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Comparing greenhouse gas emission and the social costs of paddy production with and without laser land leveling adoption

a case study of paddy mono-cropping system in Vietnam

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Abstract

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Keywords: Laser land leveling, GHG emissions, social cost, paddy production, Mekong Delta, Vietnam

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1. Introduction

Salinity intrusion and water scarcity are significant threats to agricultural production and food security in the context of climate change (IPCC, 2019; WBG and ADB, 2021; UNEP, 2021). The climate change-induced water scarcity and thus the shortage of irrigation water could reduce agricultural productivity. Rice is the most important staple food in Asia; Asia's rice production has accounted for 90% of the global level (Schneider, P., and Asch, F., 2020). However, it is estimated about 22 million hectares of paddy production in lack of irrigation (Schneider, P., and Asch, F., 2020; Tuong and Bouman, 2003). In Vietnam, the paddy cultivation has contributed about 40% of total agricultural outputs; Vietnam has been the second largest rice exporter in the world (GSO, 2022). The paddy cultivation in Vietnam has been mostly in the Mekong River Delta (MRD) with 55% of total area and 57% of total output (GSO, 2022). However, the MDR has been substantially affected by climate change, especially on rice production (WB and ADB, 2021). By the 2040s the rice yield could possibly reduce up to 23% as reported by Jiang, Z. et al. (2018) or at 5%–10% in Li, S., Wang, Q., & Chun, J. A. (2017). Thus, there is an urgent need for sustainable agriculture technologies to ensure sustainable and resilient agricultural systems in the face of a changing climate.

Vietnam has signed the Paris Agreement on climate change in 2016; and through the Intended Nationally Determined Contributions (INDC) the country committed to reduce from 8% to 25% GHG emissions compared to Business-as-Usual (BAU) levels depending on resources and to continue its climate change adaption under the National Climate Change Strategy (Government of Vietnam, 2016). In 2020, Viet Nam submitted its nationally determined contribution (NDC) to the UNFCCC Secretariat, outlining its enhanced efforts to address climate change response contributions. By 2030, Viet Nam aims to reduce its total greenhouse gas (GHG) emissions by 9% compared to the business as usual (BAU) scenario, utilizing its own resources. With international support through bilateral and multilateral cooperation, as well as the implementation of new mechanisms under the Paris Agreement, this contribution could potentially increase to 27% (Socialist Republic of Vietnam, 2020).

Greenhouse gas (GHG) emissions in agricultural activities predominantly arise from improper agro-chemical usage, mismanaged land practices, intensive cattle production, and inadequate manure management. (Sinha et al., 2018). In Vietnam, rice production is responsible for a substantial amount of 49.69 MtCo2e which is accounted for 15.69% of the country's total greenhouse gas (GHG) emissions in 2016 (Socialist Republic of Vietnam, 2020). It is the second the largest source after fuel combustion for electricity generation, accounting for 11.6% of total emission in Vietnam. Consequently, paddy cultivation has emerged as a key focus area for advancing the national green growth strategy, with the aim of enhancing climate resilience through the adoption of climate-smart practices (Schneider, P., and Asch, F. 2020; WBG and ADB, 2021; Socialist Republic of Vietnam, 2020).

As a climate-smart agriculture and resource-conserving technology, laser land leveling (LLL) is considered as a well-suited technique for paddy production to adapt climate risks and mitigate GHG emissions (Kakraliya et al., 2018, D'Souza and Mishra, 2018, Ram et al., 2018, Kumar et al., 2018). LLL reduces greenhouse gas emissions by energy saving, reducing cultivation time, and improving input-use efficiency, especially irrigation water. Literature on benefits and adoption of LLL are mostly conducted in South Asia for the rice–wheat or sugarcane-wheat cropping system and missing in the Southeast Asia as one of major paddy producing areas in the world, particularly for the paddy mono-cropping system (Jat et al. 2009; Muthayya et al. 2014; Naresh et al. 2014; Ahmad et al. 2014; Aryal et al. 2015; Ali et al. 2018). The incremental external benefit on emission reduction in paddy production under the farming system with and without LLL implementation has not been found in the literature.

Uneven paddy fields induce farmers to flood their plots to its highest point to ensure that the plots to be completely irrigated, resulting in inefficient use of irrigation water up to 25%, fertilizers, and chemicals (Lybbert et al. 2018). LLL technology aims to smooth the uneven plots to resolve this problem. In practice, the technology can level a paddy plot with a precision of ± 1–2 cm compared to the traditional leveling methods with a precision of ± 4-5 cm (Lybbert et al. 2012). The advantages of LLL can be classified into the first-order and second-order benefits (Lybbert et al. 2018). The former is the reduction in water usage and in the irrigation cost as a result. The latter are the reduction in weeding labor, agro-chemical use, and fertilizer use and the increase in yield, which implies the reduction in GHG emissions and social costs for paddy production. However, an on-farm study with the use of LCA to estimate the benefits of LLL in terms of GHG emissions and social costs has been missing in the literature. In this study, we integrate an experimental auction with a randomized control trial (RCT) to estimate the casual effects of LLL on input usage, GHG emissions, and social costs. These estimates are important for the technology promotion and are missing in literature.

Although the adoption of LLL is beneficial, the adoption rate is not as high as it is expected (Lybbert et al. 2018; Aryal et al. 2018; Ali et al. 2018). Regarding to the compatibility, there are lack of LLL adoption studies for the rice mono-cropping system in the Southeast Asia including Vietnam, which is one of major paddy producing areas in the world (Muthayya et al. 2014). Instead, the adoption of LLL in the multi-cropping system such as rice–wheat or sugarcane-wheat in South Asia including India, Nepal, Bangladesh, and Pakistan is extensively studied (Jat et al. 2009; Naresh et al. 2014; Ahmad et al. 2014; Aryal et al. 2015; Larson et al. 2016; Ali et al. 2018; Aryal et al. 2018; D'Souza and Mishra 2018). The two copping systems may differ in GHG emissions and input usage (Cha-un et al. 2017; Theisen et al. 2017). As a result, findings from these studies are limited for the application of rice mono-cropping system.

For above reasons, there is a need for studies on the social cost and benefit of LLL for the rice mono-cropping system in the Southeast Asian countries like Vietnam. In Vietnam, LLL is identified as a prerequisite for sustainable paddy production in the Mekong Delta as it can be combined with the Alternate Wetting and Drying (AWD) technique to adapt to emerging climatic variability and mitigating GHG emissions (FAO 2017). The estimation of LLL benefits also helps to provide the incentives for both investment of the government budget and farmers. The study contributes to the existing literature comparing GHGs emission and the social cost and benefit of paddy production with and without LLL adoption and the casual effects of LLL on input usage, GHG emissions, and social costs in paddy production in the Mekong Delta region, Vietnam.

2. Methods and material

2.1 Research boundary for the GHG emission analysis

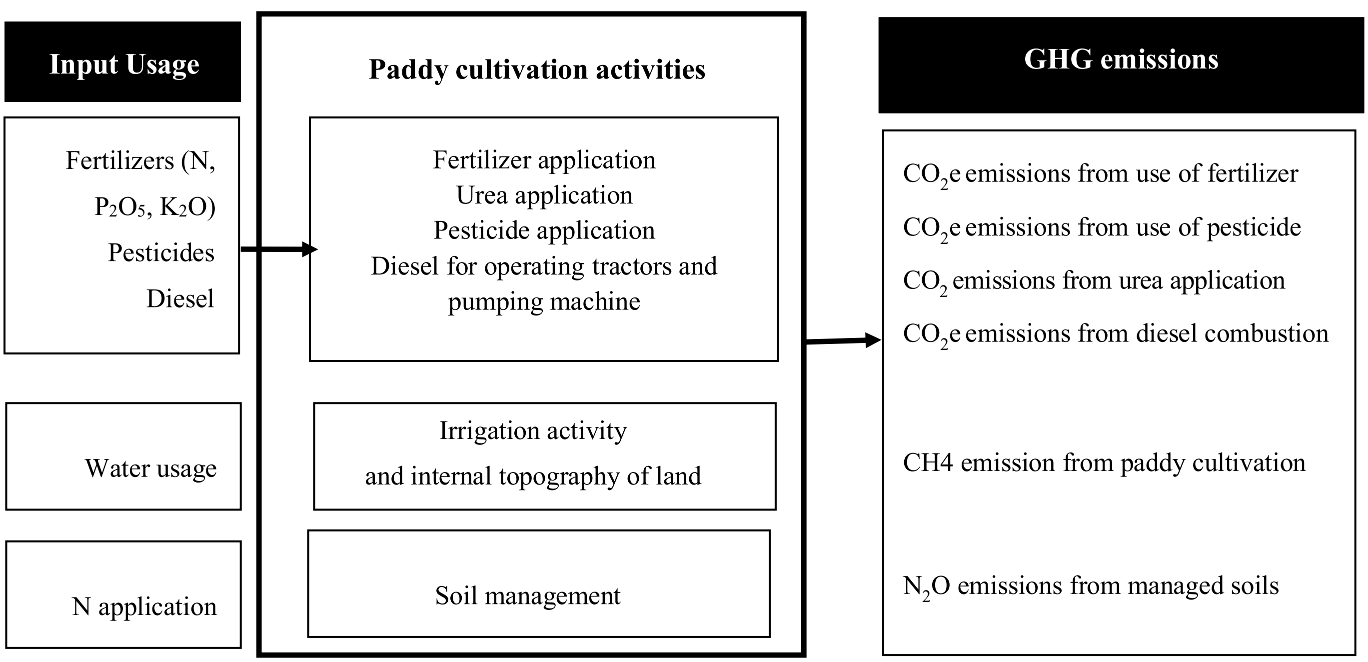


Figure 1. Life-cycle system of paddy cultivation

We use the life-cycle assessment (LCA) method for the estimation of GHG emissions with and without the use of LLL in paddy production. Life-cycle assessment (LCA) is a methodology used to gather and assess the inputs, outputs, and environmental impacts associated with a product system throughout its entire life cycle, as defined by the International Organization for Standardization (ISO, 2006). LCA is used in many thematic areas such as environmental management systems and environmental performance evaluation, certification of greenhouse gas emissions, integration of environmental aspects into product design, waste prevention and recycling, and sustainable use of natural resources. As for paddy production, the LCA methodology has been increasingly used to assess the emission effects of conventional rice farming system (Rahman MHA. et al. 2019 and Zhang, L. Et al. 2021), of laser land leveling (Balingbing, C et. al 2022), of agrochemical emission models (Rezaei, M et al. 2021); of rain-fed and irrigated cropping systems (Thanawong et al., 2014); of different drainage patterns (Tariq et al., 2017), of the minimal tillage and organic systems (Nunes et al., 2016); of diffrerent water management strategies (Pandey et al., 2014).

The application of LCA method for the estimation of GHG emissions with and without the use of LLL in paddy production has been missing in literature except for Balingbing, C et. al (2022). The benefit of LLL in the study of Balingbing, C et. al (2022) based on secondary data in previous study and primary data from their interview performance of 18 farmers in Vietnam in 2020. In this study the benefits of LLL are the average treatment effects of the RCT model with the 196 observations from the survey in the Mekong delta region from 2019 to 2022 (see Section 2.4). Figure 1 shows the life-cycle system of paddy cultivation.

2.2 Experimental design and empirical model

2.2.1 Experimental design

To elicit farmers' WTP for LLL and estimate the casual effects of LLL on input usage, we follow the approach suggested by Lybbert et al. (2018) by integrating an experimental auction with a randomized control trial (RCT). For the experimental auction, The Becker, DeGroote, Marschak (BDM)-style auction is used to induce farmers to state the WTP amount equal to the expected returns to LLL adoption because in this auction style farmers individually bid against an unknown predetermined sealed price, not against other farmers (Demont and Ndour 2015). Instead of asking farmers to state a single price and explaining why they provide that price will be the best strategy in the standard BDM auction, the elicitation of WTP is more accurate if farmers are offered a price and then asked for their binary decision to hire LLL service or not at this price and this process is replicated for a set of increasing values of prices until a maximum price is found (Berry et al. 2015; Lybbert et al. 2018). As the marginal prices of LLL are unknown within the sample, the set of prices used will be determined through a prior pilot study so that it reflects the range of WTP of a majority of farmers with heterogeneous characteristics. In addition, the predetermined sealed price will be chosen so as to involve farmers with as much heterogeneous characteristics as possible and this price will be sealed in an envelope, i.e. it is still effectively random to farmers in the experimental auction (Lybbert et al. 2018).

In this study, we also aim to estimate the causal effects of LLL on input usage and yield for further policy implications. To do so, the winners of the BDM auction will be the target population in the second experiment with the predetermined price of 450 thousand VND per hour. Our target population is the auction winners who have the WTP for LLL greater than the predetermined price. In the next step we use a lottery to determine who would actually pay for and receive LLL services.

2.2.2 The empirical model

In the last two decades, the utilization of randomized controlled trials (RCTs), also referred to as randomized evaluations, randomized trials, randomized experiments, or social experiments has significantly increased (Glewwe, Paul, and Petra Todd, 2022). In an RCT, individuals from the population are randomly assigned to either a treatment group, where they participate in the program, or a control group, where they do not partake in the program. The RCT has been conducted in the agricultural researches such as Fishman, R et al. (2023) to evaluate the potential productivity and water-saving benefits of smallholder drip irrigation in India, Yitayew, K.A et al (2021) to examine the impact of a newly introduced improved wheat variety in Ethiopia, Nakano & Magezi (2020) to examine the impact of microcredit on the adoption of technology and productivity of rice cultivation.

To address the parameters of causal inference and account for noncompliance in experiments, researchers utilize a model incorporating an instrumental variable to estimate the intent-to-treat (ITT) effects (Abadie and Cattaneo 2018; Lybbert et al. 2018). The measurement error in attenuation bias can be resolved through the instrument variable (IV) procedure (Khandker, 2009). If treatment assignment is random, selection bias is not a problem at the level of randomization. However, treatment assignment may not be random because the endogeneity may exist in placement of program, and the unobserved individual heterogeneity stemming from individual beneficiaries' self-selection into the program also confounds an experimental setup (Khandker, 2009). The preceding IVs estimation methods apply when the endogenous regressor is continuous. In cases where the endogenous regressor is binary, an alternative approach for fitting a treatment-effects model is to use the "treatreg" command in Stata, as outlined by

Brown (2011). The treatreg command estimates two regressions simultaneously. The first equation is estimated using probit regression to predict the probability of treatment. The second is either a linear regression for the outcome variables. The two error terms are assumed to be jointly normally distributed.

The first equation with D_{1i} as the endogenous regressor is probit model.

$$\Pr(D_{1i}=1|x_i) = \Phi(z_i)$$

$$z_i=\delta_0+\delta_1 assigment_i+\delta_2 llp_i+v_i$$

In which: Φ : the cumulative normal distribution

D_{1i}: = 1 san; =0 chưa san

z_i : the "z index" of probit model

x_i : assigment is instrument variable (dummy)

$\widehat{D}_{1i}$ (forecast value of the first equation) is used as the independent variable in the second equation. The second equation for input demand and paddy yield:

$$Y_{1i}=\alpha_0+\sum_{k=1}^{m}(\beta_k P_{ki})+\beta_{(m+1)}Z_i+\beta_{(m+2)}\widehat{D}_{1i}+\sum_{s=2}^{h}(\beta_{(m+1+s)}D_{si})+u_i \quad (1)$$

$$Y_{2i}=\varphi_0+\sum_{k=1}^{m}(\beta_k X_{ki})+\beta_{(m+1)}Z_i+\beta_{(m+2)}\widehat{D}_{1i}+\sum_{s=2}^{h}(\beta_{(m+1+s)}D_{si})+e_i \quad (2)$$

In which Y_{1i} is amount of input i in paddy cultivation (i=1-9) namely seed, fertilizers, chemical, labor, machine hours, diesel used in pumping water; note that these variable in logarithm and calculated for one hectare; Y_{2i} is yield per hectare in logarithm; P_{ki} is unit price of input i; Z_i standard deviation of land surface in logarithm (STD); D_{si} dummy variables of LLL performance being 1 for of paddy varieties being 1 if crop time equal or over 95 days and 0 if crop time shorter than 95 days, of crop time being 1 for the year 2021 and 0 for the year year 2022; α_o,φ_o are intercepts ; β_k are coefficients; u_i,e_i are residuals.

The coefficient of the natural log of independent variable to the the natural log of dependent variable is the elasticity. To explain the marginal effect of dummy independent variable of LLL adoption to the the natural log of dependent variable, specifically interested in an increase or a decrease, we can use the calculation based on this formular: $\%\Delta\widehat{P2O} = 100.[\exp(\widehat{\beta_d}) - 1)]$ (Wooldridge, 2015).

2.3 Incremental cost benefit analysis

2.3.1 Greenhouse gas emission in paddy production

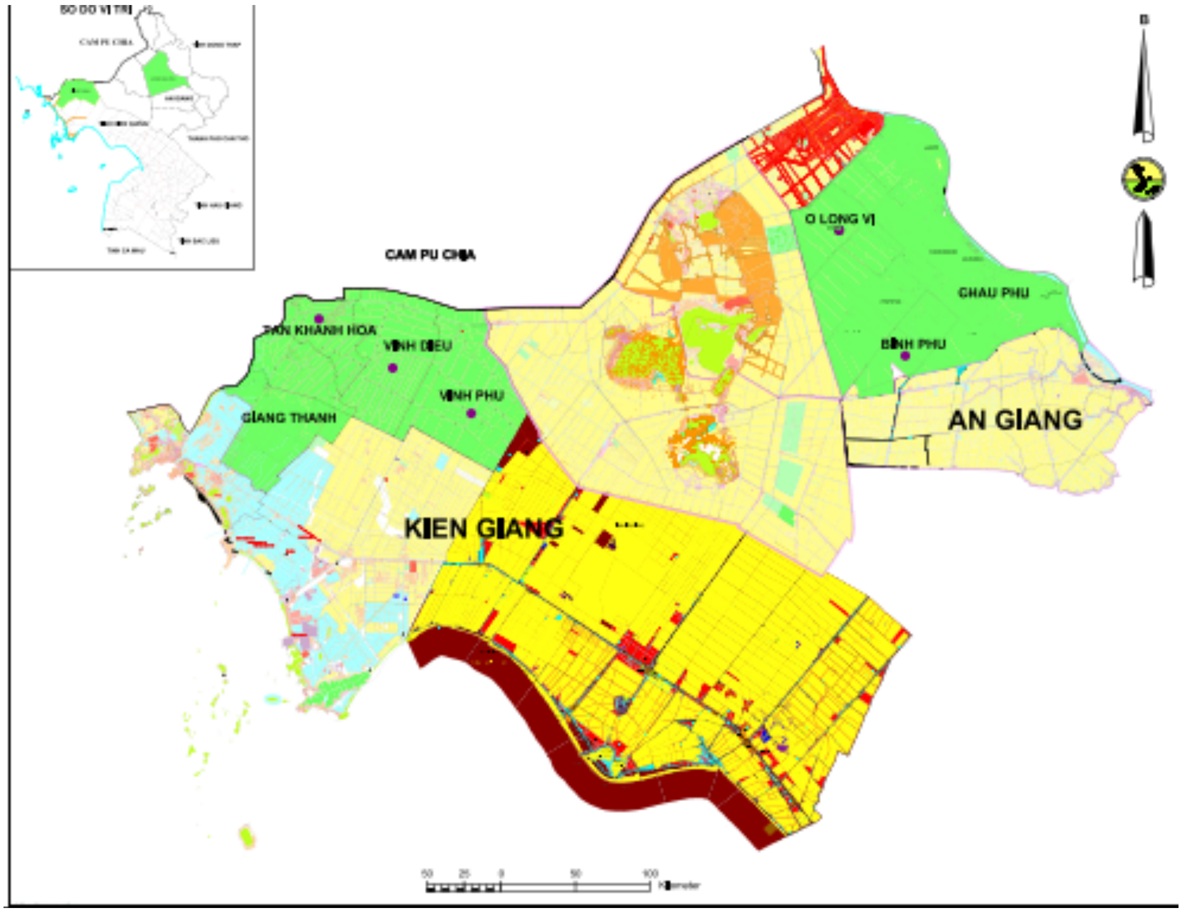
The three GHG emissions from paddy production consisting of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are aggregated to the CO_2 equivalent (CO_2e) using the global warning potential (GWP) factors (IPCC, 2021). We follow the guideline from Chapter 5 in IPCC (2019) to estimate the GHG emissions from paddy production with and without the use of LLL in terms of CO_2e per hectare. Accordingly, the emission sources are the significant different inputs from the analysis of ATE following the LLL adoption, namely fertilizer use, pesticide use, diesel consumption, urea application, N_2O emissions from managed soils, and methane (CH_4) emission from anaerobic decomposition of organic material in flooded rice fields. These emissions are calculated by multiplying the emission factors in the guideline of IPCC (2006) based on farming conditions and corresponding amounts of the incremental benefits from LLL adoption which are the average treatment effect in the RCT model.

2.3.2 Incremental cost benefit analysis for the laser land leveling adoption

Incremental cost benefit analysis is a systematic approach used to evaluate the economic feasibility of a decision by comparing the additional costs and benefits associated with this decision. The key concept is to assess the incremental or marginal impact of the change, rather than considering the overall costs and benefits. In this study, with the focus of LLL performance, the analysis takes into account both the private and external costs and benefits with the consideration of GHG emission. By quantifying and comparing the incremental social costs and benefits, the implication of this analysis to ensure if the LLL performance is economic viability.

The analysis is applied for one hectare paddy cultivation. The constant price of the year 2021 is used for the whole project, the external cost of GHG emission is calculated as the incremental change in GHG emission multiplied by the price of CO_2e emission of 10 US dollar (World Bank, 2023). The incremental benefit will be spread during the life time of 30 year and inifity under the two scenarios (see Appendix 2 for parameters in incremental cost benefit analysis).

2.4 Study sites and data collection



Source: An Giang DNRE (2023); Kien Giang DNRE (2023)

Figure 2. Study site in An Giang and Kien Giang provinces

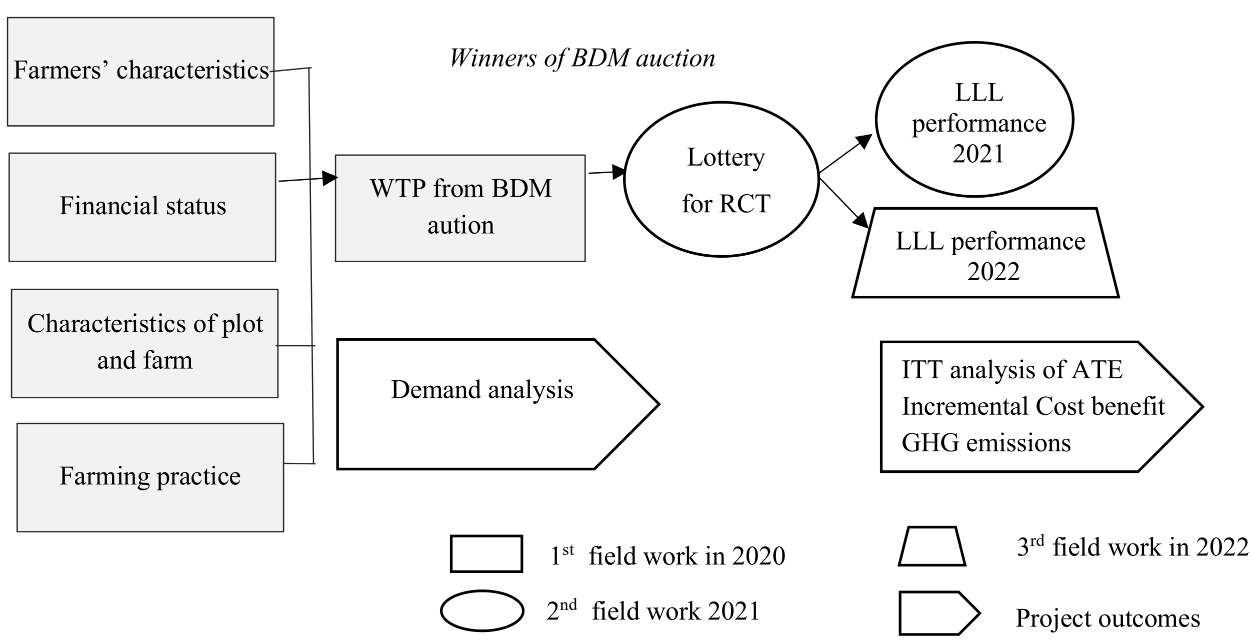


Figure 3. Field work for data collection

For primary data, we use cluster sampling method for sample selection. Specifically, we choose An Giang and Kien Giang provinces for survey since these provinces are the major paddy production and well represent paddy farming systems different in fresh water availability and technology adoption in the Mekong Delta region (GSO 2017). These provinces differ in the flatness as an indicator for the compatibility of technology implementation and in the historical promotion program (Bouvet and Le Toan, 2011; Lampayan, Rejesus et al., 2015). For each province, two communes will be chosen based on two criteria. First, LLL has not been implemented in paddy production as a common practice at the study time in 2020. Second, there are significant farmers with plot size greater than 1000 m^2 as the minimum size to carry out LLL service. For each village, we randomly choose 75 farmers that meet the two criteria. We interviewed 303 households to collect primary data on the characteristics of households and their paddy plots and farm, and LLL service auction. Our target population for the next step of loterry is the auction winners who have the WTP for LLL greater than the predetermined price of 450 thousand Vietnam Dong. In the next step we use a lottery to determine who are assigned for receiving LLL. In 2021, the LLL intervention was implemented for a total of 40 plots, and an additional 18 plots received the intervention in the following year, while the remaining plots were maintained as the control group.

3. Results

3.1 Characteristics of paddy farmers, paddy plots and land fragmentation

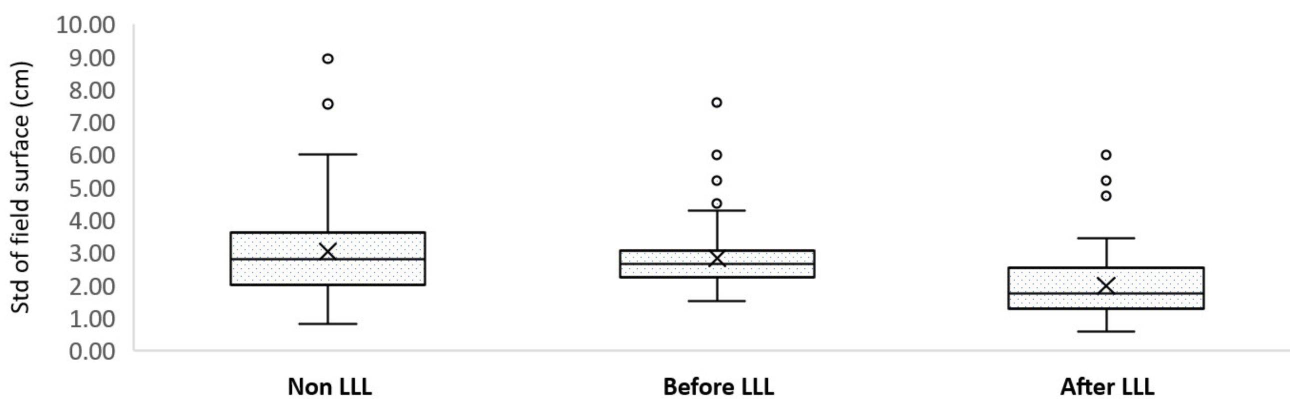
Table 1. Some characteristics of paddy plots and farming system

Unit: % of sample

Indicators	Without LLL (n_1=98 obs)	LLL (n_2=98 obs)	Total (n=196 obs)
Location			
- An Giang	13.3	8.2	10.7
- Kien Giang	86.7	91.8	89.3
Cropping system			
- Double	82.7	90.8	86.7
- Triple	17.3	9.2	13.3
Cultivation season			
- Winter Spring 2021	40.8	59.2	50.0
- Winter Spring 2020	59.2	40.8	50.0
Water source			
- Rain-fed	1.0	1.0	1.0
- Individual pumping	85.7	89.8	87.8
- Collective pumping	9.2	9.2	9.2
- Others	4.1	0.0	2.0
Plot area ('000 m^2 $plot^{-1}$)			

- Mean value	24.5	24.4	24.4
- Min	4	5	4
- Max	80	120	120

The analysis in this study is conducted using a sample of 98 plots observed during two seasons in 2021 and 2022, resulting in a total of 196 observations (Table 1). Farmers mostly performed double cropping system Most of farmers used their individual pumps for the filed irrigation, accounting for 87.8% of the sample. According to the results of the T-test, there is no significant difference in the mean values of areas between the two groups, one with LLL and the other without LLL. In the sample, the double cropping system is predominantly documented.



	Mean	*SD*	*SE*	*Min*	*Max*
Non LLL	*3.03*	*1.52*	*0.15*	*0.81*	*8.93*
Before LLL	*2.83*	*1.03*	*0.10*	*1.53*	*7.60*
After LLL	*1.99*	*0.91*	*0.09*	*0.59*	*6.00*

Figure 3. The standard deviation of paddy land surface

The standard deviation of the paddy land surface is calculated based on the measurement of heights at 20 to 30 specific points, providing an indication of the level of variation in the paddy land surface. Based on the results of the T-tests, there is no significant difference in the mean values of standard deviation between the two groups, one without LLL and the other with LLL before the LLL performance. In the sample, the double cropping system is predominantly documented. And, there is significant difference in the mean values of standard deviation for the group with LLL beween the two year 2021 and 2022. The observed decrease in the mean value after LLL implementation reflects the outcome of the intervention, indicating that the variation in the paddy land surface has been reduced by more than 5 cm.

3.2 Average treatment effects of laser land leveling in paddy production

The Apendix 1 shows the description of dependent variables and independent variables for the estimation of the intent-to-treat (ITT) effects. Table 2 and Table 3 show the regression results. The estimation result of dummy variable D reflects the treatment effect of LLL performance on yield (Table 3) and other input applied in paddy production (Table 2). The dummy variable D is statistically significant with a positive coefficient value, indicating that the treatment effect of LLL performance results in an increase in paddy yield. As mentioned in Section 2.2, the marginal effect of dummy independent variable D of LLL adoption to the the natural log of dependent variable, specifically interested in an increase or a decrease, we can use the calculation based on this formular suggested by Wooldridge (2015).

Table 2. Treatment effect of laser land leveling on the paddy yield

Variables	Coefficient	std. err.	z	P>|z|
ln_SEE	0.1644	0.0601	2.73	0.006
ln_NIT	0.0786	0.0403	1.95	0.051
ln_P2O	0.0052	0.0268	0.19	0.846
ln_K2O	-0.0178	0.0163	-1.10	0.273
ln_LAB	0.0071	0.0323	0.22	0.825
ln_MAC	-0.1628	0.0518	-3.14	0.002
ln_PES	0.0902	0.0284	3.17	0.002
ln_water	0.1282	0.0494	2.60	0.009
ln_STD	-0.0491	0.0237	-2.07	0.038
T	0.0725	0.0197	3.68	0.000
VAR	0.1199	0.0217	5.52	0.000
D	0.1031	0.0239	4.32	0.000
Constant	0.1635	0.4591	13.42	0.000

Observations: 196 Wald test of indep. eqns. (rho = 0):
Chi2(1) = 1.61 Prob > chi2 = 0.2048

Among 9 input dependent variables, the seed and ure amounts are found not significant in the estimaion. The statistical significance of the other inputs suggests that LLL performance has a treatment effect on these inputs in paddy production. Accordingly, the estimated average treatment effects reflect the incremental cost or benefit arising from the adoption of LLL. These estimation results are used to determine the incremental cost and benefit of the LLL project (see Appendix 2).

Table 3. Treatment effects of laser land leveling on input amounts in paddy production

VARIABLE	ln_SEE	ln_P2O	ln_K2O	ln_NIT	ln_URE	ln_PES	ln_LAB	ln_MAC	ln_DIE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln_p_SEE	-0.353***	-0.0280	0.0872	-0.308**	-0.407***	0.0745	-0.0492	-0.0302	-0.0215
	(0.0579)	(0.0873)	(0.172)	(0.137)	(0.0704)	(0.0720)	(0.0739)	(0.0422)	(0.0463)
ln_p_NIT	0.666***	-2.752***	-1.090*	-3.741***	18.91***	-1.715***	-1.527***	1.025***	9.007***
	(0.232)	(0.433)	(0.635)	(1.016)	(0.717)	(0.575)	(0.392)	(0.195)	(2.367)
ln_p_P2O	-0.136	-0.429***	0.530**	-0.614**	0.0227	-0.139	-0.117	-0.0885	0.0917
	(0.0841)	(0.155)	(0.243)	(0.251)	(0.178)	(0.172)	(0.114)	(0.0763)	(0.0732)
ln_p_K2O	0.0394	-0.0543	-0.460**	0.523***	0.260	0.240*	0.0241	-0.0898	0.274***
	(0.0896)	(0.130)	(0.232)	(0.180)	(0.181)	(0.138)	(0.100)	(0.0692)	(0.0744)
ln_p_URE	-0.829***	2.800***	0.894	3.437***	-19.07***	1.663***	1.612***	-0.980***	-9.167***
	(0.223)	(0.397)	(0.584)	(1.010)	(0.677)	(0.575)	(0.379)	(0.182)	(2.369)
ln_p_LAB	-0.115**	0.141*	-0.167	0.00531	0.108	0.0676	-0.435***	0.0274	0.0745**
	(0.0546)	(0.0823)	(0.161)	(0.144)	(0.0992)	(0.0852)	(0.0720)	(0.0474)	(0.0306)
ln_p_MAC	0.0568	-0.0143	0.228	0.0560	0.212*	-0.319***	-0.0201	-0.574***	-0.178***
	(0.0510)	(0.0886)	(0.186)	(0.192)	(0.112)	(0.0864)	(0.0756)	(0.0536)	(0.0422)
ln_p_PES	0.00544	0.00691	-0.0547	-0.00744	0.120***	-0.0312	0.0848*	-0.00311	-0.0270
	(0.0427)	(0.0332)	(0.0589)	(0.0584)	(0.0464)	(0.0410)	(0.0499)	(0.0201)	(0.0167)
ln_p_water	-0.0358	-0.179**	0.00294	-0.237*	-0.214**	-0.278***	0.147**	-0.0569	-0.128**
	(0.0563)	(0.0872)	(0.167)	(0.142)	(0.0854)	(0.0903)	(0.0743)	(0.0399)	(0.0500)
ln_p_PAD	0.436**	0.344	0.456	-0.0542	-0.527	-0.122	0.585	-0.00159	0.153
	(0.199)	(0.431)	(0.586)	(0.612)	(0.406)	(0.273)	(0.573)	(0.106)	(0.132)
ln_STD	0.00684	0.132**	0.364***	0.500***	0.143**	0.110	0.0814	-0.0212	0.0528*
	(0.0415)	(0.0550)	(0.121)	(0.154)	(0.0671)	(0.0824)	(0.0570)	(0.0305)	(0.0309)
T	-0.0563	-0.134	-0.129	-0.0737	0.0146	-0.114	-0.0384	-0.0372	0.0369
	(0.0595)	(0.0817)	(0.132)	(0.0965)	(0.0776)	(0.0768)	(0.0635)	(0.0373)	(0.0303)
VAR	-0.0824	0.0897	0.273***	0.206**	0.0997	-0.0153	0.0417	0.0239	0.00851
	(0.0553)	(0.0655)	(0.105)	(0.0848)	(0.0696)	(0.0742)	(0.0747)	(0.0301)	(0.0303)
D	*-0.0244*	*-0.134**	*-0.187**	*-0.167**	*0.0237*	*-0.132***	*-0.139***	*-0.117****	*-0.185****
	(0.0551)	*(0.0701)*	*(0.109)*	*(0.0940)*	*(0.0813)*	*(0.0627)*	*(0.0647)*	*(0.0292)*	*(0.0290)*
Constant	5.422***	6.720***	3.019	7.269***	-10.47***	10.05***	5.688***	5.051***	-4.011**
	(0.516)	(1.223)	(1.983)	(1.934)	(1.274)	(1.104)	(1.154)	(0.612)	(1.984)
Observations	196	196	196	196	196	196	196	196	139

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

3.3 Incremental cost benefit analysis

To provide a comprehensive perspective, the two sensitivity analyses are applied for discount rate and lifetime of the LLL performance. The incremental cost is incurred in year 0, whereas the incremental benefits occur annually throughout a 30-year lifespan and indefinitely in the two scenarios. The analysis results ensure the economic viability of the LLL technique (see Table 10 and Table 11).

Table 10: Incremental cost benefit analysis with LLL project life cycle of 30 years

Indicators	Unit	Discount rate		
		5%	7%	9%
Private analysis				
Cost	$ ha^{-1}	178.43	178.43	178.43
Benefit	$ ha^{-1}	3836.41	3,221.76	2,757.91
Yield	$ ha^{-1}	2701.92	2,269.04	1,942.35
Input	$ ha^{-1}	1134.49	952.73	815.56
Indicators				
NPV	$ ha^{-1}	3,657.98	3,043.34	2,579.49
EAB	$ ha^{-1} yr^{-1}	237.96	245.25	251.08
Cost–benefit ratio	time	21.50	18.06	15.46
Payback period	Year	0.60	0.61	0.62
IRR	%	176.18		
External cost and benefit				
Cost	$ ha^{-1}	2.91	2.91	2.91
Benefit	$ ha^{-1}	63.60	53.41	45.72
E_{INPUT}	$ ha^{-1}	15.90	13.35	11.43
E_{CH4}	$ ha^{-1}	5.50	4.62	3.95
E_{N2O}	$ ha^{-1}	42.21	35.45	30.34
Social analysis				
Cost	$ ha^{-1}	181.34	181.34	181.34
Benefit	$ ha^{-1}	3,900.01	3,275.18	2,803.64
Indicators				
Net Present Value	$ ha^{-1}	3,718.68	3,093.84	2,622.30
Equivalent annual benefit	$ ha^{-1} yr^{-1}	241.91	249.32	255.25
Cost–benefit ratio	time	21.51	18.06	15.46
Payback period	Year	0.60	0.61	0.62
Internal rate of return	%	176.23		

Table 11. Incremental cost benefit analysis with LLL project life cycle of 30 years

Indicators	Unit	Discount rate		
		5%	7%	9%
Private analysis				
Cost	$ ha^{-1}	178.43	178.43	178.43
Benefit	$ ha^{-1}	5686.17	4,268.03	3,399.74
Yield	$ ha^{-1}	4069.53	3,023.94	2,399.93
Input	$ ha^{-1}	1835.94	1,305.07	1,018.59
Indicators				
NPV	$ ha^{-1}	5,507.74	4,089.61	3,221.31
EAB	$ ha^{-1} yr^{-1}	143.97	145.61	145.94
BCR	time	31.87	23.92	19.05
Payback period	Year	0.60	0.61	0.62
IRR	%	176.18		
External cost and benefit				
Cost	$ ha^{-1}	2.91	2.91	2.91
Benefit	$ ha^{-1}	94.27	70.76	56.36
E_{INPUT}	$ ha^{-1}	26.29	18.44	14.32
E_{CH4}	$ ha^{-1}	11.47	7.04	5.16
E_{N2O}	$ ha^{-1}	63.79	47.30	37.51
Social analysis				
Cost	$ ha^{-1}	181.34	181.34	181.34
Benefit	$ ha^{-1}	5,780.44	4,338.79	3,456.10
Indicators				
NPV	$ ha^{-1}	5,599.10	4,157.46	3,274.76
EAB	$ ha^{-1} yr^{-1}	146.36	148.02	148.36
BCR	time	31.88	23.93	19.06
Payback period	Year	0.60	0.61	0.62
IRR	%	176.23		

4. Conclusion

In this study, we aim to estimate the causal effects of LLL on input usage and yield and use the results on treatment effect as inputs for the incremental cost benefit analysis in paddy production in the Mekong Delta region, Vietnam. The findings affirm the economic feasibility of the LLL technique, as indicated by both private and social analyses.

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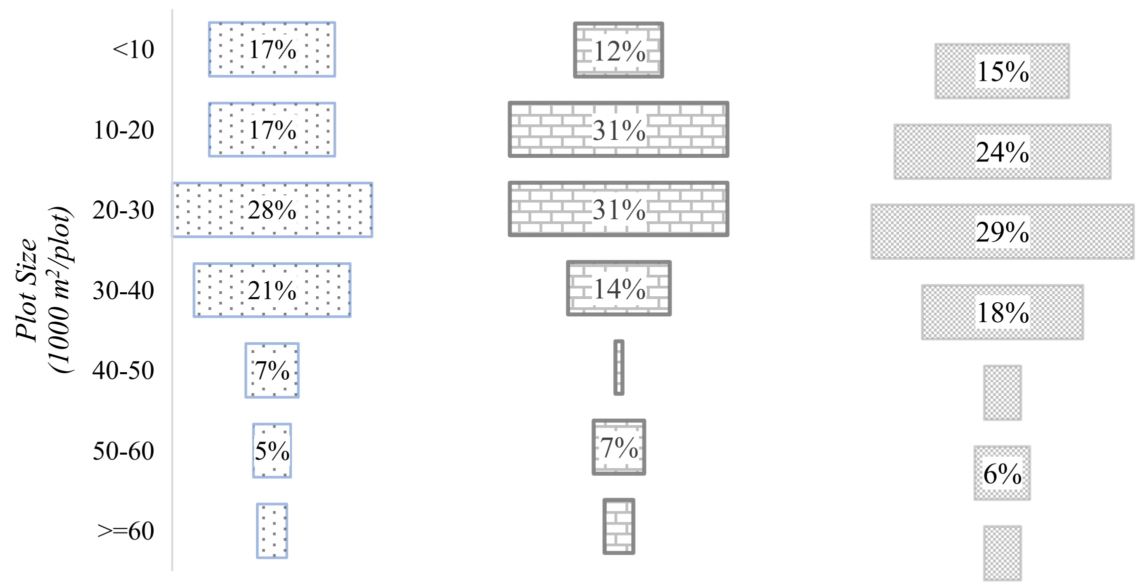
Appendices

Appendix 1. Supplementary information for RCT model

Appendix 1.1 Plot size by groups without LLL and with LLL

Non LLL	**LLL**	**Total Sample**
(n_1=98 plots)	(n_1=98 plots)	(n=196 plots)



	Mean	*SE*	*Min*	*Max*
Non LLL	24.52	15.56	4	80
LLL	24.35	18.42	5	120
Total Sample	24.44	17.01	4	120

Appendix 1.2 **Description of dependent variables**

Variables	Units	Without LLL (n_1=98 Obs.)				With LLL (n_2=98 Obs.)				Total (n=196 Obs.)			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
SEE	kg ha^{-1}	143.59	26.35	25.00	200.00	131.70	29.86	57.14	200.00	137.65	28.71	25.00	200.00
P20	kg ha^{-1}	120.83	33.71	33.10	237.69	101.99	35.10	30.00	219.18	111.41	35.60	30.00	237.69
K20	kg ha^{-1}	61.70	28.68	19.27	147.75	54.99	24.73	4.97	116.59	58.35	26.92	4.97	147.75
NIT	kg ha^{-1}	50.11	18.72	13.80	107.31	37.89	21.33	1.80	114.00	44.00	20.94	1.80	114.00
URE	kg ha^{-1}	188.58	59.78	39.64	346.15	168.81	60.59	1.00	305.00	178.70	60.85	1.00	346.15
PES	g AI ha^{-1}	3,004.09	1,094.32	1,593.00	7,064.00	2,291.08	832.91	445.00	4,432.00	2,647.59	1,033.70	445.00	7,064.00
LAB	hours ha^{-1}	20.14	5.70	3.57	44.47	21.31	5.44	5.86	36.17	20.73	5.59	3.57	44.47
MAC	hours ha^{-1}	8.41	1.28	4.00	10.64	7.03	1.83	3.50	15.93	7.72	1.72	3.50	15.93
DIE	liters ha^{-1}	39.08	5.18	28.00	52.00	30.30	4.81	21.00	43.00	34.91	6.65	21.00	52.00

Appendix 1.3 Description of independent variables

Variables	Units of measurement	Without LLL (n_1=98 Obs.)				With LLL (n_2=98 Obs.)				Total (n=196 Obs.)			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
p_SEE	'000 VND kg^{-1}	13.39	3.13	4.80	17.00	14.42	1.81	4.80	17.00	13.90	2.60	4.80	17.00
p_NIT	'000 VND kg^{-1}	29.65	10.55	15.22	43.48	32.67	8.83	16.52	44.57	31.16	9.82	15.22	44.57
p_P2O	'000 VND kg^{-1}	26.65	6.54	15.27	41.68	28.48	5.70	18.00	43.43	27.57	6.19	15.27	43.43
p_K2O	'000 VND kg^{-1}	24.94	7.22	12.73	35.64	28.28	5.99	13.82	36.36	26.61	6.82	12.73	36.36
p_URE	'000 VND kg^{-1}	13.64	4.85	7.00	20.00	15.06	4.03	7.60	20.50	14.35	4.51	7.00	20.50
p_LAB	'000 VND $hour^{-1}$	94.67	26.33	46.89	184.97	91.30	32.31	49.79	213.14	92.99	29.45	46.89	213.14
p_MAC	'000 VND $hour^{-1}$	395.20	100.75	216.10	668.83	446.28	110.91	222.33	669.70	420.74	108.74	216.10	669.70
p_PES	'000 VND gAI^{-1}	1.19	0.83	0.12	4.33	1.10	0.85	0.14	5.97	1.15	0.84	0.12	5.97
p_PAD	'000 VND kg^{-1}	6.49	0.48	4.50	7.00	6.54	0.43	4.60	7.00	6.51	0.46	4.50	7.00
STD	Millimeter	3.03	1.52	0.81	8.93	1.99	0.91	0.59	6.00	2.51	1.36	0.59	8.93
T	=1: if crop in 2020 =0: if crop in 2021	0.59	0.49	0.00	1.00	0.41	0.49	0.00	1.00	0.50	0.50	0.00	1.00
VAR	=1: if ≥95 days =0: if < 95 days	0.61	0.49	0.00	1.00	0.77	0.43	0.00	1.00	0.69	0.46	0.00	1.00
D	=1: if LLL =0: if none LLL	0.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00	0.50	0.50	0.00	1.00
ASS	=1: if assignment =0: if none assignment	0.17	0.38	0.00	1.00	0.98	0.14	0.00	1.00	0.58	0.50	0.00	1.00
LLP	Likert 10 points (1: lowest; 10: highest)	4.91	1.96	2.00	10.00	5.35	1.83	2.00	10.00	5.13	1.90	2.00	10.00

Appendix 2. GHG emissions in paddy production

$$\mathbf{E_{paddy} = E_{input} + E_{CH4} + E_{N2O} + E_{Biomas}}$$

In paddy production activities, greenhouse gas (GHG) emissions come from the three main sources. The first is the usage of agricultural inputs, namely seed, labor, fertilizers, pesticides, diesel oil from water pumps, other machine operation. Second, CH_4 emission from paddy cultivation, direct and indirect N2O emission from managed soils, emission from biomas management using the guideline from IPCC (2019).

In this study, the exclusion of GHG emissions from seed, labor, and and biomass management is due to the insignificant difference observed before and after laser levelling. The GHG emissions are estimated using Equation 1 as follows.

$$\mathbf{E_{paddy} = E_{input} + E_{CH4} + E_{N2O}} \qquad \mathbf{(1)}$$

CO_2e emissions from agriculture input

GHG from agricultural inputs in paddy cultivation including seeds, fertilizers, pesticides, labor, diesel oil from water pumps, farm machine operation. In this study, we do not consider labor emissions. GHG from agricultural inputs are estimated using Equation 2 as follows

$$\mathbf{E_{input} = E_{fertilizer} + E_{pesticide} + E_{diesel}} \qquad \mathbf{(2)}$$

$E_{fertilizer}$ = CO_2e emissions from fertilizer use (kg CO_2e kg $^{-1}$);
$E_{pesticide}$ = CO_2e emissions from pesticide use (kg CO_2e kg $^{-1}$);
E_{diesel} = CO_2e emissions from diesel consumption (kg CO_2e L^{-1});

Fertilizer

$E_{fertilizer}$ = EF_N x $Amount_N$ + EF_{P2O5} x $Amount_{P2O5}$ + EF_{K2O} x $Amount_{K2O}$

Note that the GHG emissions from manure application are taken to be zero according to Ecoinvent v3.9.1

EF_N = Emission facto of N (kg CO_2e kg^{-1} of N);
EF_{P2O5} = Emission factor of P_2O_5 (kg CO_2e kg^{-1} of P_2O_5);
EF_{K2O} = Emission factor of K_2O (kg CO_2e kg^{-1} of K_2O);
$Amount_N$ = Amount of N applied (kg of N);
$Amount_{P2O5}$ = Amount of P2O5 applied (kg of P_2O_5);
$Amount_{K2O}$ = Amount of K_2O applied (kg of K_2O).

Pesticide

$E_{pesticide}$ = $EF_{pesticide}$ x $Amount_{pesticide}$
$EF_{pesticide}$ = Emission factor of pesticide (kg CO2e kg^{-1} of pesticide);
$Amount_{pesticide}$ = Amount of pesticide applied (kg a.i).

Diesel consumption

$E_{diesel-1}$ = EF_{diesel} x LHV x $Amount_{diesel}$

EF_{diesel} = Emission factor of diesel (kg CO_2e MJ^{-1});

LHV = Low heating value of diesel (MJ l^{-1});

$Amount_{diesel}$= Amount of diesel for operating pump and cultivator, laser leveling machine (L)

CO2e emissions from CH_4 emission from paddy cultivation

$E_{CH4} = CH_{4\,paddy} * GWP_{CH4}$

In this study, CH_4 emission is estimated based the guideline from IPCC (2019) as follows

$$\mathbf{CH_{4\,\mathit{paddy}} = EF_i * t * A * 10^{-6}} \quad \textbf{(3)}$$

$CH_{4\,paddy}$ = annual methane emissions from paddy cultivation, Gg CH4 yr^{-1}

EF_i = a daily emission factor kg CH4 ha^{-1} day^{-1}

t = cultivation period of paddy, day

A = annual harvested area of paddy, ha yr^{-1}

Note that the t value applied in this study is 105 days according to the survey data and in the range suggested by IPCC (2019). The paddy field is calculated for one hectare.

$EF_i = EF_c * SF_w * SF_p * SF_o * SF_s * SF_r$

$SF_o = (1 + \sum_i ROA_i * CFOA_i)^{0.59}$

ROA_i = application rate of organic amendment i, in dry weight for straw and fresh weight for others, tonne ha^{-1}

$CFOA_i$ = conversion factor for organic amendment i (in terms of its relative effect with respect to straw applied shortly before cultivation)

The daily CH4 emission factor from paddy cultivation is calculated based on EF_c baseline emission factor for continuously flooded fields without organic amendments, SF_w scaling factor to account for the differences in water regime during the cultivation period, SF_p scaling factor to account for the differences in water regime in the pre-season before the cultivation period, SF_o scaling factor should vary for both type and amount of organic amendment applied (include ROA_i application rate of organic amendment, $CFOA_i$ conversion factor for organic amendment), SF_s scaling factor for soil type, SF_r scaling factor for paddy cultivar. In this study, we do not consider SF_s scaling factor for soil type and SF_r scaling factor for paddy cultivar. This study has no organic change, so we take SFo = 1. The difference between the plot applied LLL and not applied LLL is the coefficient SFw. Therefore, GHG from agricultural inputs are estimated using Equation 4 as follows

$$\mathbf{EF_i = EF_c * SF_w * SF_p * SF_o} \quad \textbf{(4)}$$

EF_c = baseline emission factor for continuously flooded fields without organic amendments

SF_w = scaling factor to account for the differences in water regime during the cultivation period

SF_p = scaling factor to account for the differences in water regime in the pre-season before the cultivation period

SF_o = scaling factor should vary for both type and amount of organic amendment applied

CO2e emissions from direct and indirect N2O Emission from soil management

N2O emissions managed soils estimated based on Direct N_2O-N emissions and Indirect N_2O-N emissions (IPCC, 2019). Therefore, N2O emissions are estimated using Equation 5 as follows

$$\mathbf{E_{N2O} = GWP_{N2O} x \frac{44}{28} (E_{N2O-N,dir} + E_{N2O-N,ind})} \qquad \textbf{(5)}$$

$E_{N2O\text{-}N,dir}$ = Direct N_2O-N emissions from managed soils (kg N_2O-N ha^{-1})
$E_{N2O\text{-}N,ind}$ = Indirect N_2O-N emissions from managed soils (kg N_2O-N ha^{-1})

Direct N_2O-N emissions: N_2O_{Direct}-N $=[(F_{SN} + F_{ON} + F_{CR} + F_{SOM}) * (EF_{N2O-N,dir} + EF_{N2O-N,dir,FR})$

In IPCC 2019, direct N2O emissions from managed soils are estimated N2O – N annual direct N2O–N emissions from F_{SN} as amount of synthetic fertilizer nitrogen applied to soils; F_{ON} is amount of animal manure, compost, sewage sludge and other organic N additions applied to soils; N in crop residues, including N-fixing crops, and from forage/pasture renewal, returned to soils; F_{CR} is amount of N in crop residues, including N-fixing crops, and from forage/pasture renewal, returned to soils; F_{SOM} as amount of N in mineral soils that is mineralised, in association with loss of soil C from soil organic matter as a result of changes to land use or management. F_{ON}, F_{SOM}, F_{CR} is not applied in this study for the different analysis between plots with LLL and without LLL. The direct and indirect N2O emissions are estimated using Equation 6 and Equation 7 as follows

Direct N_2O-N emissions: $\mathbf{N_2O_{Direct}\text{-}N = F_{SN} * (EF_{N2O-N,dir} + EF_{N2O-N,dir,FR})}$ **(6)**

F_{SN} = Amount of synthetic fertilizer nitrogen applied to soils (kg N yr^{-1})
$EF_{N2O\text{-}N,dir}$ = Emission factor for N_2O emissions from N inputs, kg N2O–N (kg N $input)^{-1}$
$EF_{N2O\text{-}N,dir,FR}$= Emission factor for N_2O emissions from N inputs to flooded paddy, kg N2O–N (kg N $input)^{-1}$

Indirect N_2O-N emissions: $\mathbf{E_{N2O\text{-}N,ind} = E_{N2O\text{-}N,ind,ATD} + E_{N2O\text{-}N,ind,L}}$ **(7)**

$E_{N2O\text{-}N,ind,ATD}$= Indirect N_2O-N emissions due to atmospheric deposition of nitrogen volatilized (kg N_2O-N ha^{-1})
$E_{N2O\text{-}N,ind,L}$ = Indirect N_2O-N emissions from leaching/run-off due to nitrogen application (kg N_2O-N ha^{-1})

Following IPCC (2019), the indirect N_2O-N emissions due to atmospheric deposition of nitrogen volatilized and leaching/run-off due to nitrogen application are estimated follows

$$E_{N2O\text{-}N,ind,ATD} = (F_{SN} \text{ x } Frac_{GASF} + F_{ON} \text{ x } Frac_{GASM}) \text{ x } EF_{N2O\text{-}N,ATD}$$

In IPCC 2019, direct N2O emissions from Indirect N_2O-N emissions due to atmospheric deposition of nitrogen volatilized from synthetic fertiliser N that volatilises as NH3 and NOx (F_{SN} x $Frac_{GASF}$) and applied organic N fertiliser materials (F_{ON}) that volatilises as NH3 and NOx (F_{ON} x $Frac_{GASM}$). In this study, the emissions from F_{ON} x $Frac_{GASM}$ is not applied for the different analysis between plots with LLL and without LLL. Therefore, Indirect N_2O-N emissions due to atmospheric deposition of nitrogen volatilized are estimated using Equation 7.1 as follows

$$\mathbf{E_{N2O\text{-}N,ind,ATD} = F_{SN} \text{ x } Frac_{GASF} \text{ x } EF_{N2O\text{-}N,ATD}} \qquad \textbf{(7.1)}$$

$Frac_{GASF}$ = Fraction of synthetic fertiliser N that volatilises as NH3 and NOx, kg N volatilised (kg of N applied)-1

$EF_{N2O\text{-}N,ATD}$ = Emission factor for N2O emissions from atmospheric deposition of N on soils and water surfaces, [kg N–N2O (kg NH3–N + NOx–N volatilised)$^{-1}$]

The indirect N_2O-N emissions from leaching/run-off due to nitrogen application are as follows.

$$E_{N2O\text{-}N,ind,L} = (F_{SN} + F_{ON} + F_{SOM} + F_{CR}) \times Frac_{LEACH} \times EF_{N2O\text{-}N,L}$$

F_{ON}, F_{SOM}, F_{CR} are not applied for the different analysis between plots with LLL and without LLL. Therefore, the indirect N_2O-N emissions from leaching/run-off due to nitrogen application are estimated using Equation 7.2 as follows

$$\mathbf{E_{N2O\text{-}N,ind,L} = F_{SN} \times Frac_{LEACH} \times EF_{N2O\text{-}N,L}} \qquad \mathbf{(7.2)}$$

$Frac_{LEACH}$ = Fraction of all N added to/mineralised in managed soils in regions where leaching/runoff occurs that is lost through leaching and runoff, kg N (kg of N additions)$^{-1}$

$EF_{N2O\text{-}N,L}$ = Emission factor for N2O emissions from N leaching and runoff, kg N2O–N (kg N leached and runoff)$^{-1}$

List of parameters applied in the calculation

Parameters	Value	Source
Emission factors of fertiliser and pesticide		
EF_N	6.08628	[Ecoinvent 2022] LCIA, v3.9.1
EF_{P2O5}	1.64665	[Ecoinvent 2022] LCIA, v3.9.1
EF_{K2O}	0.77650	[Ecoinvent 2022] LCIA, v3.9.1
$EF_{Pesticide}$	10.71473	[Ecoinvent 2022] LCIA, v3.9.1
Emission factor and LHV of diesel		
LHV	35.87	[Davis, S. C. et al 2021]
EF_{diesel}	0.10319	[Ecoinvent 2022] LCIA, v3.9.1
CH_4 emissions from paddy cultivation		
GWP_{CH4}	27	[IPCC 2021] Table 7.15
GWP_{N2O}	273	[IPCC 2021] Table 7.15
t	105	[IPCC 2019] Chapter 5, Table 5.11A
EF_c	1.22	[IPCC 2019] Chapter 5, Table 5.11
$SF_{w,\ LLL}$	0.5	[IPCC 2019] Chapter 5, Table 5.12
$SF_{w,\ no\_LLL}$	0.6	[IPCC 2019] Chapter 5, Table 5.12
SF_p	1	[IPCC 2019] Chapter 5, Table 5.13
SF_o	1	[IPCC 2019] Chapter 5, Table 5.14

Parameters	Value	Source
N_2O emission from managed soils		
$FRAC_{GASF}$	0.11	[IPCC 2019] Chapter 11, Table 11.3
$FRAC_{LEACH}$	0.24	[IPCC 2019] Chapter 11, Table 11.3
$EF_{NO2\text{-}N,dir}$	0.005	[IPCC 2019] Chapter 11, Table 11.1
$EF_{N2O\text{-}N,dir,FR}$	0.005	[IPCC 2019] Chapter 11, Table 11.3
$EF_{N2O\text{-}N,ATD}$	0.005	[IPCC 2019] Chapter 11, Table 11.3
$EF_{N2O\text{-}N,L}$	0.011	[IPCC 2019] Chapter 11, Table 11.3

PARAMETERS IN INCREMENTAL COST BENEFIT ANALYSIS

Indicators (Unit)		LLL (h)	Weed removing	Ploughing (h)	P_2O (kg)	K_2O (kg)	NIT (kg)	PES (gram AI)	LAB (h)	MAC (h)	DIE (l)	PAD (kg)
Discount rate	%	5.00										
Exchange rate	‘000 VND USD^{-1}	23.18										
CO_2 eq price	\$ kg^{-1} of CO_2 eq	0.01										
Incremental benefit	Unit ha^{-1}	4.85		7.00	14.89	11.63	7.96	376.04	2.85	0.98	7.04	786.40
Diesel per machine hour máy	L $hour^{-1}$	9		5						5		
Price	‘000 VND $unit^{-1}$	500.00	310.00	200.00	27.18	26.75	31.51	1.07	93.59	435.52	12.63	6.52
Price	USD $unit^{-1}$	21.57	13.38	8.63	1.17	1.15	1.36	0.05	4.04	18.79	0.55	0.28
Incremental benefit	**Scenario 1**	**Scenario 1**										
in the lifetime	Year 1-10	Năm 1-30	100%									
	Year 11-20	Năm 31-50	70%									
	Year 21-30	Năm 51- (+∞)	40%									

SCENARIO 1. LIFETIME OF 30 YEARS

Year	Unit	2020 0	2021 1	2022 2	2023 3	… …	2035 15	2036 16	… …	2049 29	2050 30
Discount factor		1.00	0.95	0.91	0.86	…	0.48	0.46	…	0.24	0.23
PRIVATE ANALYSIS											
Cash outflow	$ ha^{-1}	178.43									
LLL cost	$ ha^{-1}	104.64									
Weeding removal for LLL	$ ha^{-1}	13.38									
Ploughing for LLL	$ ha^{-1}	60.41									
Cash inflow	$ ha^{-1}		314.35	314.35	314.35	…	220.05	220.05	…	125.74	125.74
Increase in yield	$ ha^{-1}		221.39	221.39	221.39	…	154.98	154.98	…	88.56	88.56
Input reduction	$ ha^{-1}		92.96	92.96	92.96	…	65.07	65.07	…	37.18	37.18
- P_2O	$ ha^{-1}		17.46	17.46	17.46	…	12.22	12.22	…	6.99	6.99
- K_2O	$ ha^{-1}		13.43	13.43	13.43	…	9.40	9.40	…	5.37	5.37
- NIT	$ ha^{-1}		10.82	10.82	10.82	…	7.58	7.58	…	4.33	4.33
- Pesticide	$ ha^{-1}		17.44	17.44	17.44	…	12.21	12.21	…	6.98	6.98
- Labour	$ ha^{-1}		11.50	11.50	11.50	…	8.05	8.05	…	4.60	4.60
- Machine	$ ha^{-1}		18.47	18.47	18.47	…	12.93	12.93	…	7.39	7.39
- Diesel	$ ha^{-1}		3.84	3.84	3.84	…	2.68	2.68	…	1.53	1.53
Net cashflow	$ ha^{-1}	-178.43	314.35	314.35	314.35	…	220.05	220.05	…	125.74	125.74
NPV	$ ha^{-1}	3,657.98									
EAB	$ ha^{-1}	237.96									
BCR	Time	21.50									
Payback period	Year	0.60									
IRR	%	176.18									
GHG EMISSION											
Cash outflow (increase in emission)	$ ha^{-1}	2.91	0	0	0	…	0	0	…	0	0
Cash inflow (decrease in emission)	$ ha^{-1}		5.21	5.21	5.21	…	3.65	3.65	…	2.08	2.08
E_{INPUT}	$ ha^{-1}		1.30	1.30	1.30	…	0.91	0.91	…	0.52	0.52
E_{CH4}	$ ha^{-1}		0.45	0.45	0.45	…	0.32	0.32	…	0.18	0.18
E_{N2O}	$ ha^{-1}		3.46	3.46	3.46	…	2.42	2.42	…	1.38	1.38
Net cashflow	$ ha^{-1}	-2.91	5.21	5.21	5.21	…	3.65	3.65	…	2.08	2.08
SOCIAL ANALYSIS											
Net cashflow	$ ha^{-1}	-181.34	319.56	319.56	319.56	…	223.69	223.69	…	127.83	127.83
NPV	$ ha^{-1}	3,718.68									
EAB	$ ha^{-1}	241.91									
BCR	time	21.51									
Payback period	year	0.60									
IRR	%	176.23									

SCENARIO 1. INIFITY LIFETIME

Year		2020	2021	2022	2023	…	2055	2056	…	2071	… (+∞)
	Unit	0	1	2	3	…	35	36	…	51	… (+∞)
Discount factor		1.00	0.95	0.91	0.86	…	0.18	0.17	…	0.08	…
PRIVATE ANALYSIS											
Cash outflow	\$ ha^{-1}	178.43									
LLL cost	\$ ha^{-1}	104.64									
Weeding removal for LLL	\$ ha^{-1}	13.38									
Ploughing for LLL	\$ ha^{-1}	60.41									
Cash inflow	\$ ha^{-1}		314.35	314.35	314.35	…	220.05	220.05	…	125.74	…
Increase in yield	\$ ha^{-1}		221.39	221.39	221.39	…	154.98	154.98	…	88.56	…
Input reduction	\$ ha^{-1}		92.96	92.96	92.96	…	65.07	65.07	…	37.18	…
P_2O	\$ ha^{-1}		17.46	17.46	17.46	…	12.22	12.22	…	6.99	…
K_2O	\$ ha^{-1}		13.43	13.43	13.43	…	9.40	9.40	…	5.37	…
NIT	\$ ha^{-1}		10.82	10.82	10.82	…	7.58	7.58	…	4.33	…
Pesticide	\$ ha^{-1}		17.44	17.44	17.44	…	12.21	12.21	…	6.98	…
Labour	\$ ha^{-1}		11.50	11.50	11.50	…	8.05	8.05	…	4.60	…
Machine	\$ ha^{-1}		18.47	18.47	18.47	…	12.93	12.93	…	7.39	…
Diesel	\$ ha^{-1}		3.84	3.84	3.84	…	2.68	2.68	…	1.53	…
Net cashflow	\$ ha^{-1}	-178.43	314.35	314.35	314.35	…	220.05	220.05	…	125.74	…
NPV	\$ ha^{-1}	5,507.74									
EAB	Time	31.87									
BCR	\$ ha^{-1} yr^{-1}	143.97									
Payback period	Year	0.60									
IRR	%	176.18									
GHG EMISSION											
Cash outflow (increase in emission)	\$ ha^{-1}	2.91									
Cash inflow (decrease in emission)	\$ ha^{-1}		5.21	5.21	5.21	…	3.65	3.65	…	2.08	…
E_{INPUT}	\$ ha^{-1}		1.30	1.30	1.30	…	0.91	0.91	…	0.52	…
E_{CH4}	\$ ha^{-1}		0.45	0.45	0.45	…	0.32	0.32	…	0.18	…
E_{N2O}	\$ ha^{-1}		3.46	3.46	3.46	…	2.42	2.42	…	1.38	…
Net cashflow	\$ ha^{-1}	-2.91	5.21	5.21	5.21	…	3.65	3.65	…	2.08	…
SOCIAL ANALYSIS											
Net cashflow	\$ ha^{-1}	-181.34	319.56	319.56	319.56	…	223.69	223.69	…	127.83	…
NPV	\$ ha^{-1}	5,599.10									
EAB	\$ ha^{-1} yr^{-1}	146.36									
BCR	time	31.88									
Payback period	year	0.60									
IRR	%	176.23									