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# Laser land leveling technique for paddy mono-cropping system in Vietnam

*Addressing land fragmentation, demand heterogeneity, and productivity*

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# Laser land leveling technique for paddy mono-cropping system in Vietnam: Addressing land fragmentation, demand heterogeneity, and productivity[1]

**Loan T. Le[a], Luan D. Tran[b], Trieu N. Phung[c,a]**

## Abstract

The study investigates determinants of willingness to pay (WTP) for laser land leveling (LLL) technique, its demand heterogeneity across individual farmers and plot characteristics, and the technique empirical impact on paddy productivity. The study applies the Becker-DeGroote, Marschak style to elicit the WTP for LLL technique and the Cragg model to examine the determinants of the WTP to capture both the demand decision and affordability. The randomized controlled trials (RCT) incorporate with a production function model to analyze the technique effects on paddy productivity. The Cragg model finds that the key demographic and behavioral traits such as age, extension services, and risk acceptance significantly influence the adoption decision; however, the plot area, bank and financial capacity become predominant factors to the adoption affordability. The LLL treatment effect results in a statistically significant increase in paddy yield of 6.48%, equivalent to 492,138 kg ha$^{-1}$. The analysis underscores the factor complexity, illustrating that the LLL promoting interventions need to address both the adoption barriers and the enablers for a greater affordability. A composite of climate-smart agricultural programs should be employed to facilitate the LLL adoption. The empirical evidence highlights the positive effect on the agricultural productivity, potentially offering a significant boost to output and farmer income. The study contributes to existing literature by analyzing the heterogeneous demand for LLL technique with two distinguishable features of paddy mono-cropping system and land fragmentation and by incorporating the RCTs alongside a production function for the effects on paddy productivity.

**Keywords**: Laser land leveling, Demand heterogeneity, Land fragmentation, Paddy productivity, Randomized controlled trials, Mekong Delta, Vietnam

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## 1. Introduction

Climate change has been one of environmental threats in agricultural activities; a sea level rise causing salinity or water scarcity will negatively affect agricultural productivity (Li, Caixia, 2023; WBG and ADB, 2021). As the primary staple food in Asia, rice production in the region has historically constituted 90% of the global total; however, it is estimated about 22 million hectares of paddy production in lack of irrigation (Chandrasiri et al., 2023; Schneider and Asch, 2020). In Vietnam, the paddy cultivation has contributed about 40% of total agricultural outputs; the country has been the second largest rice exporter in the world (GSO, 2022). While paddy cultivation in Vietnam has predominantly centered in the Mekong River Delta (MRD), which accounts for 55% of the total area and 57% of the total output, it has faced significant challenges due to climate change, particularly impacting rice production (GSO, 2022; WB and ADB, 2021). Thus, there is an urgent need for sustainable agriculture technologies to ensure sustainable and resilient agricultural systems in the face of a changing climate, particularly in paddy cultivation.

As a climate-smart and resource-efficient agricultural technology, laser land leveling (LLL) is deemed highly suitable for paddy production not only to adapt climate risks and mitigate GHG emissions but also to boost productivity (Pal et al., 2022; Kumar et al., 2021; Kakraliya et al., 2018; D'Souza and Mishra, 2018). While small-scale paddy production in Southeast Asian countries, like Vietnam, poses a significant constraint for both farmers and LLL service providers in promoting LLL adoption, it is crucial to investigate the impact of land fragmentation on the demand for this climate-smart agriculture technology. Chi et al (2022) and Wang et al. (2023) analyzes the impact of land fragmentation on fertilizer and pesticide application; unfortunately, such investigation on technology adoption has been missing in literature (D'Souza and Mishra, 2018; Lybbert et al., 2018).

The impact of land fragmentation on precision agricultural technology is an emerging issue that has received limited attention in existing literature, despite its growing relevance. Previously, agricultural economic research on land fragmentation has focused on its effects on the agricultural productivity (Alemu et al., 2017; Looga et al., 2018), agricultural cost and profit (Manjunatha et al., 2013; Wang et al, 2020b), the agricultural technical efficiency (Zhou et al., 2024), and agricultural activities (Lu et al., 2022; Wang et al, 2020a), with little emphasis on its intersection with technology adoption. Cholo et al. (2018) has investigated if land fragmentation has facilitated or obstructed the sustainable land management practices using the probit models. Chi et al. (2022) analysed the impact of land fragmentation on Chemical fertilizer application intensity, agricultural mechanization and soil testing fertilization technologies. However, the increasing prevalence of land fragmentation, particularly in developing regions, presents new challenges to understanding or addressing in current studies. This gap in the literature suggests that the implications of fragmented land for the adoption and effectiveness of precision agriculture have been largely overlooked, making this a novel and critical area of inquiry. By exploring these issues, this paper addresses the impact of land fragmentation on demand for precision agricultural technology and policy-related challenges that arise from applying precision agriculture in fragmented landscapes.

Randomized Control Trials (RCTs) offer advantages in establishing causal relationships, minimizing bias, isolating intervention effects, and robustly evaluating the impact of interventions (Zabor et al., 2020). The literature indicates that there has been a growing utilization of this approach within the realm of agricultural production research to investigate the effects of microcredit on fertilizer application (Nakano et al, 2020), the impact of LLL performance on water and diesel usage (Lybbert et al., 2018), and the influence of extension strategies on the adoption of improved varieties and storage innovations (Dhehibi et al., 2022; Yitayew et al., 2022; Yitayew et al., 2021; Channa et al., 2022). Except for Nakano et al. (2020) analyzing the impact of microcredit on productivity, the utilisation of this approach to analyze the impact on productivity has not been explored in the existing studies.

Most studies on the effects of LLL performance have primarily focused on the rice-wheat system, employing experimental field tests (Ramya et al., 2022; Tomar 2020; Kakraliya et al., 2019; Kakraliya et al., 2018; Li et al, 2018), alongside a descriptive comparison (Aryal et al., 2015) and a review (Balingbing 2020). Econometric analyses, utilizing techniques such as propensity score matching, coarsened exact matching, and endogenous switching regression, are confined to the studies by Pal et al. (2022) and Aryal et al. (2020). Lybbert et al. (2018) employed the RCT method to assess water-saving impacts. The literature lacks reports on combining the RCT approach with the production function to explore the effects of the LLL technique on productivity, particularly in mono rice systems (Balingbing, 2020; Ramya et al., 2022; Pal et al., 2022). However, the literature lacks reports on an integration of the RCT paradigm with production function models to assess the ramifications of the LLL technique on agricultural productivity, specifically within the context of monoculture rice systems (Balingbing, 2020; Ramya et al., 2022; Pal et al., 2022).

In 2016, Vietnam ratified the Paris Agreement, pledging to cut its greenhouse gas (GHG) emissions by 8% to 25% from Business-as-Usual levels under the National Climate Change Strategy. By 2020, Vietnam updated its commitment to the UNFCCC, aiming to reduce GHG emissions by 9% by 2030 using domestic resources, with the potential to increase to 27% with international support under the Paris Agreement mechanisms (Socialist Republic of Vietnam, 2020). LLL is identified as a prerequisite for sustainable paddy production in the Mekong Delta, Vietnam as it can be combined with the Alternate Wetting and Drying technique to adapt to emerging climatic variability and mitigating GHG emissions and to enhance productivity (Le, 2021; FAO 2017). In light of constrained governmental allocations for this service, the participation of farmers in contributing financially has been indispensable for its promotion. Consequently, it becomes essential to evaluate the potential contributions of farmers to the LLL service, in conjunction with the development of a financing strategy that incorporates governmental assistance.

This study aims to analyze determinants of the WTP for LLL service, the heterogeneity in the demand for LLL technique across individual farmers and plot characteristics, notably focusing on land fragmentation, and the empirical impact of LLL performance on paddy productivity. The study contributions lie firstly in the analysis of heterogeneous demand for LLL service with two distinguishable features of paddy mono-cropping system and impacts of land fragmentation with the Simpson index synthesized both numbers of plots and plot sizes on the WTP for LLL service. Secondly, this research incorporates the RCT approach alongside a production function model to analyze the effects of the LLL technique on agricultural productivity for the monoculture rice system.

The structure of paper is as follows. Section 2 presents the methodology with Simpson index, experimental design, econometric model, study sites, and sample description. Section 3 describes the results and discussion. Section 4 contains the conclusion of this study.

## 2. Methodology

### *2.1 Land fragmentation and simpson index*

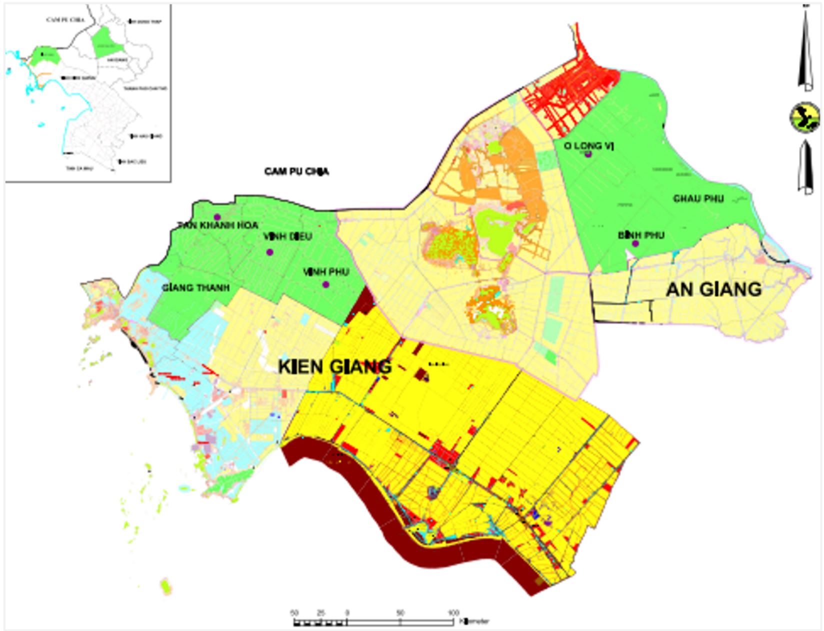
Land fragmentation is a spatial concept which depends on six factors of total farm area, number of plots, plot area, plot shape and the spatial distribution and size distribution of plots (Liu et al., 2022; Janus et al., 2018). Pertaining directly to the dimension of the plot, the three of land fragmentation metrics encompasses i) the Average Plot Size Index ($avpls_i$); ii) the Januszewski Index ($janus_i$); and iii) the Simpson Index ($simps_i$) (Liu et al., 2022; Janus et al., 2018).

$$\text{avpls}_i = \frac{A_i}{K_i}; \quad \text{janus}_i = \frac{\sqrt{A_i}}{\sum_{k=1}^{K_i}\sqrt{a_k}}; \quad \text{simps}_i = 1 - \frac{\sum_{k=1}^{K_i} a_k^2}{A_i^2}$$

where i is to identify the farm; $A_i$: total area of the farm i; k is to denote the number of plots of farm i (k=1, 2,… , Ki); $a_k$ is the plot area of plot k. The average plot size index (avplsi) is calculated by dividing the total land area by the number of plots, ignoring the specific area of each plot, while both the Simpson and Januszewski indexes capture four out of six land fragmentation factors, excluding plot shape and plot spatial distribution. These two indexes range from 0 to 1; their interpretation is contradictory: a higher Januszewski index implies lesser fragmentation, whereas a higher Simpson index indicates greater fragmentation. The farm is considered consolidated with one plot when the simpson index is 0; the farm is very fragmented when it is approaching 1. Given the uniformity of plot shapes in paddy production within the MDR and the absence of spatial distribution data, the Simpson index is employed to assess land fragmentation in this research.

### 2.4 Study sites and 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 2022). 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 764 paddy plots, and LLL service auction.




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

**Figure 1. Study site in An Giang and Kien Giang provinces**

### 2.2 Analytical framework and experimental design

This study employs the theoretical framework established by Lybbert et al. (2018) and Foster and Rosenzweig (2010) to provide a microeconomic foundation. Accordingly, a farmer, possessing heterogeneous paddy plots in the Mekong Delta region that vary in soil quality, size, and location, decides his/her LLL adoption to each plot on the basis of expected returns from the technology adoption. These returns, in turn, determine the farmer's WTP for the technology, which is derived through experimental auctions so-called heterogeneous valuation.

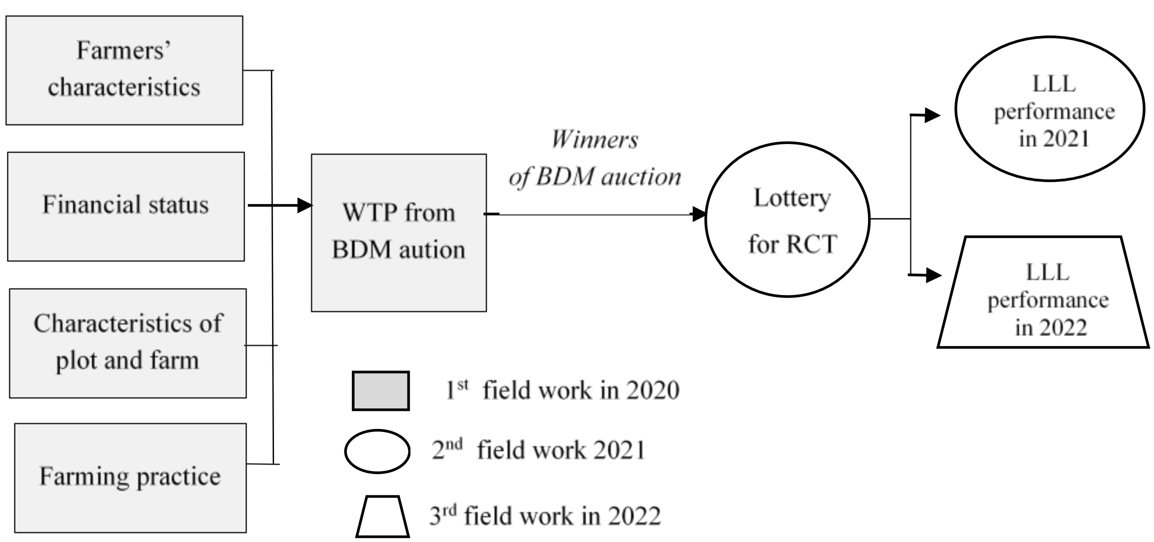


**Figure 2. Analytical framework**

To estimate farmers' WTP for the sustainable agricultural technology of LLL, we follow the approach suggested by Lybbert et al. (2018) by an experimental auction. Accordingly, 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). A sealed bid mechanism was employed with the predetermined price set at 400,000 Vietnamese Dong (VND) per hour, approximating the prevailing rental rate for LLL within the specified study areas. The BDM auction experiment was executed across 764 plots belonging to 303 households to identify 201 plots with the WTP greater than the predetermined sealed bid as the target population for the next step of loterry.

In the project stage 2, the random assignment of plots to either the LLL adoption or control groups is carried out using the RCT method. Accordingly, an intervention's impact on agriculture is assessed by randomly allocating plots to intervention or control groups, comparing outcomes, and attributing differences solely to the intervention, ensuring an unbiased evaluation. Due to the constraints of limited LLL service availability and short interval between the winter-spring and summer-autumn crops, a lottery is implemented to randomly identify the 56 plots in the assigned treatment group and 41 plots in the assigned control group in a compliance with the integrity of the RCT methodology.

The on-field LLL implementation after the completion of Winter-Spring crop in February 2021 was performed through careful timing, expert support for field flatness measurement for both control and treatment groups, and collaboration among EfD experts, local agricultural agencies and service providers for the proper LLL services from land preparation and handling laser leveling machine. In

2021, out of 56 assigned plots in the treatment group, the LLL intervention was carried out on 40 plots due to a lack of service availability and the impact of early-season rainfall on some plots. The 16 remaining plots in the assigned treatment group were received the intervention in the following year 2022 while the remaining plots were maintained as the control group. Farmers pay for the market price for the LLL service per hour based on their budget constraints, and thus this determines the number of hours of leveling for each of their plots and affects the flatness achieved which are measured right after the LLL adoption for the treatment group.

### 2.3 Empirical models

**Estimation of the demand for LLL service**

The econometric model considers the two decisions from farmers, i.e., first they decide whether or not to adopt the technology and second, they decide how much to be willing to pay for the technology implementation in the second stage. In this study, we use Cragg double hurdle model (Cragg, 1971) can be used to capture these decisions as it allows the differences in the sign and magnitude of the parameters in the two decisions (Anang and Dagunga, 2023; Ishara et al., 2023).

The sample included 303 farmers with 764 paddy plots. Since the WTP value of 100 is the minimum level to receive the LLL service, we use it as the threshold to split the plot sample divide the 764 paddy land plots into two groups. Farmers in the first group are those without demand or not willing to pay for LLL service. Meanwhile, those in the second group have the demand for the technology service supply and are willing to pay for the LLL service. In the first hurdle of this model, the adoption is modeled by a Probit model with a binary dependent variable; the adoption intensity is modeled by a truncated normal regression model in the second hurdle. The Cragg model can be written as:

The participation equation: $y_{1i}^* = X_i\beta + u_i$ (1)

$$y_{1i} = \begin{cases} 1 \text{ if } (X_i\beta + u_i) > 100 \\ 0 \text{ if } (X_i\beta + u_i) \leq 100 \end{cases}$$

The intensity equation: $y_{2i}^* = X_i\alpha + v_i$ (2)

$$y_{2i} = \begin{cases} y_{2i}^* \text{ if } y_{2i}^* > 0 \text{ and } y_{1i} = 1 \\ 0 \text{ otherwise} \end{cases}$$

where: $y_i^*$ : a latent variable

$y_i$: observed variable

$X_i$: explanatory variables

$\alpha, \beta$: estimated coeffience

$u_i, v_i$: error terms

The likelihood function of the sample in Cragg model can be written as:

$$L_{Craggit} = \prod P(y_{1i}^* \leq 0) \prod P(y_{1i}^* > 0) \prod f(y_{2i}|y_{1i}^* > 0) \quad (3)$$

And then, Amemiya (1984) clarified, for $u_i$ and $v_i$ as:

$$L_{Craggit} = \prod I(y_{1i}^* \leq 0)[1-\Phi(\frac{X_i\beta}{\sigma_1}) \prod I(y_{1i}^* > 0)\Phi(\frac{X_i\beta}{\sigma_1})\frac{1}{\sigma_2}\Phi(\frac{y_{2i}-X_i\alpha}{\sigma_2}) \quad (4)$$

where $\phi(\cdot)$ is the univariate standard normal probability density function;

$\Phi(\cdot)$ is the cumulative distribution function;

i: plot observation

Maximizing the logarithm of this log likelihood function will give the MLE estimates of the parameters of the Cragg model.

The choice of independent variables is based on previous agricultural technology adoption studies (e.g., Brenya et al., 2023; Lybbert et al. 2018; Takahashi et al., 2020; Mariano et al., 2012). These have mostly identified determinants to capture characteristics of households, plots, and farm, farming technology performance, and financial status. Wealth index (WI) was estimated using the principal component analysis (PCA) including a set of variables for productive assets, living assets, livestock types, crops, housing conditions, savings, and insurance. After the PCA, the value of WI is normalized to the normal distribution N(0,1). The Simpson index is considered in this model as the proxy for land fragmentation (Table 1).

**Table 1. Variables in the model for LLL demand analysis**

| Variables | Notation | Unit |
|---|---|---|
| **Dependent Variable** | | |
| - Adoption | DUM | = 0 if WTP <100; = 1 if WTP ≥100 |
| - Intensity of adoption | WTP | = WTP if WTP ≥100 |
| **Independent Variables** | | |
| ***Farmers' characteristics*** | | |
| - Age | AGE | Number of years old |
| - Gender | SEX | = 1: Male; = 0: Female |
| - Education | EDU | Number of schooling year |

| | | |
|---|---|---|
| - Extension | EXT | = 1: Participation; = 0: Non participation |
| - Risk acceptance | RIS | Likert scale of 1-10 points |
| ***Financial status*** | | |
| - Wealth index | WEI | Index |
| - Credit purchase | PAY | = 1: Yes; = 0: No |
| ***Characteristics of plot and farm*** | | |
| - Plot area | ARE | 1000 square meters |
| - Plot elevation | ELE | Likert scale of 1-10 points |
| - Land surface roughness | ROU | Likert scale of 1-10 points |
| - Soil types of plot | SOI | = 1: None alum, none salty<br>= 0: alum, salty, and both |
| - Plot banks | BAN | Number of other plot banks to reach the plot |
| - Simpson index | SIM | = Range from 0 to 1 |
| **Farming practice** | | |
| - Paddy cultivation techniques | TEC | = 1: Applying the advance techniques<br>= 0: None |
| - Irrigation System of Agricultural Cooperative | IRR | = 1: Yes; 0: No |
| - Intensive farming | INT | = 1: 3 crops/year; = 0: 2 crops/year |
| - Kien Giang Province | KGP | =1: Kien Giang; =0: An Giang |

**Causal effect estimation**

The utilization of randomized controlled trials (RCTs), also referred to as randomized evaluations, randomized trials, randomized experiments, or social experiments has significantly increased in the last two decades (Glewwe and Petra, 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 et al. (2023) to evaluate the potential productivity and water-saving benefits of smallholder drip irrigation in India, Yitayew et al. (2021) to examine the impact of a newly introduced improved wheat variety in Ethiopia, Nakano and Magezi (2020) to examine the impact of microcredit on the adoption of technology and productivity of rice cultivation.

For the causal effect of LLL adoption on paddy yield, the parameters will be consistently estimated with perfect compliance, i.e., all plots randomly assigned to the treatment group will apply LLL, while those allocated to the control group will not. By incorporating a dummy variable for LLL adoption in the Equation (5), the analysis will isolate its influence on yields, accounting for the unique attributes of each plot and separating it from other variables that may affect outcomes.

$$Y_i = \beta_0 + \beta_1 LLL_i + \beta_2 Z_i + \varepsilon_i \quad (5)$$

where $Y_i$ represents the outcome for plot i; $LLL_i$ is a dummy variable that takes the value of 1 if the plot i is laser levelled, and 0 otherwise; vector $Z_i$ captures specific features of plot i and $\varepsilon_i$ is an individual error term accounting for unobserved heterogeneity.

To address the parameters of causal inference and account for noncompliance in experiments, researchers utilize a model incorporating an instrumental variable to estimate the Local Average Treatment Effect (LATE) (Abadie and Cattaneo 2018; Lybbert et al. 2018). The measurement error in attenuation bias can be resolved through the instrument variable procedure (Glewwe and Petra, 2022; 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 (Glewwe and Petra, 2022; Khandker, 2009).

In this study, to address the challenge of imperfect compliance in the analysis with 16 plots assigned to the treatment group but not adopted LLL, it is crucial to address the endogeneity with the common use of an instrumental variable that influence the actual adoption of LLL but are not directly related to the outcome variable under the two-stage least squares (2SLS) estimation. This two-step process helps to mitigate the bias that arises from the endogeneity of the actual adoption decision. In the first stage, the LLL actual adoption is predicted based on the instrumental variable and other exogenous variable. The probit regression is used to estimate the probability of adopting LLL as follows:

$$P\left(LLL_i = 1 \middle| ASS_i, \mathrm{ELE}_i\right) = \Phi(\mu_0 + \mu_1 ASS_i + \mu_2 \mathrm{ELE}_i) \quad (6)$$

Where $P\left(LLL_i = 1 \middle| ASS_i, \mathrm{ELE}_i\right)$ is the conditional probability that plot i actually adopts LLL given its elevation characteristics ($\mathrm{ELE}_i$) and its assignment to the treatment group ($ASS_i$ ); $\Phi$ represents the cumulative distribution function of the standard normal distribution valuing 0 and 1; $\mu_0$ is the intercept term; $\mu_1$is the coefficient for the assignment variable ($ASS_i$) which is an instrumental variable indicating whether plot i was randomly assigned to adopt LLL (1 if assigned, 0 otherwise); $\mu_2$ is the coefficient for the elevation characteristics.

In the second stage of estimating the LLL impact on the outcome of paddy yield, the predicted values of LLL are used to estimate its impact on the paddy yield ($\widehat{LLL_\iota}$). The LATE parameter measures the average effect of the receipt of the LLL technology on the outcome among those who follow the LLL program based on their lottery selection. The estimation of the local average treatment effect (LATE) on paddy yield as in Equation 7.

$$\mathrm{YIE}_i = \varphi_0 + \beta_0(\Sigma LL_i) + \sum_{k=1}^{m}(\beta_m Z_{ki}) + \beta_9 \mathrm{STD}_i + \beta_{10}\mathrm{CRO}_i + \beta_{11}\mathrm{VAR}_i + e_i \quad (7)$$

In which $\mathrm{YIE}_i$ is the outcome of paddy yield per hectare of plot i in logarithm; $Z_{ki}$ (k=1-8, m=8) amount of input k applied for one hectare of plot i namely seed, fertilizers of nitrogen, phosphorus, and potassium, pesticide, labor, machine hours, water; $\mathrm{STD}_i$ standard deviation of land surface in logarithm; $\mathrm{VAR}_i$ is dummy variable of varieties being 1 if the crop's growing period is 95 days or longer, and 0 if the growing period is shorter than 95 days; $\mathrm{CRO}_i$ is dummy variable representing the crop time, where it takes the value 1 for the crop interval from November 2020 to March 2021 and 0 for the crop interval from November 2021 to March 2022; $\alpha_o$,$\varphi_o$ are intercepts ; $\beta$ are coefficients; $u_i$,$e_i$ are residuals. The parameter $\beta_0$ is the main parameter of interest, reflecting the local average treatment effect on the outcome dependent variable of the actual LLL adoption, under the assumption of unchanged additional variables (Glewwe and Petra, 2022).

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**Table 2. Variables in the model for local average treatment effect on paddy productivity**

| Variables | Notation | Unit |
|---|---|---|
| *Dependent variables* | | |
| - Actual adoption | LLL | = 1 if LLL actual adoption, = 0 if non adoption |
| - Paddy yield | YIE | = kg $ha^{-1}$ |
| *Independent variables* | | |
| Seed | SEE | kg $ha^{-1}$ |
| Fertilizer | | |
| - Phosphorus | P20 | kg $ha^{-1}$ |
| - Potassium | K20 | kg $ha^{-1}$ |
| - Nitrogen | NIT | kg $ha^{-1}$ |
| Pesticide | PES | g AI $ha^{-1}$ |
| Labor | LAB | hours $ha^{-1}$ |
| Machine | MAC | hours $ha^{-1}$ |
| Water | WAT | $m^3$ $ha^{-1}$ |
| Land surface | STD | centimeter |
| Crop time | CRO | =1 if Winter-Spring crop from November 2020 to March 2021<br>=0 if Winter-Spring crop from November 2021 to March 2022 |
| Paddy varieties | VAR | = 1 if crop growing period is 95 days or longer<br>=0 if crop growing period is shorter than 95 days |

## 3. Results

## 3. Results

### 3.1 Characteristics of paddy farmers, paddy plots and land fragmentation

The survey sample includes 303 paddy farmers, distributed across two provinces, with 107 farmers located in An Giang and 196 in Kien Giang. For An Giang province, the sample comprises 51 farmers in Binh Phu commune and 56 farmers in O Long Vy commune. Meanwhile, Kien Giang province accounts for 91 and 105 farmers respectively in Tan Khanh Hoa and Vinh Phu communes. The interviewees are LLL making-decision farmers in their households with middle age and high experience in paddy cultivation (Table 3). The gender disparity is pronounced, where male making-decision farmers comprise 91.7% of the population, underscoring the male-dominated nature of paddy farming. The majority of farmers have attained education up to primary and secondary school levels, reflecting the challenges in adopting new agricultural technologies among paddy farmers in these regions. A significant number of farmers in both provinces have 10-20 years of experience, indicating a seasoned workforce. While local trainings on paddy cultivation have garnered considerable farmer participation, with 62.4% of farmers taking part, there remains a notable 37.6% who have not participated, highlighting a potential area for improvement in agricultural extension services.

**Table 3. Characteristics of paddy farmers**

Unit: % of total sample

| Indicators | Range | An Giang (n=107) | Kien Giang (n=196) | Full sample (N=303) |
|---|---|---|---|---|
| Age of farmers (years old) | <35 | 9.3 | 14.8 | 12.9 |
| | 35 - 50 | 33.6 | 50.5 | 44.6 |
| | ≥50 | 57.0 | 34.7 | 42.6 |
| Gender of farmers | Female | 0.9 | 12.2 | 8.3 |
| | Male | 99.1 | 87.8 | 91.7 |
| Education of farmers | Illiteracy | 4.7 | 5.6 | 5.3 |
| | Primary school | 45.8 | 40.3 | 42.2 |
| | Secondary school | 29.9 | 41.3 | 37.3 |
| | High School | 12.1 | 10.7 | 11.2 |
| | Under-greaduated | 7.5 | 2.0 | 4.0 |
| Experience of paddy cultivattion (years) | < 10 | 12.1 | 27.6 | 22.1 |
| | 10-20 | 35.5 | 39.3 | 38.0 |
| | 20-30 | 29.0 | 22.4 | 24.8 |
| | ≥ 30 | 23.4 | 10.7 | 15.2 |
| Training times (time $year^{-1}$) | 0 | 40.2 | 36.2 | 37.6 |
| | 1-3 | 41.1 | 39.3 | 39.9 |
| | 4-6 | 14.0 | 18.9 | 17.2 |
| | ≥ 7 | 4.7 | 5.6 | 5.3 |
| Total | | 100.0 | 100.0 | 100.0 |

**Table 4. Characteristics of paddy land fragmentation**

Unit: % of total sample

| Indicators | Range | An Giang (n=107) | Kien Giang (n=196) | Full sample (N=303) |
|---|---|---|---|---|
| Farm size (ha $farm^{-1}$) | < 2.5 | 52.3 | 32.7 | 39.6 |
| | 2.5-5.0 | 32.7 | 35.7 | 34.7 |
| | ≥ 5.0 | 15.0 | 31.6 | 25.7 |
| Number of plots (plot $farm^{-1}$) | 1 | 32.71 | 32.65 | 32.67 |
| | 2-3 | 42.06 | 45.92 | 44.55 |
| | 4-5 | 21.50 | 13.78 | 16.50 |
| | ≥6 | 3.74 | 7.65 | 6.27 |
| Simpson index | 0 | 32.7 | 32.7 | 32.7 |
| | >0 to 0.6 | 36.4 | 34.2 | 35.0 |
| | >0.6 | 30.8 | 33.2 | 32.3 |

| Total | | 100.0 | 100.0 | 100.0 |
|---|---|---|---|---|

Regarding the farm size, farmers in Kien Giang province have a fairly similar distribution among the three size ranges (Table 4). The full sample reflects a moderate distribution, indicating a mix of smallholder and larger-scale farming operations across the two provinces. An Giang exhibits a higher prevalence of smaller farms, with more than 50% being less than 2.5 hectares, while Kien Giang has a more balanced distribution, including a substantial proportion of 31.6% of farms larger than or equal to 5.0 hectares. Farmers in the MDR mostly have from 2 to 3 plots; the distribution of plot numbers is not significantly different in the two provinces. For land fragmentation, the Simpson index of zero represents farmers with one paddy plot, meaning none land fragmentation; the Simpson index greater than 0.6 means high land fragmentation. Though the Simpson index values are not significantly different in the two provinces, they demonstrate 32.7% of the sample without land fragmentation and 32.3% with high land fragmentation, underscoring the importance of understanding land fragmentation in shaping sustainable agricultural practices and technology adoption

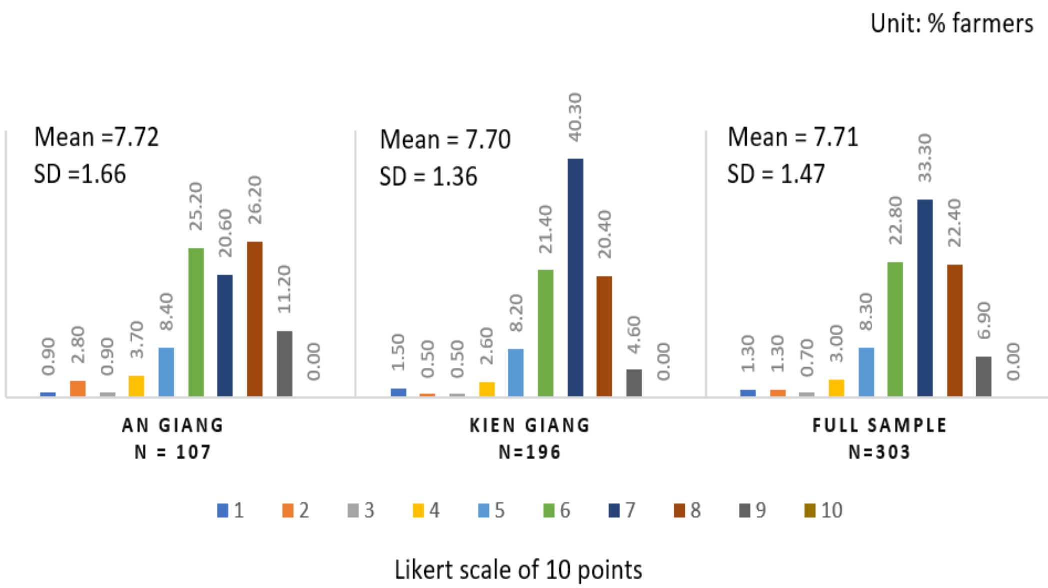


**Figure 3. Farmers' risk acceptance to LLL adoption**

The farmers' risk acceptance to the LLL adoption pertains to their willingness to accommodate deviations between the actual technology performance outcomes and their expected outcomes from the technology investment, e.g., incompletion of LLL service due to rain or unexpected paddy yield. In this study the 10-points Likert scale is used with the higher the point meaning the greater of risk acception (Figure 3). The average point of the Likert scale of 7.71 with the standard deviation of 1.47 shows that farmers mostly accept a high level of risk when investing in the technology.

**Table 5. Characteristics of paddy plots**

Unit: % of total sample

| Indicators | Unit | An Giang (N=268) | Kien Giang (N=496) | Full sample (N=764) |
|---|---|---|---|---|
| Technology in paddy cultivation | =1 if 1M6R | 0.4 | 0.0 | 0.1 |
| | if 1M5R | 26.9 | 15.3 | 19.4 |
| | if 3R3G | 11.2 | 9.9 | 10.3 |
| | if IPM practice | 0.7 | 0.2 | 0.4 |
| | = 0 if farmer's experience | 60.8 | 74.6 | 69.8 |
| Soil types | = 1 without acid and salt | 65.3 | 26.0 | 39.8 |
| | = 0 otherwise | 34.7 | 74.0 | 60.2 |
| Irrigation System of Agricultural Cooperative | = 0 if No | 29.5 | 95.6 | 72.4 |
| | = 1 if Yes | 70.5 | 4.4 | 27.6 |
| Intensive | = 1 if 3 crop year-1 | 78.0 | 13.9 | 36.4 |
| | = 0 if 2 crop year-1 | 22.0 | 86.1 | 63.6 |
| Plot elevation (10 point Likert scales) | 1 - 3 | 17.1 | 20.8 | 19.5 |
| | 4 - 6 | 62.3 | 51.6 | 55.4 |
| | 7 -10 | 20.6 | 27.7 | 25.1 |
| Land surface roughness | 1 - 3 | 49.6 | 27.8 | 35.5 |
| | 4 - 6 | 42.1 | 49.2 | 46.7 |
| | 7 -10 | 8.2 | 23.0 | 17.9 |
| Total | | 100.0 | 100.0 | 100.0 |

Note 1M6R is "one must do, six reduction". 1M5R is "one must do, five reduction". Of which, "One must" recommends that farmers must use certified seeds; "Five Reductions" include reducing seed rate, fertilizer, pesticide, water and post harvest loss; and the sixth reduction is greenhouse gas emissions; 3R3G is "three reductions, three Gains" with the reductions of seeds, fertilizer and pesticides and the increase of productivity, quality and efficiency.

The technology implementation in the MDR is not positive with a significant reliance on traditional farmer experience-based approaches; An Giang stands out a bit better than Kien Giang (Table 5). Moreover, the disparity in infrastructure, particularly in irrigation systems, are evident. An Giang has a higher percentage of agricultural cooperatives equipped with irrigation systems compared to Kien Giang. The plot characteristics of soil type, intensive farming, and roughness exhibit mostly different in the two provinces, reflecting the data variation for the analysis.

### 3.2 Analysis of LLL demand heterogeneity

By provinces, the boxes demonstrate similarity in the two provinces for the WTP greater than or equal to 100 thousand Vietnamese dong (VND) (Figure 4). For the full sample, a substantial majority of farmers possess a WTP exceeding 100 thousand VND. The WTP data has a wider dispersion in An Giang province compared to that in Kien Giang province.

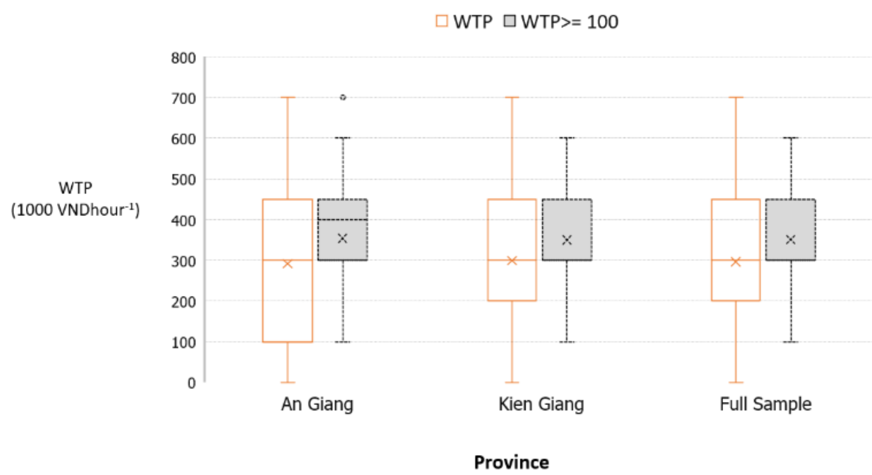


**Figure 4. WTP box plot by provinces**

By the farm sizes, the WTP means are mostly the same in three groups (Figure 5). The larger farm size, the lower the dispersion of WTP, especially at the subsample with greater 5 ha, the interquartile range (IQR) is the distance between the upper and lower quartiles is smallest of 150 thousand VND. Surprisingly, the subsample with greater 5 ha for the whole range of WTP, the dispersion is quite large, IQR equal to 300 thousand VND and the mean WTP tends to be the lowest. Farmers possessing multiple plots are inclined to select specific plots for the LLL adoption, demonstrating a willingness to pay lower prices for plots that do not align with their preferences.

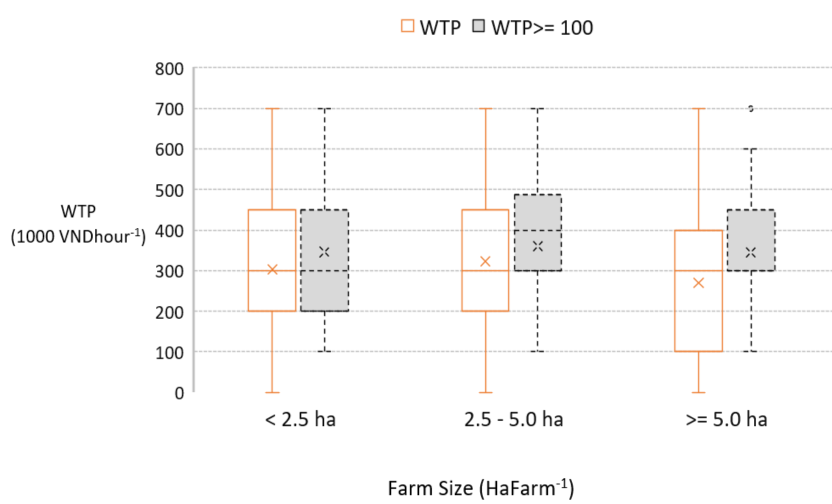


**Figure 5. WTP box plot by farm sizes**

For the box with the subsample of WTP greater than or equal to 100 thousand VND, the WTP dispersion for one-plot subgroup tends to be wider than the two other subgroups (Figure 6). Specifically, the first quartile of this box is 200 thousand VND, and the max is 700 thousand VND.

The dispersions for the two other subgroups are quite similar. The farmers with 4 or more plots have a lower WTP mean and more widely dispersed than others.

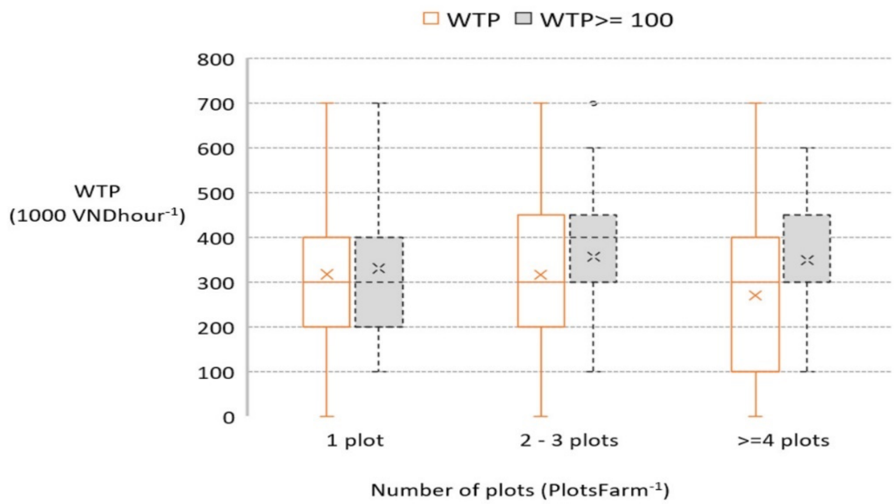


**Figure 6. WTP box plot by numbers of plots**

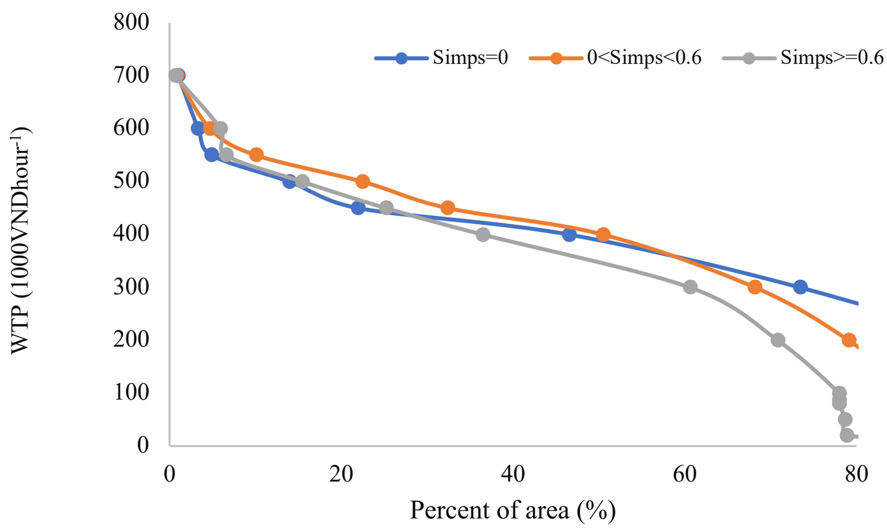


**Figure 7. LLL Demand by land fragment**

Note: The elastiscity of LLL demand at mean: ”simps = 0”: -0.5445; 0<Simps<0.6: -0.5448; ”Simps≥0.6”: -0.5591
At WTP=500, Marginal effects of WTP to the percent of LLL area: : ”simps = 0”: -7.96; 0<Simps<0.6: -9.93; ”Simps≥0.6”: -9.75

Figure 7 depicts three demand curve for three Simpson index groups. The Simpson index values at 0 if farmers have only one paddy plot. The higher Simpson index value, the more land fragmentation. The vertical axis shows the WTP for LLL service, the horizontal axis shows the percentage of area afforable at each WTP level. The LLL demand curves have the same shape among different level of land fragmentation in the three groups of Simpson index. The Kolmogorov-Smirnov (KS) tests also support these WTP distributions are insignificantly different overall as the p value is greater than the 5% level. In other words, the demand curve for LLL services is pairwise similar in comparing three groups of Simpson index. The elasticity of LLL demand at mean is respectively -0.54 and -0.56. Marginal effects will vary at each WTP level; for example WTP changes from 300 to 400 thousand VND hour$^{-1}$, the proportion of paddy area afforable for the three groups will decrease by 17.72% to 26.87% respectively.

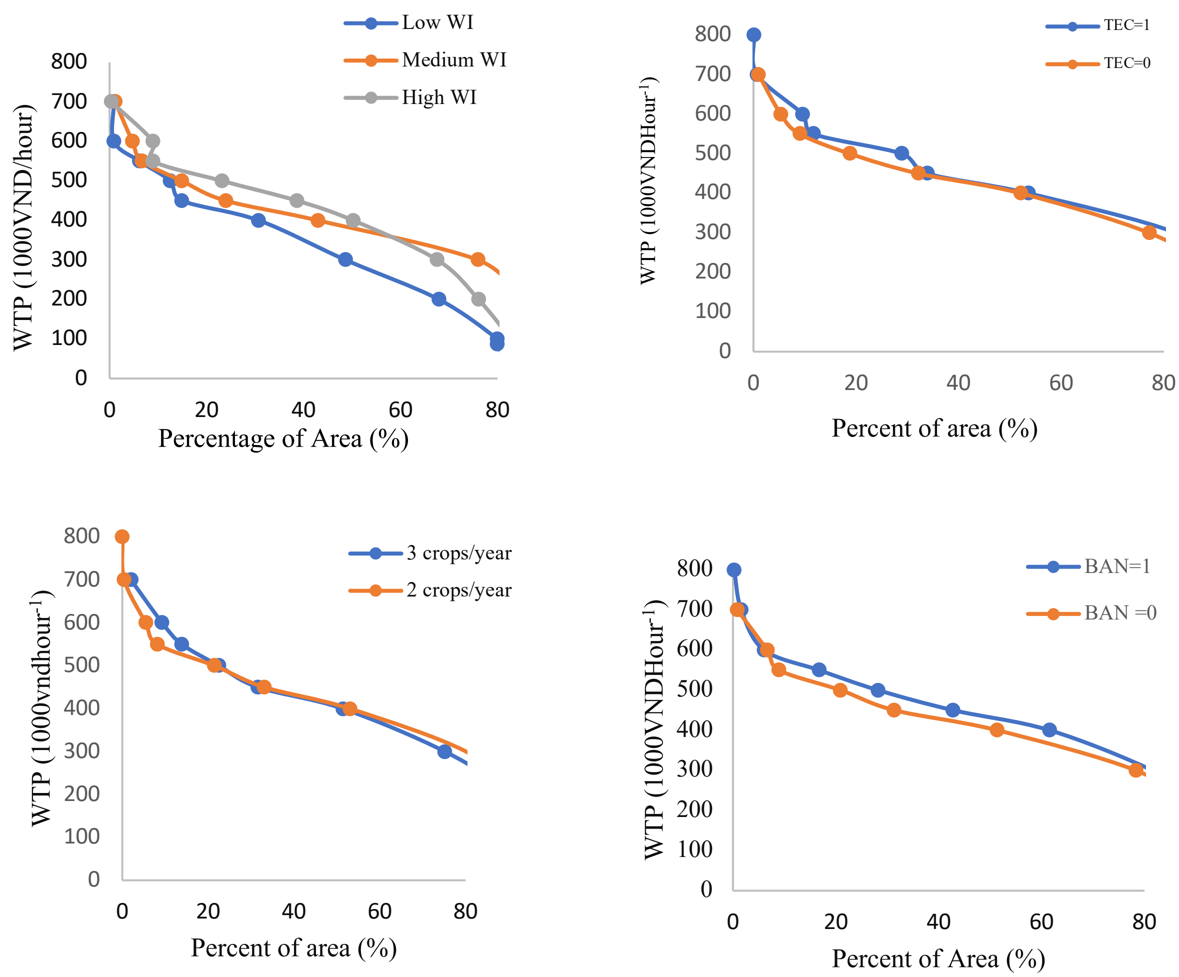


**Figure 8. Demand curve for LLL service**

The full sample is divided into 3 weath index groups (Figure 8). The results show that the LLL demand curve when WTP greater than or equal to 400 thousand VND is quite similar among three demand curves. However, for WTP lower than 400 thousand VND, the demand curve of the medium group of weath index has a lower slope. Assuming that, when the WTP is from 400 to 300 thousand VND, the percentage of land area afforable for the LLL implementation increases more strongly than that of the two remaining groups. Considering the application of technology and intensive farming, there seems to be not difference between the two groups. The plot bank number indicates the plot's geographical positioning, with higher values reflecting increase in the challenges in accessing the plot for the delivery of LLL services. The analysis suggests that farmers with any bank in the auction exhibit a willingness to pay lower compared to their counterparts with plot banks.

### 3.3 Determinants of the demand for LLL service

This study utilizes Cragg model to estimate the factors affecting to WTP for the LLL service. Appendix A4 describes the statistics of the model variables; the results of Cragg model are found in Table 6. This analysis spans various dimensions including farmers' characteristics, financial status, characteristics of plots and farms, and farming practices. In the Probit model utilized for Tier 1 analysis, a majority of the variables demonstrate a statistically significant impact on the adoption of LLL services. Variables such as age, extension services, and risk acceptance demonstrate statistically significant positive coefficients, suggesting that older farmers, those who have access to agricultural extension services, and those with a higher tolerance for risk are more inclined to adopt LLL services.

The analysis further delves into the financial dimensions influencing LLL service adoption and intensity. Both the wealth index variable exhibit significant positive effects on both the likelihood of adoption and the intensity of adoption, underscoring the importance of financial resources in the decision-making process related to demand for the LLL service. For the plot and farm characteristics, the plot area, its elevation, and the roughness of the land surface show significant effects on adoption decisions.

**Table 6. Determinants of the demand for LLL service**

| Variables | Notation | Adoption | | Intensity of adoption | |
|---|---|---|---|---|---|
| | | Coef. | Robust Std. Err. | Coef. | Robust Std. Err. |
| ***Farmers' characteristics*** | | | | | |
| - Age | AGE | 0.0130** | (0.00609) | -0.218 | (0.562) |
| - Gender | SEX | -0.591* | (0.355) | 39.87** | (19.70) |
| - Education | EDU | 0.00754 | (0.0189) | -1.915 | (1.820) |
| - Extension | EXT | 0.351** | (0.139) | 20.81 | (13.31) |
| - Risk acceptance | RIS | 0.180*** | (0.0381) | 7.538* | (4.043) |
| ***Financial status*** | | | | | |
| - Wealth index | WEI | 0.117* | (0.0647) | 25.48*** | (6.108) |
| - Credit purchase | PAY | 0.254* | (0.139) | 14.62 | (14.08) |
| ***Characteristics of plot and farm*** | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| - Plot area | ARE | -0.0098** | (0.00464) | 0.852* | (0.511) |
| - Plot elevation | ELE | -0.0724** | (0.0301) | 2.881 | (2.563) |
| - Land surface roughness | ROU | 0.0762** | (0.0313) | -2.692 | (2.858) |
| - Soil types of plot | SOI | -0.350*** | (0.134) | -10.38 | (12.65) |
| - Plot banks | BAN | 0.0213 | (0.0214) | 4.568** | (2.038) |
| - Simpson Index | SIM | -1.416*** | (0.312) | 25.27 | (20.78) |
| ***Farming practice*** | | | | | |
| - Paddy cultivation techniques | TEC | 0.390** | (0.158) | 4.627 | (12.29) |
| - Irrigation system of Agricultural cooperative | IRR | -0.203 | (0.197) | -9.364 | (16.72) |
| - Intensive farming | INT | 0.167 | (0.166) | -22.83 | (17.61) |
| - Kien Giang province | KGP | 0.0742 | (0.194) | -18.52 | (17.18) |
| *Constant* | | 0.245 | (0.661) | 240.6*** | (55.49) |
| *Sigma* | | 134.5*** | (3.967) | | |
| *Log Likelihood* | | -4331.5238 | | | |
| Observations | | 764 | | 645 | |

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

The robust standard errors were used to correct the heteroscedasticity, a common problem with the cross- section data, by using “vce(robust)” option with craggit command on the stata software. In this table, dependent variable of tier 1 is Adoption (Yes=1; No=0), dependent variable of tier 2 is intensity of adoption (WTP≥100); independent variables including farmer’s characteristics, financial status, characteristics of plot and farm and farming practice.

Interestingly, the constraint on the plot bank to reach the LLL implementation does not exhibit statistical significance within Tier 1, yet it demonstrates statistical significance within Tier 2. Furthermore, land fragmentation significantly impedes the decision to adopt LLL, as evidenced by its negative impact at a 1% significance level; this suggests an inverse relationship between land fragmentation and the likelihood of LLL adoption. Additionally, the implementation of other technology in paddy cultivation appears to facilitate the adoption of LLL.

Regarding the intensity of adoption in the truncated model in Tier 2, the variables paint a complex picture of the factors driving the depth of engagement with the LLL service. The intensity of adoption is significantly increased with the wealth index and negatively influenced by age, indicating a complex interplay between financial capability and demographic factors and a crucial role of financial resources in determining the level of engagement with agricultural sustainable technology. This demonstrates that wealth not only facilitates the initial decision to adopt but also enables a greater investment in the technology.

This nuanced analysis suggests that the plot physical attributes of area and location play pivotal roles in shaping decisions on the extent of willingness to invest in LLL services. The Simpson index for land fragmentation is not significant with the positive coefficient, meaning that the land fragmentation significantly impedes the LLL technology adoption; however, it does not affect the WTP from those with adoption decision in a statistically significant manner. Interestingly, significant plot area variable reveals farmers' preference to invest in the technology for large size plot. Farmers with the plot bank constraints are willing to increase their WTP in accordance to the numbers of plot bank to reach the LLL delivery. The other plot characteristics of elevation, roughness, and soil type are significant in the Tier 1 but not significant in the Tier 2. Understandably, farmers consider these factors in the adoption decision and drop out them for the WTP. These insights highlight the interplay between financial resources, land characteristics, and technological adoption, suggesting that strategies to increase the intensity of LLL service utilization must consider both the economic capabilities of farmers and the physical attributes of their plots.

Key demographic and behavioral traits such as age, extension services, and risk acceptance significantly influence the decision to adopt LLL services, with older farmers and those exposed to agricultural knowledge or willing to embrace risk more likely to adopt. However, when examining the intensity of adoption, financial capacity, as indicated by the wealth index, becomes a predominant factor, underscoring the role of economic resources in not just deciding to adopt but in determining the level of investment. Interestingly, while demographic factors initially drive the adoption decision, the intensity of adoption is further influenced by specific plot characteristics, such as plot area and the presence of plot banks. This distinction highlights a nuanced interplay between the initial decision-making process, driven largely by personal and behavioral factors, and the subsequent investment affordability of technology, which is influenced more by economic and physical land attributes. The analysis thus underscores the complexity of factors at play, illustrating that interventions aimed at promoting LLL services need to address both the barriers to adoption and the variables that enables a greater affordability and thus a more intensive use of such technologies.

### 3.4 Local average treatment effects of laser land leveling on paddy productivity

The analysis in this study is conducted using a sample of 97 plots observed during two seasons in 2021 and 2022, resulting in a total of 194 observations. The variable description is presented in the Table A.4 in the Appendix. 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 assigned groups. 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.

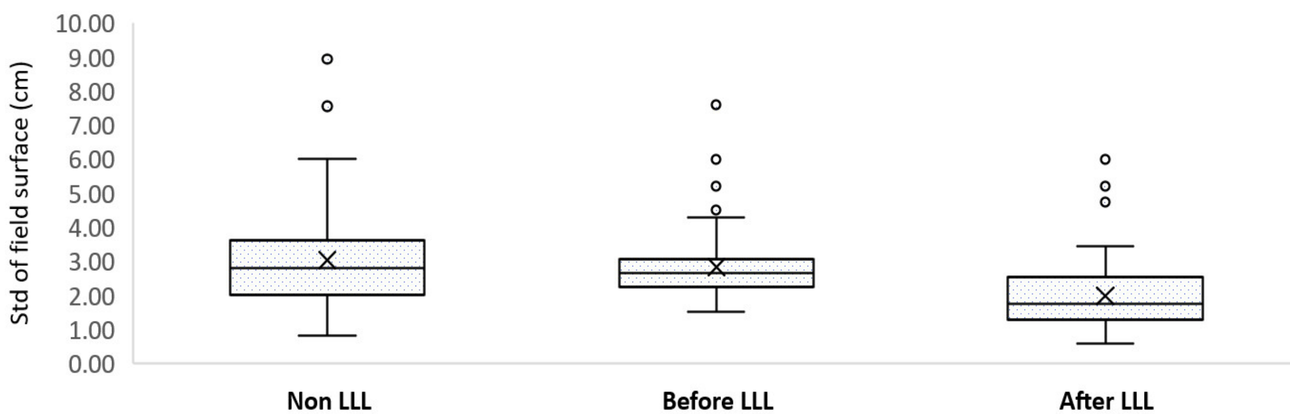


Figure 9. The standard deviation of paddy land surface

The balance test was performed using the t-test for the difference in variables to verify the correctness of the randomization process. The baseline data of the winter-spring crop in the year 2019 for the two assigned groups of control and treatment is utilized in the balance test. The T-test result in Table A.5 in the Appendix indicates there is no variable that shows a statistically significant difference at the 10% significance level in the mean values between the treatment and control groups, meaning that there is no significant difference in the mean values in each variable between the two assigned groups. This implies that the randomization process was successful in creating comparable groups and thus ensures that any observed effects can be directly linked to the intervention being studied rather than underlying differences between the groups.

**Table 7. Local average treatment effects of LLL adoption on paddy productivity**

| Variables | Notation | Coefficient | Std. err. | z | P>\|z\| |
|---|---|---|---|---|---|
| Seed | SEE | 0.1434** | 0.0598 | 2.40 | 0.018 |
| Fertilizer | | | | | |
| - Phosphorus | P2O | 0.0699*** | 0.0179 | 3.91 | 0.000 |
| - Potassium | K2O | -0.0057 | 0.0178 | -0.32 | 0.748 |
| - Nitrogen | NIT | 0.0378 | 0.0426 | 0.89 | 0.376 |
| Pesticide | PES | 0.0633* | 0.0333 | 1.90 | 0.058 |
| Labor | LAB | 0.0014 | 0.0344 | 0.04 | 0.967 |
| Machine | MAC | -0.166*** | 0.0549 | -3.02 | 0.003 |
| Water | WAT | 0.0566 | 0.0484 | 1.17 | 0.244 |
| Land surface | STD | -0.0706*** | 0.0253 | -2.79 | 0.006 |
| Crop time | CRO | 0.0588*** | 0.0198 | 2.97 | 0.003 |
| Paddy varieties | VAR | 0.1106*** | 0.0223 | 4.96 | 0.000 |
| Actual adoption | LLL | 0.0648** | 0.0291 | 2.23 | 0.027 |
| Constant | | 7.0421*** | 0.5034 | 13.99 | 0.000 |
| Observations: 194<br>F (12, 181) = 9.54 | | Wald test of indep. eqns. (rho = 0):<br>Prob > chi2 = 0.0000<br>R-squared = 0.3727 | | | |

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

Table 7 shows the regression results. The Wald test for the independence of equations and the R-squared value are crucial for understanding the robustness and explanatory power of the model. These results indicates that the independence of model equations and the overall model validity in explaining variations in paddy productivity due to LLL adoption. The estimation result of dummy variable D reflects the treatment effect of LLL performance on yield (Table 3). 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. The coefficient estimate implies that the actual adoption of LLL resulted in a 6.48% increase in paddy yield, equivalent to 492,138 kg per ha. This analysis highlights the positive effect of LLL technology in improving agricultural productivity, potentially offering a significant boost to agricultural output and farmer income.

## 4. Conclusions and policy implications

The study investigates determinants of willingness to pay (WTP) for laser land leveling technique and the heterogeneity in the demand for LLL technique across individual farmers and plot characteristics, notably focusing on land fragmentation, and the empirical impact of LLL performance on paddy productivity. The Cragg model is applied to examine the determinants of WTP for LLL service to capture both decisions on LLL demand and their affordability for LLL service. The Cragg model found that the key demographic and behavioral traits such as age, extension services, and risk acceptance significantly influence the decision to adopt LLL services; however, the plot characteristics of area and bank and financial capacity become a predominant factor to the intensity of adoption. The design of randomized controlled trials incorporate with a production function model to analyze the effects of the LLL technique on paddy productivity. The treatment effect of LLL performance results in a statistically significant increase in paddy yield of 6.48%, equivalent to 492,138 kg per ha. increase in paddy yield.

The distinction between the determinants influencing the demand for LLL technology and the magnitude of investment highlights a complex interaction between the preliminary decision-making mechanisms, predominantly influenced by individual and behavioral elements, and the ensuing extent of investment in technology, which is more significantly shaped by economic factors and the physical characteristics of land. The analysis thus underscores the complexity of factors for policy implications, illustrating that interventions aimed at promoting LLL services need to address both the barriers to adoption and the variables that enables a greater affordability and thus a more intensive use of such technologies. The results also provide managerial implications with a combination of climate smart agriculture program to promote LLL service in the decision making stage. The empirical evidence on LLL performance highlights the positive effect of LLL technology in improving agricultural productivity, potentially offering a significant boost to agricultural output and farmer income.

With respect to avenues for further research, the empirical analysis of land fragmentation utilized the Simpson index capturing four out of six land fragmentation factors, excluding plot shape and spatial distribution. Nevertheless, this is acceptable given the uniformity of plot shapes in paddy production within the MDR and the absence of spatial distribution data. The study focuses on local average treatment effect which reflects on the subpopulation of the compliers. Future research could scrutinize the fully land fragmentation index with the support of data availability in the future and generalize the analysis of average treatment effect.

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## Appendices

### Table A2. Characteristics of paddy farms

| Provinces | Indicators | Unit | Descriptive Statistic | | | |
|---|---|---|---|---|---|---|
| | | | Mean | SD | Max | Min |
| An Giang | - Farm Area | ha $farm^{-1}$ | 3.05 | 2.74 | 17.20 | 0.26 |
| | - Plot area | ha $plot^{-1}$ | 1.21 | 0.81 | 5.00 | 0.20 |
| | - Number of plots | plots $farm^{-1}$ | 2.50 | 1.51 | 7.00 | 1.00 |
| Kien Giang | - Farm Area | ha $farm^{-1}$ | 5.05 | 4.62 | 26.50 | 1.00 |
| | - Plot area | ha $plot^{-1}$ | 2.13 | 1.13 | 6.50 | 0.40 |
| | - Number of plots | plots $farm^{-1}$ | 2.53 | 1.77 | 13.00 | 1.00 |
| Total | - Farm Area | ha $farm^{-1}$ | 4.34 | 4.16 | 26.50 | 0.26 |
| | - Plot area | ha $plot^{-1}$ | 1.80 | 1.11 | 6.50 | 0.20 |
| | - Number of plots | plots $farm^{-1}$ | 2.52 | 1.68 | 13.00 | 1.00 |

### Table A3. LLL service auction

| Indicators | An Giang | | Kien Giang | | Full sample | |
|---|---|---|---|---|---|---|
| | Frequency | % | Frequency | % | Frequency | % |
| Number of farmers with WTP < 100 | 3 | 2.8 | 8 | 4.1 | 11 | 3.6 |
| Number of farmers with WTP ≥100 | 104 | 97.2 | 188 | 95.9 | 292 | 96.4 |
| Total | 107 | 100.0 | 196 | 100.0 | 303 | 100.0 |

### Table A4. Paddy plot distribution by WTP level

| WTP (000VND $hour^{-1}$) | Number of plots | | % of total plots | % of plots WTP≥100 |
|---|---|---|---|---|
| | WTP <100 | WTP≥100 | | |
| 0 | 119 | - | 15.58 | - |
| 100 | - | 53 | 6.94 | 8.22 |
| 200 | - | 100 | 13.09 | 15.50 |
| 300 | - | 172 | 22.51 | 26.67 |
| 400 | - | 119 | 15.58 | 18.45 |
| 450 | - | 69 | 9.03 | 10.70 |
| 500 | - | 85 | 11.13 | 13.18 |
| 550 | - | 13 | 1.70 | 2.02 |
| 600 | - | 26 | 3.40 | 4.03 |
| 700 | - | 8 | 1.05 | 1.24 |
| Total | 119 | 645 | 100.00 | 100.00 |

### Table A5. STD Variable before and after LLL actual adoption

| | Mean | Std.Dev | SE | Min | Max |
|---|---|---|---|---|---|
| Without LLL | 3.05 | 1.53 | 0.15 | 0.81 | 8.93 |
| With LLL | | | | | |
| - Before | 2.83 | 1.03 | 0.10 | 1.53 | 7.60 |

| | | | | | |
|---|---|---|---|---|---|
| - After | 1.99 | 0.91 | 0.09 | 0.59 | 6.00 |

## Table A.6 Variable description in the model for LATE on paddy productivity

| Variable | Unit | Without LLL ($n_1$=97 Obs.) | | | | With LLL ($n_2$=97 Obs.) | | | | Total (n=194 Obs.) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Std.Dev | Min | Max | Mean | Std.Dev | Min | Max | **Mean** | Std.Dev | Min | Max |
| YIE | kg $ha^{-1}$ | 7656 | 1020 | 6000 | 12500 | 8716 | 1654 | 5800 | 12500 | 8186 | 1470 | 5800 | 12500 |
| SEE | kg $ha^{-1}$ | 143.01 | 25.84 | 25 | 200 | 131.4712 | 29.9324 | 57.14 | 200 | 137.24 | 28.48 | 25.00 | 200.00 |
| P2O | kg $ha^{-1}$ | 105.15 | 41.12 | 33.1 | 237.69 | 101.1904 | 37.2655 | 36.92 | 198 | 103.17 | 39.19 | 33.10 | 237.69 |
| K2O | kg $ha^{-1}$ | 50.78 | 28.52 | 3.44 | 147.75 | 49.8841 | 24.3255 | 10.4 | 125.75 | 50.33 | 26.44 | 3.44 | 147.75 |
| NIT | kg $ha^{-1}$ | 131.70 | 36.15 | 79.2 | 256.15 | 117.7204 | 33.2703 | 53.03 | 192.15 | 124.71 | 35.35 | 53.03 | 256.15 |
| PES | g AI $ha^{-1}$ | 2626.56 | 1188.74 | 1031 | 7064 | 2438.9070 | 832.4707 | 1319 | 4432 | 2532.73 | 1027.84 | 1031 | 7064 |
| LAB | hours $ha^{-1}$ | 21.06 | 5.96 | 3.57 | 44.47 | 20.1998 | 5.1793 | 5.86 | 32 | 20.63 | 5.58 | 3.57 | 44.47 |
| MAC | hours $ha^{-1}$ | 8.40 | 1.28 | 4 | 10.64 | 7.0618 | 1.8140 | 3.5 | 15.93 | 7.73 | 1.70 | 3.50 | 15.93 |
| WAT | $m^3$ $ha^{-1}$ | 9624 | 2736 | 5274 | 22333 | 5999 | 1267 | 3551 | 9981 | 7811 | 2797 | 3551 | 22333 |
| STD | centimeter | 3.05 | 1.53 | 0.81 | 8.93 | 1.9895 | 0.91541 | 0.59 | 6 | 2.52 | 1.36 | 0.59 | 8.93 |
| CRO | 0,1 | 0.38 | 0.49 | 0.00 | 1.00 | 0.32 | 0.47 | 0.00 | 1.00 | 0.35 | 0.48 | 0.00 | 1.00 |
| VAR | 0,1 | 0.62 | 0.49 | 0.00 | 1.00 | 0.76 | 0.43 | 0.00 | 1.00 | 0.69 | 0.46 | 0.00 | 1.00 |

## Table A.7 Balance test of variables for the baseline

| Variable | Assi = 0 (N=42) | | | Assi = 1 (N=56) | | | T Test for equality of mean | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | STD | SE | Mean | STD | SE | Mean diff | P- value | Conclusion |
| YIE | 7,715.00 | 908.56 | 140.19 | 7,860.79 | 1,410.16 | 188.44 | -145.79 | 0.536 | equality |
| SEE | 147.25 | 23.48 | 3.62 | 145.35 | 28.51 | 3.81 | 1.90 | 0.726 | equality |
| P2O | 107.70 | 42.60 | 6.57 | 104.57 | 40.91 | 5.47 | 3.13 | 0.713 | equality |
| K2O | 49.52 | 31.34 | 4.84 | 54.84 | 29.32 | 3.92 | -5.32 | 0.390 | equality |
| NIT | 132.09 | 36.86 | 5.69 | 132.91 | 32.69 | 4.37 | -0.82 | 0.908 | equality |
| PES | 547.03 | 673.09 | 112.18 | 400.90 | 530.06 | 73.51 | 146.12 | 0.258 | equality |
| LAB | 23.98 | 7.11 | 1.10 | 27.20 | 7.40 | 1.12 | -3.22 | 0.120 | equality |
| MAC | 8.42 | 1.96 | 0.30 | 8.06 | 1.73 | 0.23 | 0.37 | 0.327 | equality |
| WAT | 9,723.95 | 3,266.16 | 503.98 | 9,084.95 | 2,003.83 | 267.77 | 639.01 | 0.267 | equality |
| STD | 3.00 | 1.62 | 0.25 | 2.83 | 0.91 | 0.12 | 0.17 | 0.544 | equality |

For the two dummy variables of COR and VAR, the Chi-square tests give the conclusion of statistically insignificant different with the Fisher's exact value greater than 5%.