Spatial Dependency of Technical Efficiency in Rice Farming: The Case of Bohol, Philippines

Valerien O. Pede
International Rice Research Institute
v.pede@irri.org

Justin McKinley
International Rice Research Institute
j.mckinley@irri.org

Alphonse Singbo
International Crops Research Institute for the Semi-Arid Tropics
a.singbo@cgiar.org

Kei Kajisa
International Rice Research Institute
and Aoyama Gakuin University
k.kajisa@sipeb.aoyama.ac.jp

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Valerien O. Pede[1*], Justin McKinley[1], Alphonse Singbo[2], and Kei Kajisa[1,3]

[1] International Rice Research Institute, DAPO Box 7777, Metro Manila, Philippines

[2] International Crops Research Institute for the Semi-Arid Tropics, BP 320 Bamako, Mali

[3] Aoyama Gakuin University, 4-4-25 Shibuya, Shibuya-ku, Tokyo 150-8366, Japan

[*]Corresponding Author:
Valerien O. Pede
Email: v.pede@irri.org
Phone: +63 2 580-5600

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1. Abstract

We investigate spatial dependency among technical efficiency levels of rice producers on the Central Visayan island of Bohol, Philippines in two separate ecosystems: rainfed and irrigated. Results revealed evidence of spatial correlation in technical efficiency levels for both residential and plot neighborhood. There is a stronger spatial dependency among farmers in the rainfed ecosystem and particularly in the farm plot neighborhood structure. These results are most likely a result of producers facing similar environments with less control over their fields than producers in the irrigated ecosystem. This study also used spatial panel econometrics techniques to investigate spatial dimension in farmers' technical efficiency in regression models. Results strongly show evidence of spatial dependence in household and farm plot neighborhood.

Keywords: Efficiency analysis, rice, spatial dependency, technical efficiency

2. Introduction

Spatial dependency has often been overlooked in economic modeling. It wasn't until the 1990's that the role of space was more frequently incorporated into economic modeling (Anselin 2002; Bockstael 1996). Spatial econometrics originated in regional science, which was focused primarily on spatial problems and solutions for urban centers and regions (Anselin 1988). The use of spatial econometrics in agriculture also began in the 1990's with the realization that factors such as climate, pest populations, land configurations, and soil characteristics all had spatial variability (Bockstael 1996; Weiss 1996). Another geographical issue that is investigated in agriculture is the neighborhood effect. Anselin (2003) discusses the significance of neighbors' influences on economic decisions. Neighborhood interactions change individuals' decisions, information sets, preferences, and behavioral outcomes. In agriculture, neighborhood interactions have primarily been deployed to investigate drivers of technology adoption (Case 1992; Bandiera & Rasul 2006; Conley & Udry 2010; Ward & Pede 2014; Langyintuo & Mekuria 2008; Maertens & Barrett 2012)

In a broad term, technical efficiency (TE) refers to the ability of a farmer to achieve the maximum output possible given a set of inputs. TE is often measured in terms of the ratio of the observed output to the frontier output, given the corresponding level of inputs used by the farm. TE scores can be driven by several factors, including technology adoption among farmers. Although there is a robust literature on TE in agriculture (Zhu et al. 2012; Idiong 2007; Dung et al. 2011; Ogundari & Ojo 2007; Michler & Shively 2014; Karagiannis & Tzouvelekas 2009; Kolawole & Ojo 2007; Rejesus et al. 2013; Shantha et al. 2013; Oyekale 2012; Alvarez 2004; Bravo-Ureta et al. 2011; Gebregziabher et al. 2012; Quilty et al. 2014; Balde et al. 2014;

Hossain & Rahman 2012; Khai & Yabe 2011; Battese & Rao 2002; Coelli & Battese 1996; Sauer & Latacz-Lohmann 2014; Baruwa & Oke 2012) there have been few attempts to investigate spatial dependency among levels of TE. Farrell (1957), expressed concerns about spatial factors such as climate and location influencing efficiency (Farrell 1957, p. 270). Although concerns existed, the econometric techniques required to complete such an analysis was not available in Farrell's time. There is in fact very little research that incorporates spatial dependency in TE scores presently available.

Although limited, some research has been conducted that incorporates spatial dependency in TE scores. Druska and Horrace (2004), extended the estimator presented by Kelejian and Pruncha (1999) applied to a stochastic frontier model (see Aigner et al. 1977; Meeusen & Van Den Broeck 1977) for panel data (see Schmidt & Sickles 1984) of 171 Indonesian rice farmers. Schmidt et al. (2008) combined stochastic frontier analysis with spatial econometric analysis following the Bayesian paradigm (see Koop & Steel 2001; Kumbhakar & Tsionas 2005) to investigate geographical variation of outputs and farm productivity for 370 municipalities in Brazil. Areal et al. (2012) investigated the spatial dependence of 215 dairy farms in England at a sub-municipality level also using a Bayesian paradigm.

Spatial considerations are important to capture how individuals may behave similarly. Manski (1993) puts forth three hypotheses that help to describe why individuals in the same group tend to act in a similar fashion. These hypotheses are: 1.) endogenous effect: the propensity of an individual to act in some way varies with group behavior, 2.) exogenous (contextual)[1] effects: the propensity of an individual to act in some way varies with the exogenous characteristics of

[1] Referred to as contextual effect in sociological literature (see Coleman 1968; Sewell & Armer 1966; Crane 1991; Mayer & Jencks 1989).

the group, and 3.) correlated effects: individuals in the same group act similarly because they face similar institutional environments and have similar individual characteristics. In the case of agriculture, all of these hypotheses hold, especially correlated effects. Neighboring producers face similar climatic conditions, similar access to technology and information, and are likely to come from a similar background. It is for this reason that spatial considerations should not be ignored.

This study is unique in that it investigated spatial dependency of individual farmers in two separate neighborhood structures using GPS coordinates from both the household and the farm plot. The purpose of this study was to explore spatial dimensions in farmers' TE scores. There are several reasons why spatial dependency may exist in farmers' TE levels in either irrigated or rainfed environments. Firstly, despite the presence of agricultural extension agents, it is still expected that farmers rely on their social networks for information on input allocation, management practices, etc. (Ward & Pede 2014; Bandiera & Rasul 2006; Conley & Udry 2010; Foster & Rosenzweig 1996; Banerjee et al. 2013; Case 1992; Maertens & Barrett 2012; Langyintuo & Mekuria 2008). When the proportion of adopters increases in an individual's social network, so too does the individuals probability to adopt (Ward & Pede 2014). Sociology literature concurs that peer influences have a influence on individual behavior (Ostrom 2000). This social network influence is likely to result in observed correlation among farmers' TE levels. Secondly, farmers who belong to the same production ecosystem and sharing a common resource pool, not only exchange agricultural information but also depend on the regulations set within the resource pool for their agricultural system management. This effect is expected to be accentuated among irrigated farmers as they are members in water user groups, also called Turnout Service Areas (TSA) groups which collectively make irrigation management decisions regarding their shared turnout gate and farm ditches. This formal TSA group could also result in dependency in farmers' TE levels. In fact, a forthcoming publication in the same region from Tsusaka et al. (2015), used artefactual field experiments to unveil that neighborhood effects influenced social behavior more strongly using the household neighborhood structure over the farm plot neighborhood structure. This result could be from the interactions of the TSA group in irrigation management, consistent with the theory of social norm evolution through common pool resource management (Ostrom 2000). Lastly, farmers belonging to a rainfed ecosystem face similar environmental and climatic challenges with less control over their field environments than their irrigated counterparts. This means that the farming skills in the rainfed area is very location specific and thus the exchanging of such skills among the neighbors strongly influence their productivity. This could result in higher spatial dependencies among rainfed farmers' TE levels.

Data from 492 individual rice producers in Bohol, Philippines, which were collected by the authors for four consecutive rice growing seasons in 2009 and 2010, were used in this study to build a panel over four periods. Analyses were performed following the spatial panel estimation procedure outlined in Millo and Piras (2012). This study differs from previous studies on spatial dependencies among TE scores in that it uses farm-specific data, whereas previous studies were aggregated to sub-municipalities. Furthermore, this conducts a spatial panel data analysis, a field that has recently experienced increased methodological progress (Millo & Piras 2012). This study aimed to investigate the presence of spatial dependency among TE levels of rice farmers in the Central Visayan island of Bohol in the Philippines by employing the most recent methodologies in both TE analysis and spatial analysis. This study investigated the difference in spatial dependency between farmers from both rainfed and irrigated ecosystems by using two different neighborhood structures constructed using GPS location from the farmers' households as well as their farm plots. These analyses will be carried out on balanced spatial panel data covering four growing seasons in Bohol, Philippines.

3. Theory

Stochastic frontier production function model specification

Since the seminal works of Aigner et al. (1977) and Meeusen and van der Broeck (1977), the stochastic frontier approach (SFA) has been the most commonly used to model production and measure efficiency on farm-level data. The SFA approach estimates the parametric form of a production function and recognizes the presence of random error terms in the data. One component of the error term reflects the inefficiency in production while the other component represents the random effects outside producer control. The production frontier itself is stochastic since it varies randomly across farms due to the presence of the random error component.

Following the model proposed by Battese and Coelli (1992), the stochastic frontier production function for a panel data with a time trend component can be defined by:

$$Y_{it} = f(x_{it}; \boldsymbol{\beta}) \exp(V_{it} - U_{it}) \tag{1}$$

and

$$U_{it} = \eta_{it}u_i = u_i\exp\left(-\eta(t-T)\right), \tag{2}$$

where Y_{it} denotes the production at the t-th observation $(t = 1,2,\dots,T)$ for the i-th farm $(i = 1,2,\dots,N)$; $f(x_{it};\boldsymbol{\beta})$ is a function of a vector x_{it} which represents a *1 x k* vector of know functions of inputs of production and other explanatory variables associated with the i-th farm at the t-th observation (farm-specific variables); $\boldsymbol{\beta}$ is a *k x 1* vector of unknown parameters to be estimated; the V_{it}s are assumed to be iid $N(0,\sigma_V^2)$ random errors, independently distributed of the U_{it}s; the u_is are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed, such that u_i is obtained by truncation of the $N(\mu,\sigma_u^2)$ distribution; η is an unknown scalar parameter and T is the last time period. This model is such that the non-negative farm effects, U_{it}, decrease, remain constant or increase as t increases, if $\eta > 0$, $\eta = 0$ or $\eta < 0$, respectively. A positive value of η implies that paddy farmers tend to improve their level of technical efficiency over time. Further, if the Tth time period is observed for the ith farm then $U_{it} = u_i$, $i = 1,2,\dots,N$.

In the island of Bohol, located in the central Visayas Region of the Philippines, paddy farms are specialized farmers that produce only paddy for market and consumption. A translog functional for the stochastic frontier production is chosen for the technical efficiency analysis. The translog is a flexible functional that can be viewed as a second-order Taylor expansion in logarithms of any function of unknown form. Unlike the Cobb-Douglas function, it imposes no restriction a priori on the elasticities of substitution between inputs and outputs. Time is included in the specification to capture the effect of Hicksian neutral technological progress. The interaction terms of inputs with the time variable allow for technological progress to be nonneutral. The data for all inputs and the output are normalized by respective geometric means prior to estimation. This makes the model's parameter estimates directly interpretable as elasticities evaluated at the geometric mean of the data. To cope with the great number of zero observations for fertilizer inputs, we follow the procedure proposed by Battese (1997). We replace original variable for fertilizer with $x_{it}^k = \max\left(x_{it}^k, D_{it}^k\right)$, where D_{it}^k is dummy variable defined by $D_{it}^k = 1$ if $x_{it}^k = 0$ and $D_{it}^k = 0$ if $x_{it}^k > 0$. Thus, the final estimable form of the translog stochastic production function becomes

$$\ln y_{it} = \alpha_0 + \sum_k \alpha_k \ln\left(x_{it}^k\right) + \beta_k D_{it}^k + \frac{1}{2}\sum_k \sum_j \alpha_{kj} \ln\left(x_{it}^k\right) \log\left(x_{it}^j\right) +$$

$$\theta_1 t + \theta_2 t^2 + \textstyle\sum_k \lambda_k t \ln\left(x_{it}^k\right) + V_{it} - U_{it} \tag{3}$$

And

$$U_{it} = u_i \exp\big(-\eta(t - T)\big) \tag{4}$$

y is the output, t is a time index ($t = 1, \dots, T$), k and j are the inputs and α_0, α_k, α_{kj}, θ_1, θ_2, λ_k, and η are the parameters to be estimated. The symmetry property is imposed by restricting $\alpha_{kj} = \alpha_{jk}$. The term u_i are farm specific inefficiency terms as defined above. To explore the possibility of unobserved heterogeneity between paddy farmers, the following technical inefficiency effect specification of the parameter u_i is defined

$$u_i = \omega_1 \text{Educ} + \omega_2 \text{Size} + \omega_3 \text{Gender} + \omega_4 \text{Remittance} \tag{5}$$

Where the variable *Educ* consist of the years of formal schooling of the primary decision maker of the household, *Size* is the total number of people living in the household, *Gender* represents the gender of the primary decision maker of the household, and *Remittance* consists of the ratio of remittance as it relates to total household income. The first three variables capture the human capital endowment of the sample farmer: education for quality, size for amount, and the gender for advantage or disadvantage of female head. The remittance indicates the importance of rice farming. Hence, we hypothesize that it has a negative effect on efficiency.

Educated farmers are generally assumed to have better farming capacity and access to information and, therefore to be more efficient (Battese & Coelli 1995). In the instance that one of the farm-specific variables takes a value one and the coefficients of all other variables are zero, then the model should be specified following Stevenson (1980) and Battese and Coelli (1992). If all elements of the ω-vector are equal to zero, then technical inefficiency effects are not related to the explanatory variables and the model specification from Aigner, Lovell and Schmidt (1977) following a half-normal distribution is obtained.

The level of technical efficiency (TE_{it}) measures how close a given farm i is from the estimated efficient frontier at time t. The deviations of the TE_{it} measures from 1 indicate the percentage by which output produce would increase to reach the production frontier. Following Battese and Coelli (1992), the minimum-mean-squared-error predictor of the technical efficiency of the ith farm at the t-th time period is defined by

$$TE_{it} = E[\exp(-U_{it})\,|V_{it} - U_{it}] \tag{6}$$

The method of maximum likelihood is proposed by Battese and Coelli (1995) for simultaneously estimation of the parameters of the stochastic frontier and the model for technical inefficiency effects (Schmidt 2011). The likelihood function and its partial derivatives with respect to the parameters of the model are presented in Battese and Coelli (1992). The likelihood function is expressed in terms of the variance parameters, $\sigma^2 \equiv \sigma_V^2 + \sigma_U^2$ and $\gamma \equiv \sigma_U^2/\sigma^2$.

Spatial dependency

In order to fully exploit the panel nature of the data in investigating the determinants of farmers' TE scores, a spatial panel estimation procedure was considered. Following Millo and Piras (2012), the general panel model with spatially lag dependent and autoregressive errors is given as:

$$\boldsymbol{y} = \lambda(\boldsymbol{I_T} \otimes \boldsymbol{W_N})y + \boldsymbol{X}\beta + \mu \tag{7}$$

$$u = (\boldsymbol{i_T} \otimes \boldsymbol{I_N})\mu + \varepsilon \tag{8}$$

$$\varepsilon = \rho(\boldsymbol{I_T} \otimes \boldsymbol{W_N})\varepsilon + v\ , \tag{9}$$

where, $\boldsymbol{y}$ is an *NT x 1* vector of observations on the dependent variable, $\boldsymbol{X}$ is an *NT x k* matrix of observations on k independent variables, $\boldsymbol{I_T}$ is a *T x T* identity matrix, $\boldsymbol{W_N}$ is the *N x N* spatial weight matrix with zeros as diagonal elements, $\boldsymbol{i_T}$ is a *T x 1* vector of ones, $\boldsymbol{I_N}$ is a *N x N* identity matrix, is a vector of time invariant individual specific effects assumed to be spatially not autocorrelated. The error term ε has spatial autoregressive structure. The spatial parameters are λ and ρ. Additional assumptions to be considered are: $v_{it} \approx iid(0, \sigma_v^2)$ and $\varepsilon_{it} \approx iid(0, \sigma_\varepsilon^2)$.

The individual effects could follow a fixed or random effect structure. In case the random effect model appropriately fit the data, the error structure u is given as:

$$u = (\boldsymbol{i_T} \otimes \boldsymbol{I_N})\mu + \lfloor \boldsymbol{I_T} \otimes (\boldsymbol{I_N} - \boldsymbol{\rho W_N})^{-1} \rfloor v \qquad (10)$$

whereas, he model with spatial autocorrelation process in the individual effects can be written in reduced form as:

$$\boldsymbol{\mu} = \lfloor \boldsymbol{I_T} \otimes (\boldsymbol{I_N} - \boldsymbol{\rho W_N})^{-1} \rfloor \varepsilon \qquad (11)$$

$$\varepsilon = (\boldsymbol{i_T} \otimes \boldsymbol{I_N})\mu + \boldsymbol{v} \qquad (12)$$

where, $\boldsymbol{\mu}$ represents a vector of cross-sectional specific effects, and $\boldsymbol{v}$ a vector of innovations that vary over cross-sectional and time periods (see Kapoor, Kelejian, & Prucha (2007), cited in Millo and Piras (2012)).

This estimation strategy follows the procedure outlined in Millo and Piras (2012). Firstly, The spatial Hausman test was used to determine the most appropriate model specification between a fixed effect and a random effect model specification. Next, the Lagrange Multiplier tests developed in Millo and Piras (2012) were used to determine the appropriate spatial processes.

Estimation of spatial models requires specification the spatial structure of observation units considered in the study. As such, a distance-based weight matrix $\boldsymbol{W_N}$, of a Boolean type with elements w_{ij} was defined, taking value 1 when observation i and j are neighbors and 0 when they are not.[2]

4. Data

Data for this study were collected for the Japan International Cooperation Agency (JICA) by the International Rice Research Institute (IRRI) to conduct an impact assessment of the Bohol Irrigation Development Project in the Philippines. The project area of the Bohol Irrigation System (BIS) in the northeastern portion of the provincial island of Bohol, located in the central Visayas Region of the Philippines (Figure 1). Data used in this study covered four growing seasons with unique rainfall and dam water supply characteristics: 1.) 1st season 2009, 2.) 2nd season 2009, 3.) 1st season 2010, and 4.) 2nd season 2010 (Table 1). In total, 1,160 observations remain in the balanced panel. There are 492 observations per season from two different ecosystems: 202 observations and 290 observations from rainfed and irrigated ecosystems, respectively. Over the four surveyed seasons, the study area experienced drought, floods, and normal seasons (Table1.)

[Figure 1 about here]

[Table 1 about here]

To make comparison between two agro-ecosystems fair, our rainfed sample must be the counterfactual of the irrigated sample. There are several methods to address the issue of selection bias such as difference-in-difference (DID), propensity score matching (PSM), or instrumental variables (IV) method (Khandker et al. 2009). The data for this study were

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[2] The weight matrix $\boldsymbol{W_N}$ is of dimension $N \times N$ and has 0 as diagonal elements.

selected using a counterfactual observation for adjacent rainfed ecosystems in order to match the rainfed producers with "similar" irrigated producers (JICA 2012). These counterfactuals were determined using agronomic and socio-economic characteristics (JICA 2012).

The Bayongan irrigation system spans 14 villages in three municipalities and is expected to service as many as 4,104 hectares in the future (JICA 2012). This irrigation system is made up of a reservoir, main irrigation canal, secondary canals, turnouts, and farm ditches. Management of the system changes at different levels. The National Irrigation Administration is responsible for the maintenance of the reservoir and main canal. Secondary canals fall under the management of the Irrigators' Association (IA). IAs are made up of several TSA groups, which is the name given to farmers who share one turnout gate. Finally, the turnouts and farm ditches are managed by individual TSA consisting of 20 individual farmers on average (JICA 2012). These data are unique because GPS coordinates were recorded at both the farm plot as well as the farmers' residences. This allows for two types of neighborhoods (plot and residential) to be defined for each farmer.

5. Results

Descriptive Statistics

Statistics for variables that were used in the efficiency analysis are available in Table 2. Farmers from the rainfed ecosystem were found to have a higher rate of education on average, 6.10 years of formal schooling as compared to 5.73 years for farmers from the irrigated ecosystem. Household size was found to have the same average mean across ecosystems with 5.61 persons per house as the average. There were more female led households in the rainfed ecosystem than the irrigated ecosystem with 7.55% and 4.91%, respectively. Also, the percent of income coming from remittances was also higher in the rainfed ecosystem than the irrigated at 7.42% and 4.70%, respectively. Average yields were higher on average for farmers from the irrigated ecosystem than the rainfed ecosystem with yields of 2.35 tons ha^{-1} and 1.44 tons ha^{-1}, respectively (Figure 2).

[Table 2 about here]

[Figure 2 about here]

Technical efficiency estimates

The maximum likelihood parameters (MLE) of the stochastic production frontier with inefficiency effects are estimated using the software Stata version 13.0 (Stata Corp, College Station, TX, USA). The complete set of results is provided in Table 3. A one-sided likelihood is used to test whether technical inefficiency is present in the dataset. For the dataset, the null hypothesis of no inefficiency is rejected, and thus, it is appropriate to analyze the dataset with a stochastic production frontier. For the inefficiency effects, a positive sign of a coefficient implies a positive impact on efficiency – whereas a negative coefficient sign implies an efficiency reducing effect. For the two paddy faming systems, the variance parameters, σ^2 and γ in Table 3, are statistically significant at the 5% level. Moreover, the ratio parameter γ is estimated at 0.63 and 0.43 for irrigated and rainfed ecosystems, respectively, indicating that technical inefficiency plays an important role in explaining output variability among paddy rice farmers in the Bohol island. This also indicates that the inefficiency is higher among the rainfed farmers. Further, the hypotheses that time-invariant models for paddy farm effects apply is rejected as the parameter η is statistically significant at the 1%, level, indicating that technical efficiency highly varied across the year. Because the estimate for the parameter, η, is positive for the rainfed system ($\hat{\eta} = 0.188$) the technical efficiencies increase over time, according to the assumed exponential model, defined by Equation (2). In contrast, the negative value of this parameter for the irrigated farming indicates that technical efficiencies for rice producers using irrigated farming system decrease over time.

[Table 3 about here]

Table 3 reports the parameter estimates of the first-order terms of stochastic production frontier and the structural parameters of the inefficiency effects. As the output and input variables are normalized around their geometric mean values, the first order parameters can be interpreted as input elasticities for the sample average farm. All estimated elasticities have the correct sign and the coefficients associated with labor, land and fertilizer are statistically significant and positive. The largest effect on the inefficiency in both ecosystems was found to be that of labor with a coefficient 0f 0.4747 and 0.4443 for irrigated and rainfed ecosystems, respectively. Fertilizer use had the second largest effect on inefficiency with a coefficient of 0. 0.3021 and 0.2295 for irrigated and rainfed ecosystems, respectively. Interestingly, the magnitudes of the elasticities for most inputs in the irrigated ecosystem were higher than those in the rainfed ecosystem, indicating complementarity of controlled irrigation water and physical inputs. This holds particularly so for fertilizer.

The time trend parameters (θ_1 and θ_2) are statistically significant for irrigated farming system and suggests that a hypothetical sample average irrigated farm would have had an annual decline rate of technical change of 21.1 percent

Moving to the factors explaining efficiency levels, regression estimates show that for both rice farming systems, education of the producer positively affects technical efficiency. Moreover, the coefficient is larger in the rainfed. This indicates the farming in rainfed is more skill demanding than in irrigated. The main reason behind this may be that in the irrigated area the farming is already standardized under controlled ecology, while in the rainfed area farming requires skills dealing with various situations occurring under uncontrolled ecology. Household size statistically affects producer of the irrigated farms. Remittance ratio has a negative effect on the efficiency as we have hypothesized.

Table 4 contains summary statistics for the estimated efficiency scores, and Figure 3 presents histograms of the efficiency estimates for the two farming systems. The shape of these histograms suggests a higher variability of efficiency scores for the two farming systems.

[Figure 3 about here]

[Table 4 about here]

Spatial dependency of TE scores

Irrigated farmers were found to have higher levels of technical efficiency on average but until this point spatial dependencies in the data have been excluded. To incorporate spatial dependencies, two *N x N* neighborhood weight matrices were constructed with N=492. Both matrices capture the entire sample, inclusive of 202 rainfed and 290 irrigated farmers. Two neighborhood structures were defined: the household neighborhood structure with neighbors being defined as those within a threshold distance of 0.82 kilometers and the farm plot neighborhood structures with neighbors being defined as those within a threshold distance of 1.15 kilometers. Because these are panel data with the same respondents returning for each of the four seasons the same weight matrix can be used for the panel analysis. Given that the surveys have been conducted on two consecutive years, it is assumed that the residential as well as plot coordinates likely remain the same throughout the four seasons thus maintaining constant neighborhood structures. The weight matrix used for the household neighborhood structure had dimension 492 x 492, with a total of 4528 non-zero links. On average, each household had 9.2 links. The weight matrix used for the farm plot neighborhood structure had dimension 492 x 492, with a total of 8546 non-zero links. On average, each household had 17.4 links.

Using a dataset inclusive of both irrigated and rainfed ecosystems and the before-mentioned weight matrix a Moran's *I* statistics was estimated was estimated for the TE levels for both plot and residential neighborhood.[3] Interestingly, the Moran statistics was found to be significant in both plot and the residential neighborhood structure, indicating a pattern of spatial dependency in TE estimates. Although both neighborhood structures show spatial dependency, the magnitude of the dependency is slightly higher for residential neighborhood (Figure 4). The figures provided in Figure 4 are known as Moran's scatter plots. These scatter plots shows the TE estimates of every individual (on the x axis) against the average TE of their neighbors (on the y axis). Observations in the lower left quadrant represent farmers with low TE and having neighbors with low TE. Similarly, observations in the upper right quadrant represent farmers with high TE and having neighbors with high TE. Observations in the other quadrants represent

[3] The Moran's *I* statistics is defined as:

$$I = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x}) / \sum_{i=1}^{n}(x_i - \bar{x})^2$$

where w_{ij} are elements of the weight matrix, and the variable x is measured in deviation from its mean.

association of low TE farmers and having high TE neighbors, and vice versa. Spatial dependency can be seen when the fitted line has a positive slope.[4] The spatial dependency seen in Figure 4 may be explained by the neighborhood effect where social interactions with neighbors can result in knowledge dispersion about farming practices and technologies. Spatial dependency was found to be more pronounced in the rainfed ecosystem (Figure 5). One likely explanation for this is that farmers in the rainfed ecosystem have very localized skills whereas the farming practices used in the irrigated ecosystem are already very standardized across the irrigation system. Additionally, farmers growing in a rainfed ecosystem are subject to the same variations in climatic conditions as their neighbors. Result in Figure 5 showed that higher levels of spatial dependency existed in the rainfed ecosystem.

[Figure 4 about here]

[Figure 5 about here]

Results of spatial analysis are presented in Table 5. The first two columns show estimation results for the non-spatial model. The Hausman test is insignificant, indicating that a random effect model appropriately fits the non-spatial estimation of the panel data. The next set of columns shows the spatial estimation of the panel data under two neighborhood structures: residential and plot. In both cases, the Hausman test is insignificant, supporting a random effect model. We therefore went on to estimate a random-effects model with spatially lag dependent and autoregressive errors (RE-SARAR) for the two neighborhood structure. Estimation results show that the spatial dependency parameters (Lambda and Rho) are significant in residential as well plot neighborhood. In particular the spatially lagged parameter is positive and significant,

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[4] The slope of the fitted line in the scatter plot represents the Moran's *I* statistics.

with a close magnitude for residential and farm plot neighborhood structures. This indicates that correlation exist between the efficiency levels of farmers proximate farmers, and could be the result of information exchange, and it seems that this happens at the residential and also farm plot level. This is somewhat expected as the residential and plot neighborhoods are both environments in which one would expect information exchange to happen. Social interactions are more likely to be more intensified within the residential neighborhood structure than at the farm plot level. Social events such as weddings, receptions, meetings, parties are often held at farmers' residence and represent ideal opportunities for information exchanges. Additionally, farmers often socialize after work and exchange information about their farming practices and experience. Similarly, the farm plot neighborhood offers opportunities for farmers to witness the input decision and management practices of their peers and their observed outcome. The spatial error parameter rho, though negative is also significant with a higher magnitude at the plot neighborhood. This could be capturing the correlated effects discussed in Manski (1993). Farmers from the same neighborhood tend to have similar TE levels because they face similar political, institutional, or environmental conditions. This makes sense in the context of rained environment where farmers' management practices depend mainly on rain and weather conditions. Likewise, farmers in a commonly managed irrigation environment like the Bohol irrigation face same regulations on water supply and usage, and this could be translated into similar TE levels. Conversely, access to water decreases from the beginning of the river to the end, the changes in water access could reduce the spatial dependency of farmers in the irrigated ecosystem.

The estimated regression also shows some noteworthy results. Education has a consistent and positive effect in both residential and plot neighborhood.[5] More years of formal schooling increased technical efficiency. Assuming that more years of formal schooling is positively correlated with willingness or ability to learn new techniques and technologies, increased education can further support the hypothesis that the neighborhood effect and social networks are driving technical efficiency through the dissemination of new techniques and technologies. Household size and remittances was found to be insignificant in all estimated models. While one would expect household size not to significantly affect because more farmers reach out to hired labor for farm operations, the non significance of remittances appears counter-intuitive, especially in the context of the Philippines where many farmers rely on remittances to buy inputs and hire labor for farm operations.

[Table 5 about here]

6. Conclusions

This study used two different neighborhood structures and spatial panel econometrics techniques to investigate spatial dimension in farmers' technical efficiency levels. The analysis was carried out with data for four seasons in Bohol, Philippines and using a balanced spatial panel. Results revealed that yield over approximately 2 ton ha^{-1}, depending on the season, resulted in similar TE scores. Meaning, the additional output of paddy production was the result of additional inputs. Education was found to be significant in non-spatial estimates as well as in both neighborhood structures. Although higher levels of formal education increase efficiency

[5] It should be noted that the non-spatial model over-estimate the effect of education on farmers' TE. Moreover, the non-spatial model indicates a negative and significant effect of households' size, which the non-spatial models do not show under the two neighborhood structures.

the exact reason is uncertain. One potential explanation is that increased education could increase managerial abilities as seen in Kalaitzandonakes & Dunn (1995). Managerial ability has been shown in previous studies to increase efficiency in TE estimates (Wilson et al. 2001; Kalaitzandonakes & Dunn 1995; Kirkley et al. 1998).

The neighborhood effect in TE scores was most pronounced in the rainfed ecosystem using the farm plot neighborhood structure. This result is most likely explained by the hypothesis of correlated effects brought forth by Manski (1993). In the rainfed ecosystems, producers face more similar environments with less control over them than their counterparts in the irrigated ecosystem. Moreover, access to irrigation water can change significantly while moving from head to tail on the river. This could not only decrease the level of dependency as a result of sudden changes in irrigation access but so too could the directionality of the neighborhood structure involved with water access from a flowing river.

Future studies should revisit the levels of TE using a directional neighborhood structure in the irrigated ecosystem. This could help further investigate how a neighborhood structure influences TE specifically in regards to producers' proximity to the head of the river and concurrent water access.

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7. References

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Table 1 Rainfall and dam water characteristics by season (JICA 2012).

Season	**Characteristics**
Wet season 2009	Normal rainfall & Plenty of dam water supply
Dry season 2009	Low rainfall & Limited dam water supply
Wet season 2010	Normal rainfall & Moderate dam water supply
Dry season 2010	Abnormally high rainfall & Moderate dam water supply

Table 2 Socio-economic characteristics of producers by ecosystem.

	Rainfed (n=808)	Irrigated (n=1160)	Difference
Yield (Ton/ha)	1.44	2.35	0.91***
	(0.95)	(1.17)	
Education (Yrs.)	6.10	5.73	0.37***
	(3.48)	'(3.01)	
Household size	5.61	5.61	0.00
	(2.33)	(2.59)	
Female led house (%)	7.55%	4.91%	2.64%
Remittance†	7.42%	4.70%	2.72%

Note: '***' difference is statistically different at the one percent level
†: Calculated as remittance as a portion of total income

Table 3 Stochastic Production Frontier Estimated Parameters

Variable	Irrigated Ecosystem		Rainfed Ecosystem	
	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	0.4080***	0.118	–0.0957	0.149
Ln seed	–0.0504	0.070	0.0655	0.097
Ln labor	0.4747***	0.105	0.4443***	0.112
Ln land	0.1199	0.123	0.2510	0.166
Ln fertilizer	0.3021***	0.053	0.2295***	0.073
Ln Capital	0.1217	0.088	0.0158	0.116
Dummy for fertilizer	0.1648***	0.059	0.1792**	0.077
Ln seed × Ln seed	–0.0063	0.019	0.0428**	0.019
Ln labor × Ln labor	–0.066	0.043	–0.0367	0.060
Ln land × Ln land	0.0387	0.086	–0.1623	0.163
Ln fertilizer × Ln fertilizer	0.0456***	0.007	0.0586***	0.013
Ln capital × Ln capital	0.0168	0.046	–0.0076	0.105
Ln seed × Ln labor	–0.0086	0.056	0.0497	0.068
Ln seed × Ln land	0.0384	0.075	–0.1033	0.107
Ln seed × Ln fertilizer	–0.0483	0.037	–0.0413	0.044
Ln seed × Ln capital	–0.0055	0.059	–0.0317	0.076
Ln labor × Ln land	–0.0423	0.086	0.2438*	0.139
Ln labor × Ln fertilizer	–0.0011	0.039	–0.1130**	0.049
Ln labor × Ln capital	0.1094	0.072	–0.1150	0.098
Ln land × Ln fertilizer	0.0457	0.048	0.0494	0.078
Ln land × Ln capital	–0.1253	0.110	0.1110	0.238
Ln fertilizer × Ln capital	–0.0191	0.033	–0.0196	0.061
Time	–0.211**	0.101	–0.0474	0.117
Time × Time	0.0605**	0.024	–0.0053	0.028
Time × Ln seed	0.0334	0.030	0.0333	0.046
Time × Ln labor	–0.0330	0.0428	–0.0032	0.052
Time × Ln land	0.1038**	0.051	–0.0511	0.075
Time × Ln fertilizer	–0.0417*	0.021	–0.0154	0.033
Time × Ln capital	–0.0366	0.036	0.0311	0.054
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.4144***	0.050	0.3961***	0.040
$\gamma = \sigma_u^2/\sigma^2$	0.6378***	0.046	0.4356***	0.063
η	–0.2215***	0.056	0.1885***	0.043
μ	–0.1706*	0.102	–0.2153**	0.104
Log likelihood	–883.72		–965.64	
Observations	1,584		1,240	

Note: '***', '**', and '*' are statistically different from zero at the 1, 5, and 10 percent levels, respectively
Figures in parentheses are standard errors

Table 4. Summary Statistics of Efficiency Score Estimates

Ecosystem	Observations	Mean	Std. Err.	Min.	Max.
Irrigated	1584	0.7906	0.7906	0.2724	0.9672
Rainfed	1240	0.7463	0.7463	0.2103	0.9395

Table 5 Results of SARAR model

	Non-Spatial Models		Spatial Models			
			Farm Plot		Residential	
	FE	RE	FE	RE	FE	RE
Intercept	0.7480***	0.7442***		0.0155***		0.0280***
	(0.0088)	(0.0111)		(0.046)		(0.0045)
Education	0.0032**	0.0028***	0.0006*	0.0006**	0.0006**	0.0007**
	(0.0011)	(0.0009)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Household Size	–0.0021*	–0.0018*	0.0004	0.0003	0.0002	0.0001
	(0.0011)	(0.0010)	(0.0003)	(0.003)	(0.0003)	(0.0003)
Female Household Head	0.0026	–0.0002	0.0008	0.0005	0.0007	0.0019
	(0.0134)	(0.0115)	(0.0033)	–0.004	(0.0033)	(0.0037)
Remittance	0.0027	0.0023	–0.0012	–0.0010	–0.0003	–0.0002
	(0.0075)	(0.0074)	(0.0018)	(0.0022)	(0.0018)	(0.0021)
Irrigation		0.0078		–0.0002		–0.0008
		(0.0105)		(0.0002)		(0.0050)
Lamda			0.98***	0.97***	0.97***	0.96***
Rho			–1.30***	–0.99***	–0.92***	–0.92***
Phi				56.00***		54.11***
AIC						
Diagnostic Tests						
Chi^2 Hausman Test	0.8941		9.1513		8.4789	
LM1†				0.0239		0.0239
LM2‡				0.005		0.0062
LMH $^{\Phi}$				2276.65***		2323.30***
CLMlamda ά				13.50***		13.89***

Note: '***', '**', and '*' are statistically different from zero at the 1, 5, and 10 percent levels, respectively

†: tests the null hypothesis of no random effect assuming no autocorrelation

‡: tests the null hypothesis of no autocorrelation assuming no random effect

$^{\Phi}$: tests the joint null hypothesis of no random effect and no spatial autocorrelation

ά: tests the null hypothesis there is no autocorrelation assuming that there is random effects

Figures in parentheses are standard errors

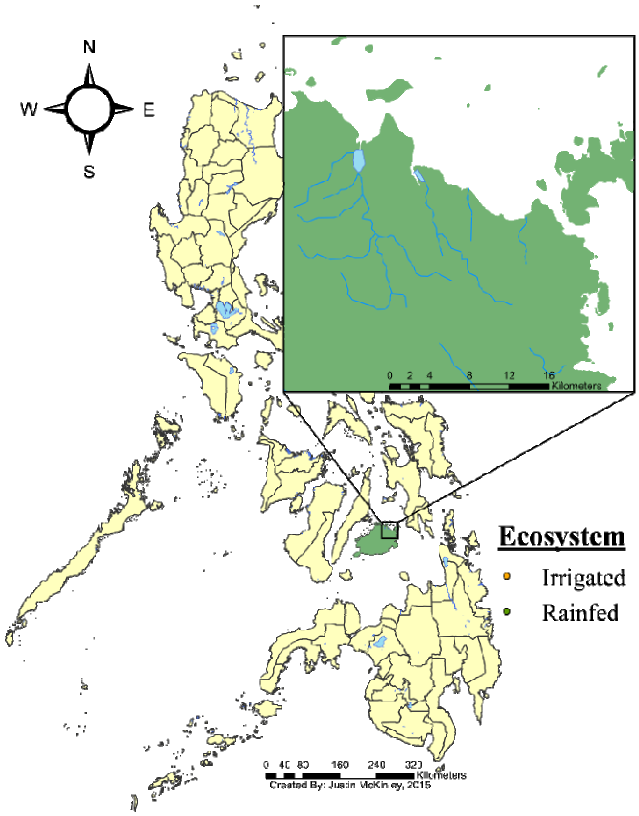

Figure 1 Locations of study sites designated by ecosystem

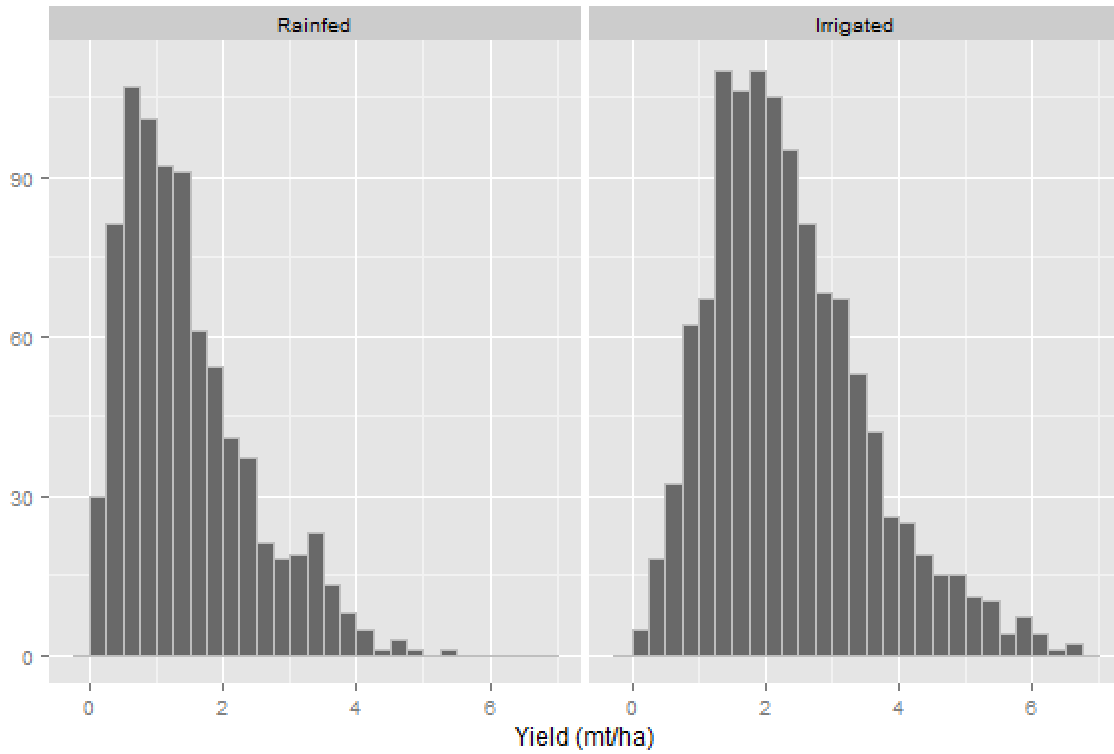

Figure 2 Histograms of paddy yield for rainfed and irrigated ecosystems

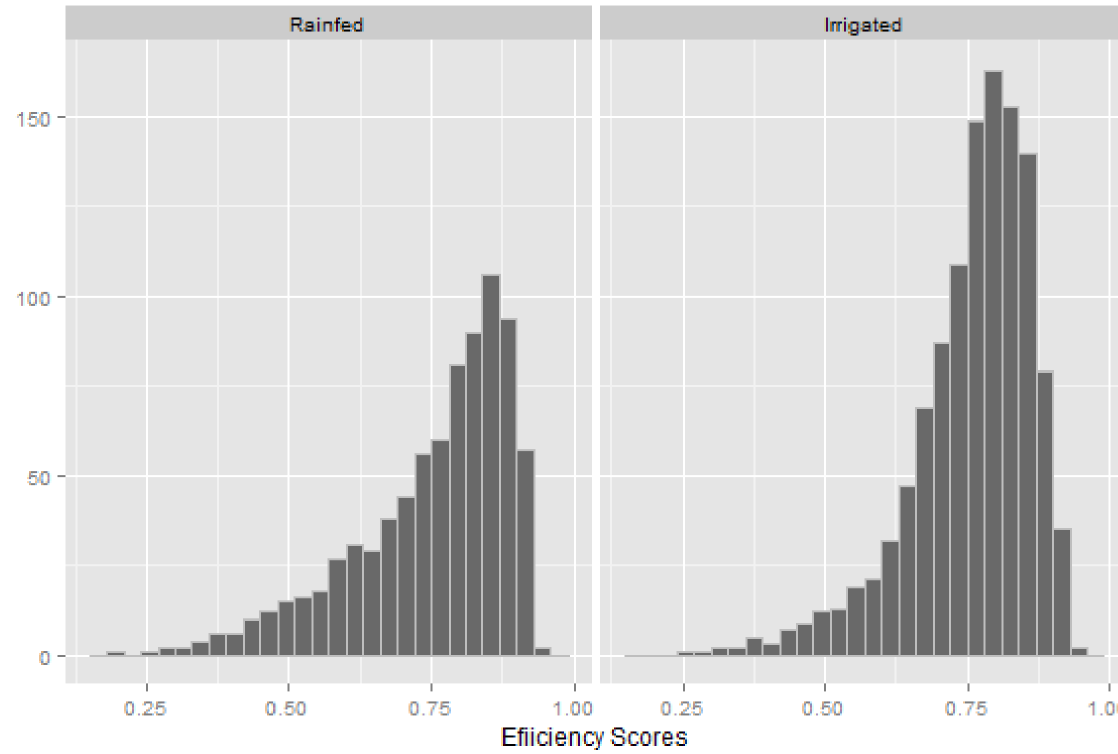

Figure 3 Histograms of efficiency score estimates for rainfed and irrigated ecosystems

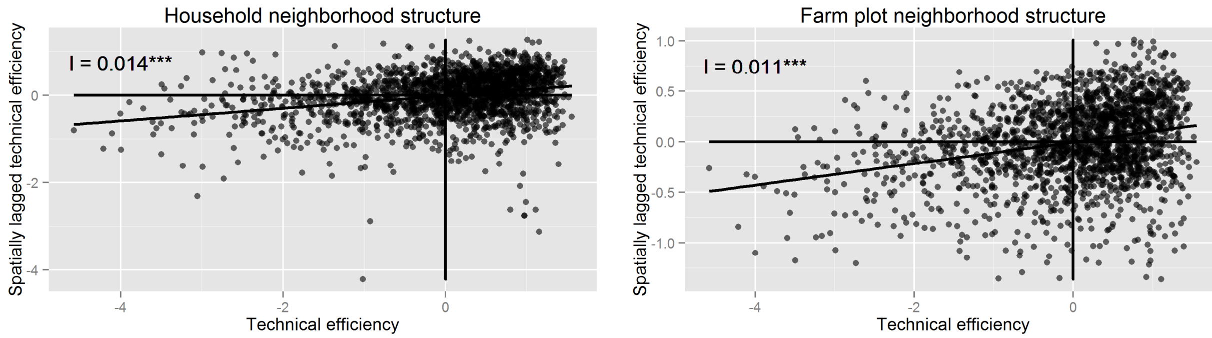

Figure 4 Moran's scatter plots for all ecosystems at the residential and farm plot neighborhood

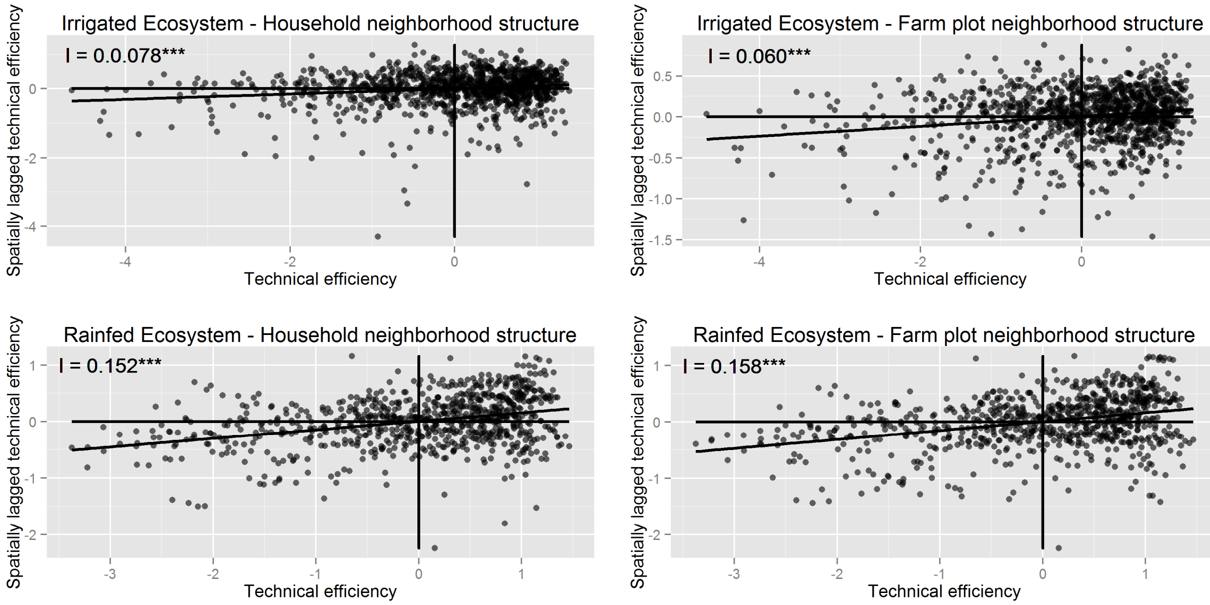

Figure 5 Moran's scatter plots for irrigated and rainfed ecosystems in different neighborhood structures.