\right)\right) - A \tag{13}$$

Since $A < 0$, so we have $\log\left(f_2'\left(\tilde{a}_K^*\right)\right) > \log\left(f_2'\left(a_K^*\right)\right)$, and hence then $f_2'\left(\tilde{a}_2^*\right) \geq f_2'\left(a_K^*\right)$.

Due to the concavity of the functions f_1 and f_2, we could derive that,

$$\tilde{a}_K^* < a_K^* \tag{14}$$

Recall that $\tilde{a}_K^*$ is the optimal phosphorus (P)/potassium (K) fertilizer input under the misspecified model and that a_K^* represents the optimal phosphorus (P)/potassium (K) fertilizer input under the true model.

As for nitrogen fertilizer use, by taking the first order condition of Equation (1) and (3) with respect to a_N, we have:

$$f_1'\left(a_N^*\right)\exp\left(\theta_N+\sigma_N^2/2\right)=c_N.$$

$$\lambda f_1'\left({a'_N}^*\right)\exp\left(\theta_N+\sigma_N^2/2\right)=c_N.$$

where ${a'_N}^*$ is defined as the optimal nitrogen use under the misspecifed model, and a_N^* is defined as the optimal nitrogen application under the true model. Obviously, we can get:

$${a'_N}^* > a_N^* \tag{15}$$

Prediction 1. *${a'_N}^* > a_N^*$, $\tilde{a}_K^* < a_K^*$, and $\tilde{b}_K^* < b_K^*$, where ${a'_N}^*$ and $\tilde{a}_K^*$ are the optimal nitrogen and phosphorus (P)/potassium (K) usages under the misspecified model. a_N^* and a_K^* are the the optimal nitrogen and phosphorus (P)/potassium (K) applications under the true model. And $\tilde{b}_K^*$ and b_K^* represent farmers' beliefs about the effectiveness of phosphorus/potassium fertilizers at equilibrium under the misspecified and true models, respectively.*

Prediction 2. *If farmers' fertilizer input a_N decreases and moves closer to a_N^* and $\tilde{a}_K$ increases and moves toward a_K^* in the current period, then their belief about the effectiveness of phosphorus (P)/potassium (K) fertilizer $\tilde{b}_K$ will also increase and rise up toward b_k. To be specific, if farmers are nudged to adopt less nitrogen fertilizer and more phosphorus (P)/potassium (K) fertilizers in their actions in the current period, then their subjective beliefs $\tilde{b}_K$ about the effectiveness of P/K in the next period will move upwards toward the true value of the effectiveness. As such, farmers' undervaluation of P/K will decrease.*

Proof.

$$\begin{aligned}\tilde{b}_K\left(a'_N,a'_K,b_K\right)&=\log\left(C'+f_2\left(a'_K\right)\exp\left(b_K\right)\right)-\log\left(f_2\left(a'_K\right)\right)\\&=log(\frac{(1-\lambda)f_1(a'_N)exp(b_N)}{f_2(a'_N)}+exp(b_K))\end{aligned} \tag{16}$$

Define a'_N and a'_K are the input level at some certain period, and a''_N and a''_k are different input

levels. Obviously, $\tilde{b}_K\left(a'_N, a'_K, b_K\right)$ is increasing as a'_N decreases and a'_K increases. If $a''_N > a'_N > a^*_N$, $a''_K < a'_K < a^*_K$, then we'll have $\tilde{b}_K\left(a'_N, a'_K, b_K\right) > \tilde{b}_K\left(a''_N, a''_K, b_K\right)$. □

Prediction 3. *Correcting the overestimation/misspecification of the return to nitrogen fertilizer leads to a lower level of nitrogen fertilizer input a_N directly and a higher application of phosphorus (P)/potassium (K) fertilizer a_K. Farmers' belief about the effectiveness of phosphorus (P)/potassium (K) fertilizers will gradually move toward the true realized state. Specifically, the correction could reduce farmers' nitrogen use to the optimal value immediately (one period), but also induce gradual learning about the utilization of phosphorus and potassium fertilizers.*

Proof of Prediction (3) Based on equation (8), if λ=1, then $C = (1-\lambda) f_1\left(a_N\right) \exp\left(b_N\right) = 0$

$$\tilde{b}_K\left(a_N, a_K, b_K\right) = \log\left(C + f_2\left(a_K\right) \exp\left(b_K\right)\right) - \log\left(f_2\left(a_K\right)\right) = b_k$$

Proof of Convergence

We prove convergence by verifying the conditions specified in Assumption 1 in Heidhues, Kőszegi, and Strack (2021).

(I) There exists a constant $\Delta > 0$ such that $|b_K - \tilde{b}_K(b_k, a_N, a_K)| \leq \Delta$ for all b_K,a_N and a_K.

$$|b_K - \tilde{b}_K(b_k, a_N, a_K)| =$$
$$|log(\frac{C}{exp(b_K) f_2(a_K)} + 1)|$$

We need $\frac{(1-\lambda) f_1(a_N) \exp(b_N)}{exp(b_K) f_2(a_K)}$ to be bounded away from -1. In other words, there exists $\epsilon > 0$ such that for all feasible a_N, b_N, a_K, b_K,

$$\frac{(1-\lambda) f_1\left(a_N\right) \exp\left(b_N\right)}{exp(b_K) f_2(a_K)} > -1 + \epsilon \tag{17}$$

Equation (17) indicates that the output component of phosphorus (P)/potassium (K) should not be too smaller than the output component of nitrogen (N). For instance, if $\lambda = 2$, then phosphorus (P)/potassium (K) and nitrogen (N) have equivalent contributions to the total output.

(II) $\frac{\partial \tilde{b}_K(a_N, a_K, b_K)}{\partial a_K}$ is bounded.

Since we can rewrite the expression of $\tilde{b}_K\left(a_N, a_K, b_K\right)$ as follows

$$\tilde{b}_K\left(a_N, a_K, b_K\right) = log(\frac{C}{f_2(a_K)} + exp(b_K))$$

If $\frac{(1-\lambda)f_1(a_N)\exp(b_N)}{exp(b_K)f_2(a_K)}$ is bounded away from -1, then $f_2(a_K)$ must be positive and large enough. As long as $f_2'(a_K) < \infty$, equation 17 suffices to ensure that the derivative with regard to a_K is bounded.

(III) There exist constants $d, m > 0$ such that for any t and any $\tilde{\theta}_K$, we have $\left|a_K^*(t, \tilde{\theta}_K) - a_K^*(\tilde{\theta}_K)\right| \leq \frac{1}{t^m} d$.

Recall that according to the definition of $a_K^*(t, \tilde{\theta}_K)$ and $a_K^*(\tilde{\theta}_K)$ can be rewritten as follows:

$$a_K^*(t, \tilde{\theta}_K) = argmax_a \int [\int \tilde{\Pi}(a_{Kt}, \tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; x, \sigma^2)d\tilde{b}_{Kt}]\phi(x; \tilde{\theta}_K, v_{t-1})dx$$

$$a_K^*(\tilde{\theta}_K) = argmax_a \int \tilde{\Pi}(a_{Kt}, \tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; \tilde{\theta}_K, \sigma^2)d\tilde{b}_{Kt}$$

where $\tilde{\Pi}(a_{Kt}, \tilde{b}_{Kt})$ is the abbreviation of $\tilde{\Pi}(a_{Nt}, b_{Nt}, a_{Kt}, \tilde{b}_{Kt})$. $\phi(\tilde{b}_{Kt}; x, \sigma^2)$ refers to the density function of $\tilde{b}_{Kt}$, with the mean being x and variance being σ^2.

As $\frac{\partial^2 \tilde{\Pi}(a_{Kt}, \tilde{b}_{Kt}}{\partial a_{Kt} \partial \tilde{b}_{Kt}}$ is continuous in our setting, $a_K^*(t, \tilde{\theta}_K)$ and $a_K^*(\tilde{\theta}_K))$ can be implicitly defined as follows:

$$f_2'(a_K^*(\tilde{\theta}_K))) \int exp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; \tilde{\theta}_K, \sigma^2)d\tilde{b}_{Kt} = c_K \tag{18}$$

and

$$f_2'(a_K^*(t, \tilde{\theta}_K)) \int [\int exp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; x, \sigma^2)d\tilde{b}_{Kt}]\phi(x; \tilde{\theta}_K, v_{t-1})dx = c_K \tag{19}$$

Equations 18 and 19 illustrate that $\int exp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; \tilde{\theta}_K, \sigma^2)d\tilde{b}_{Kt}$ can be approximated by $\int [\int exp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; x, \sigma^2)d\tilde{b}_{Kt}]\phi(x; \tilde{\theta}_K, v_{t-1})d$, then $f_2'(a_K^*(\tilde{\theta}_K))$ can be approximated by $f_2'(a_K^*(t, \tilde{\theta}_K))$. If the inverse of $f_2'(.)$ is well behaved, then $a_K^*(\tilde{\theta}_K)$ can be approximated by $a_K^*(t, \tilde{\theta}_K)$. More precisely, if there exists $\epsilon > 0$ such that for any a_{Kt},

$$|f_2''(a_{Kt})| \geq \epsilon \tag{20}$$

then it would be possible to complete the aforementioned reasoning of approximation. Below we prove that condition 20 is sufficient.

Observe that expression $\int exp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; x, \sigma^2)d\tilde{b}_{Kt}$ can be simplified as follows:

$$intexp(\tilde{b}_{Kt})\phi(\tilde{b}_{Kt}; x, \sigma^2)d\tilde{b}_{Kt} =$$
$$\int \frac{1}{\sigma\sqrt{2\pi}} exp(\tilde{b}_{Kt}) exp(-\frac{(\tilde{b}_{Kt} - \tilde{\theta}_K)^2}{2\sigma^2}) d\tilde{b}_{Kt} =$$
$$exp(\tilde{\theta}_K + \frac{\sigma^2}{2})$$

We have

$$\left| a_K^*(t, \tilde{\theta}_K) - a_K^*(\tilde{\theta}_K) \right| =$$
$$exp(\frac{\sigma^2}{2}) \int [exp(\tilde{\theta}_K)) - exp(x)] \frac{1}{\sqrt{2\pi} v_{t-1}} exp(-\frac{(x - \tilde{\theta}_K)^2}{2v_{t-1}^2}) dx$$

Let $\varphi = \frac{x - \tilde{\theta}_K}{v_{t-1}}$, the expression above can be rewritten as follows:

$$\left| a_K^*(t, \tilde{\theta}_K) - a_K^*(\tilde{\theta}_K) \right| =$$
$$\frac{\sigma^2}{2\sqrt{2\pi}} exp(\tilde{\theta}_K) \int [1 - exp(v_{t-1}\varphi)] exp(-\frac{\varphi^2}{2}) d\varphi$$

We claim that $\frac{1}{\sqrt{2\pi}} \int [1 - exp(v_{t-1}\varphi)] exp(-\frac{\varphi^2}{2}) d\varphi$ is of order $O(\frac{1}{t^2})$. To see this, consider simplifying this expression:

$$\frac{1}{\sqrt{2\pi}} \int [1 - exp(v_{t-1}\varphi)] exp(-\frac{\varphi^2}{2}) d\varphi =$$
$$1 - \frac{1}{\sqrt{2\pi}} \int exp(v_{t-1}\varphi) exp(-\frac{\varphi^2}{2}) d\varphi =$$
$$1 - \frac{1}{\sqrt{2\pi}} \int exp(-\frac{(\varphi - v_{t-1})^2}{2} + \frac{v_{t-1}^2}{2}) d\varphi =$$
$$1 - exp(\frac{v_{t-1}^2}{2})$$

Since $v_{t-1} = \frac{1}{v_0^{-1} + (t-1)\sigma^{-2}}$ is of order $O(\frac{1}{t})$, we have

$$\frac{1}{\sqrt{2\pi}}\int[1-exp(v_{t-1}\varphi)]exp(-\frac{\varphi^2}{2})d\varphi =$$
$$1-exp(\frac{v_{t-1}^2}{2}) =$$
$$1-1+O(\frac{v_{t-1}^2}{2}) =$$
$$O(\frac{v_{t-1}^2}{2}) = O(\frac{1}{t^2})$$

Thus, Assumption (III) is satisfied when condition 20 holds.

Appendix C: Documentation about Implementation of Experiments

Figure C1: The Last Two Pages of the Mobile Application

(a) Connect Fertilizer Producer for Customized Fertilizer Recommendations



(b) Generate Recommendation Messages to Non-smart Phone



Note: Figure C1a shows that farmers can choose a specific fertilizer producer from which to order customized fertilizers by inputting names, contacts and coordinates of the plots. Figure C1b shows that the app can generate a message with fertilizer recommendations to non-smart phone users.

Use Leaf Color Chart to Help Fertilizer Application

This leaf color chart divides the greenness of a rice crop's leaf color into six standard degrees. **Farmers can use the leaf color chart to diagnose the nutrition status of rice.** It helps to diagnose the nitrogen concentration in rice crops and to determine the optimal amount of **top-dressing nitrogen fertilizer to use**. When the amount of nitrogen fertilizer application is low, the number of tillers in crops will be low, and the color of leaves will be yellow. Conversely, when the amount of nitrogen fertilizer use is too high, the plant will have more tillers and the color of the rice leaves will be close to dark green.



Instructions

1. **Randomly select more than 10 rice plants** in the rice field that are not infected with disease on their leaves and take the leaf color during the rice **tillering period (growing stage) (20-30 days after transplanting)** and the **panicle-primordium-differentiation stage (40-50 days after transplanting)**, that is, before the second top dressing and panicle fertilizer application.

2. For each rice plant, **the middle section of the uppermost leaf which has been fully expanded** is selected to measure leaf color.

3. **First pull the leaves** whose leaf color is to be measured to **the inner shade of the investigator** to determine the color, and compare the level of the leaf color (the color board is divided into 16 levels according to intensity). Avoid placing the leaf color board under the sun for direct observation, so as not to affect the accuracy of leaf color interpretation due to light reflection.

4. Determine the overall nutritional status of the rice in the area based on the average leaf color grade [performance] of 10 rice plants measured in the field, in order to determine the amount of top dressing nitrogen fertilizer needed. **The optimum leaf color** ranges from **leaf color 3** to **leaf color 4**. When leaf color is **lower than level 3** (the color is yellower than level 3), the rice plant has **poor nutrition**, and **the amount of nitrogen fertilizer (urea) should be increased**. When leaf color is **located at 3.5** (leaf color is between levels 3 and 4), the leaf color is normal, and the rice plant has **good nutrition**. The normal amount of fertilizer can be used. When the leaf color grade is at level 4, it indicates that the nitrogen content

of the plant is slightly higher, and less nitrogen fertilizer should use When the leaf color grade is at **level 5** (leaf color is dark green), **the fertilizer application rate is too high, no more nitrogen fertilizer is needed**.