# Assessment of Neighborhood and Spillover Effects on Technical Efficiency of Irrigated Rice Farmers

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ABSTRACT

*Neighborhood and spillover effects on technical efficiency were investigated among 270 randomly drawn farming households from 18 irrigated villages in Guimba, Nueva Ecija, Philippines, using a two-step procedure. In the first stage, stochastic frontier production function was used to estimate farmer's technical efficiency; in the second stage, appropriate spatial econometric models of technical efficiency were estimated. Spatial econometric models adopted in this study detected spatial dependency on technical efficiency in the error term of the spatial model across seasons and locations, which can be associated with unobserved factors that similarly influence farmers' technical efficiencies at the same time. Farm size, income, and regular contact and consultation with agricultural technicians were found to significantly affect technical efficiency. Results of the spatial regression show that owner-cultivator status and loamy soil are associated with increased technical efficiency. The local government of Guimba can use findings of this study in formulating agricultural policies and implementing essential interventions to improve the technical efficiency of rice farmers.*

**Keywords:** technical efficiency, production function, rice, spatial dependence, spatial econometric
**JEL Classification:** C59, O12, Q12, R15

## INTRODUCTION

Rice is the most important food crop of many developing countries and the staple food of more than half of the world's population (IRRI 2013a). More than a billion people (about 20% of the world's population) depend on rice cultivation for their livelihood. Asia, where about 90 percent of rice is grown, has more than 200 million rice farms, most of them smaller than 1 hectare (ha) (IRRI 2013b).

Rice is an essential part of the diet of many Filipinos and is grown by many farmers. The Philippines is the eighth largest rice producer in the world, accounting for 2.8 percent of global rice production (Virola 2011). In 2012, the area harvested to rice in the Philippines was about 4.7 million ha, producing 18 million tons (T) of rice (FAO 2013). Even so, the country was the world's largest rice importer in 2010. With less than 50 percent of agricultural area planted to rice, coupled with the country's high population growth rate, its rice production could supply only about 90 percent of its requirements (Dawe, Moya, and Casiwan 2006).

Aiming at self-sufficiency in food staples by 2013 and maintaining this through 2016, the Department of Agriculture of the Philippines launched the Food Staples Sufficiency Program (FSSP) in 2011 (Lesaca 2011). Self-sufficiency means satisfying the domestic requirements for food, seed, processing, and feeds through domestic production. While the program's overall goal is self-sufficiency in food staples, FSSP is mainly focused on raising productivity and competitiveness in rice, the country's main staple (Department of Agriculture 2012). One way of increasing rice production is by expanding the land area devoted to rice. However, land availability for rice production is constrained by the country's growing population and rate of urbanization. This constraint highlights the importance of farm productivity and technical efficiency in order to increase rice production.

Technical efficiency relates to the degree by which a farmer produces the maximum feasible output from a given bundle of inputs (an output-oriented measure) or uses the minimum feasible level of inputs to produce a given level of output (an input-oriented measure) as defined in Galawat and Yabe (2012). It also shows the ability of a farmer to use best practices so that no more than the necessary amount of a given set of inputs is used in producing the best level of output (Carlson 1968).

The most popular approach to measuring technical efficiency is the use of stochastic frontier production function (Aigner, Lovell, and Schmidt 1977; Rahman 2003; Coelli et al. 2005). Its specification for cross-sectional data involves a production function, which has an error term with two components: one to account for random effects and the other to account for technical inefficiency. This approach has been used in studies to analyze technical efficiencies in industrial firms in Spain (Hernandez-Sancho et al. 2012), swine production in Hawaii (Sharma, Leung, and Zaleski 1999), plantain production industry in Nigeria (Bifarin et al. 2010), tomato farms in northern Pakistan (Khan 2012), and rice production in China (Fan 1999), Brunei Darussalam (Galawat and Yabe 2012), and the Philippines (Villano and Fleming 2004; Pate and Tan-Cruz 2007; Luis et al. 2010; Gomez and Neyra 2010; Koirala, Mishra, and Mohanty 2013, 2016).

Areal, Balcombre, and Tiffin (2012) noted that the assessment of economic processes such as efficiency estimates in agricultural production is a spatial phenomenon. Spatial dependence in production efficiency refers to the correlation between the efficiency levels of the farms and those of neighboring farms

(Areal, Balcombre, and Tiffin 2012). It has a number of potential sources, including soil quality, climatic conditions, socio-economic aspects, and other location-specific attributes. For instance, spatial dependence in technical efficiency can be observed because farmers in an area may imitate their neighbors, especially when the neighboring farmers earn good profit. Other factors that cause spatial dependency are level of infrastructure in the area and the climatic and topographic conditions of the area where the residence or farm is located (Areal, Balcombre, and Tiffin 2012). According to the literature (Maertens 2009; Nivievskyi 2009), farmers imitating other farmers is part of the process of technology diffusion or adoption.

Ordinary least square (OLS) regression is unsuitable when there is spatial dependence between observations because spatial dependency leads to spatial correlation, which violates standard statistical techniques that assume independence among observations. Disregarding the spatial aspects of the data may produce inefficient or biased estimates and consequently misled inference (Anselin 2001; Mitchell 2013).

To cope with situations where data observations are spatially related, spatial econometric techniques have been developed. Spatial econometrics is a subfield of econometrics that deals with the treatment of spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data (Anselin 2003). Spatial econometrics provides ways to modify the standard OLS regression approach to overcome the problem of spatial dependence (Mitchell 2013).

Igliori (2005); Areal, Balcombre, and Tiffin (2012); Tsionas and Michaelides (2015); and Affuso (2010) employed spatial econometric techniques in their analysis of technical efficiency in agriculture. In the Philippines, Tsusaka et al. (2015) studied rice farmers in rural areas using methodologies from experimental and behavioral economics, household survey, and spatial econometrics. This study tested the neighborhood dependence of such social behaviors using a spatial econometric technique, while controlling the socio-economic factors. Its most remarkable finding is that in the irrigated areas, the farmers' altruistic behavior and contributory behavior spill over to their neighbors. Pede et al. (2015) also investigated spatial dependency of technical efficiency levels among rice producers in Bohol (in central Philippines) in two ecosystems: rainfed and irrigated. The analyses used balanced spatial panel data covering four growing seasons. The study had two separate neighborhood structures using global positioning system (GPS) coordinates from both the household and the farm plot and adopted the specification strategy of Millo and Piras (2012) to determine the appropriate spatial processes. It found that spatial correlation was present in technical efficiency levels for both residential and plot neighborhood and that spatial dependency was stronger among farmers in the rainfed ecosystem, particularly in the farm plot neighborhood.

Similar to Pede et al. (2015), this study looks at the neighborhood and spillover effects on technical efficiency of Filipino rice farmers, using separate neighboring structures for residence and farm locations. However, this study was conducted in an irrigated area in northern Philippines and used cross-sectional data. To the authors' knowledge, this is the first attempt that spatial correlogram is used to determine the optimal cut-off distance of the neighborhood structure for the spatial models.

The main objective of the study is to assess the neighborhood and spillover effects on technical efficiency of irrigated rice farmers in Guimba, Nueva Ecija, northern Philippines. Specifically, this study aims to: (1) assess the technical efficiency of irrigated rice farmers in Guimba, Nueva Ecija; (2) examine if there is a spatial dependence or neighboring effect on farmers' technical efficiency; and (3) evaluate and examine the spatial dependence and neighborhood spillover effects of socio-economic and agronomic characteristics, social capital, and technical efficiency.

## THEORETICAL FRAMEWORK

### Production Function and Technical Efficiency

Technical efficiency is the effectiveness with which a given set of inputs is used to produce an output. A firm is said to be technically efficient if it is producing the maximum output from the minimum quantity of inputs, such as labor, capital, and technology (Pettinger 2012). Under the assumption of fixed input, technical efficiency is measured as the ratio between the observed output and the maximum output. Alternatively, it is the ratio between the observed input and the minimum input under the assumption of fixed output (Porcelli 2009). To estimate the technical efficiency, the study used the stochastic frontier production function proposed by Aigner, Lovell, and Schmidt (1977); Meeusen and Van den Broeck (1977); Bravo-Ureta and Rieger (1991); and Bravo-Ureta and Evenson (1994). This specification has an error term with two components: one to account for random effects and the other to account for technical inefficiency (Coelli 1996). This model can be expressed as:

$$Y_i = f(X_i; \beta) + \varepsilon_i \tag{1}$$

where:

$Y_i$ denotes output of the $i^{th}$ farm,

$X_i$ is a vector of functions of actual input quantities used by the $i^{th}$ farm,

$\beta$ is a vector of parameters to be estimated, and

$\varepsilon_i$ is the composite error term, which is defined as:

$$\varepsilon_i = v_i - u_i \tag{2}$$

where $v_i$ are random variables that are assumed to be independently and identically distributed $N(0,\sigma_v^2)$ random errors and independent of $u_i$, where $u_i$ are non-negative random variables that are assumed to account for technical inefficiency in production and are often assumed to be independently and identically distributed as truncations at zero of normal distribution with mean $\mu$ and variance $\sigma_v^2(|N(\mu, \sigma_u^2)|)$.

Estimators for $\beta$ and variance parameters ($\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$) are provided by the maximum likelihood estimation of Equation (1). Expanding Equation (1) and subtracting $v_i$ from both sides yields;

$$Y_i^* = Y_i - v_i = f(X_i;\beta) - u_i \tag{3}$$

where $Y_i^*$ is the observed output of the $i^{th}$ firm, which was adjusted for the stochastic noise captured by $v_i$. Equation (3) is the basis for deriving the technical efficiency input vector. The measure of technical efficiency of each farm relative to Equation (1) is defined as:

$$TE_i = E(Y_i^* \mid u_i, X_i) / E(Y_i^* \mid u_i = 0, X_i) \tag{4}$$

where $Y_i^*$ is the production of the $i^{th}$ farm. When the dependent variable is in the original units, then

$$TE_i = (X_i\beta - u_i)/(X_i\beta) \tag{5}$$

However, when the dependent variable is in logs, then

$$TE_i = \exp(-u_i) \tag{6}$$

Here, the values of technical efficiency are between 0 and 1.

**Spatial Econometric Model**

In a cross-sectional setting with $n$ observations, the estimation procedure starts with a general model where a farmer's technical efficiency depends on his/her own agricultural and socio-economic characteristics, human capital, and social capital:

$$y = X\beta + \varepsilon \tag{7}$$

where **y** represents an $(n \times 1)$ column vector of technical efficiency of individual farmers; $X$ represents an $(n \times k)$ matrix containing $k$ variables, which measures the farmer's own agricultural and socio-economic characteristics, human capital, and social capital; $\beta$ represents an $(k \times 1)$ column vector containing the coefficients of explanatory variables; and $\boldsymbol{\varepsilon}$ represents an $(n \times 1)$ column vector of the residual or error term.

To include a neighborhood effect in the model, a spatial lag operator is used, which is a weighted average of random variables at "neighboring" locations. Spatial lag refers to a new variable that emphasizes the similarity to a distributed lag term rather than a spatial shift (Anselin and Griffith 1988). Spatial lag is represented by an $(n \times n)$ spatial weight matrix $W$, which is constructed from the geographical coordinates of $n$ sampled farmers. In this study, the weight matrix was based on a cut-off distance (standardized values). Anselin (2003) formally expressed a spatial lag for $y$ at $i$ as:

$$[Wy]_i = \sum_{j-1}^{n} w_{ij}\, y_j \tag{8}$$

or in matrix form as $Wy$, where $y$ is an $(n \times 1)$ vector of the technical efficiency of the farmers. The elements of the spatial weight matrix are typically row-standardized, such that for each $i$, $\sum_{j-1}^{n} w_{ij} = 1$. Consequently, the spatial lag may be interpreted as a weighted average (with $w_{ij}$ being weights) of the neighbors.

To capture the neighborhood effect, Equation (7) can be modified into four spatial models adopted from Anselin and Bera (1998):

$$y = \rho Wy + X\beta + \varepsilon \tag{9}$$

$$y = X\beta + \varepsilon,\ where\ \varepsilon = \lambda W\varepsilon + \mu \tag{10}$$

$$y = \rho Wy + X\beta + \varepsilon,\ where\ \varepsilon = \lambda W\varepsilon + \mu \tag{11}$$

$$y = X\beta + \varphi WX + \varepsilon \tag{12}$$

where:

| | |
|---|---|
| $y$ | is the $(n \times 1)$ column vector of technical efficiency of individual farmers; |
| $X$ | is the $(n \times k)$ design matrix containing the explanatory variables, |
| $\beta$, | the $(k \times 1)$ vector with parameters, |
| $\rho$, | the scalar spatially autoregressive parameter; |
| $\lambda$ | is the scalar spatial autoregressive disturbance parameter; |
| $W$ | is an $(n \times n)$ weight matrix; |
| $Wy$ | is the neighbor's weighted average technical efficiency; |
| $WX$ | is the neighbor's weighted average socio-economic characteristics; |
| $\varepsilon$ | is an $(n \times 1)$ column vector of the residual or error term; and |
| $\mu$ | is an $(n \times 1)$ independently and identically distributed vector of error terms. |

The described specifications are also referred to as autoregressive or spatial lag model (Equation 9), spatial error model (Equation 10), a combination of spatial lag and spatial error or ARAR[1] model (Equation 11), and cross regressive model (Equation 12).

In the spatial lag model, spatial dependence was incorporated as an additional regressor in the form of a spatially lagged dependent

1 Double autoregressive (AR)

variable (**Wy**). This model assesses the existence and strength of spatial interaction. Spatial dependence in the regression disturbance term ($E[\varepsilon_i \varepsilon_j] \neq 0$) is referred to as nuisance dependence and is captured in the spatial error model. This model is appropriate when the concern is correction for the potentially biasing influence of the spatial autocorrelation due to the use of spatial data (Anselin 2003). In the ARAR model, spatial dependence was incorporated as an additional regressor in the form of a spatially lagged dependent variable and in the error structure. In the case where spatial dependence is incorporated as additional regressor(s) in the form of spatially lagged exogenous variable(s), the appropriate spatial model is the cross regressive model because it can capture the occurrence of substantive spatial interaction among observations.

Appropriate model specifications among the four models were determined after performing a set of modified Lagrange multiplier tests initially introduced by Anselin and Rey (1991), and following the procedure outlined in Florax, Folmer, and Rey (2003). More details of the specification strategy are discussed in the next section.

## METHODOLOGY

### Production Function and Technical Efficiency

Cobb-Douglas and translog production functions were estimated. Both are linear in parameters and can be estimated using the least squares and maximum likelihood methods. The translog production function is a generalization of the Cobb-Douglas production function and provides second-order approximation. The likelihood ratio (LR) test was used to identify the appropriate functional form for the stochastic production frontier analysis. The null hypothesis was that all the second-order and the cross-product coefficients are equal to 0. The alternative hypothesis was that at least one among the second-order and cross-product coefficients is not equal to 0. If the result of the LR test is significant, then translog production function (Equation 13) would be used. Otherwise, the Cobb-Douglas production function (Equation 14) would be used.

$$ln\ Y = \beta_0 + \sum_{i-1}^{n} \beta_i\, ln\ X_i + \frac{1}{2} \sum_{i-1}^{n} \sum_{j-1}^{n} \beta_{ij}\, ln\ X_i\, ln\ X_j + \varepsilon \tag{13}$$

$$ln\ Y = \beta_0 + \sum_{i-1}^{n} \beta_i\, ln\ X_i + \varepsilon \tag{14}$$

where:

- $i$ denotes input 1,2,…n,
- $\beta$ are unknown parameters to be estimated,
- $Y$ is the quantity of production (kg/ha),
- $X_i$ is the amount of input (unit/ha), and
- $\varepsilon$ is the error term.

Given the production function identified, the stochastic frontier production function was estimated using the maximum likelihood method. The technical efficiency of each farm was computed using STATA version 10.

### Spatial Autocorrelation and Correlogram

Exploratory spatial data analyses (ESDA) were conducted to determine the most appropriate model for spatial prediction through the exploration of spatial auto correlation among the measured technical efficiencies. The test for spatial autocorrelation relates a vector of attribute values for various locations to all other locations through a matrix representing the structure of the spatial system. One of the best known spatial association techniques is Moran's I. The univariate Moran's I statistics is given by:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (15)$$

or in matrix terms:

$$I = \frac{n}{S_0} \cdot \frac{x'Wx}{x'x} \quad (16)$$

where:

- $x$ is an $(n \times 1)$ vector of observation $x_i$ measured in deviation from the mean $\bar{x}$;
- $W$ is a weight matrix, which is a symmetric matrix with $(n \times n)$ element $w_{ij}$ representing the distance or closeness of farm $i$ with farm $j$; and
- $S_0$ is the sum of the elements of the spatial weight matrix.

To measure the distance of a farm (or residence) to a neighbor farm (or residence), this study used Euclidean distance: $d_{ij}=[(x_i-x_j)^2+(y_i-y_j)^2]^{1/2}$, where $x_i$ and $y_i$ are the coordinates of the farm (or residence).

If Moran's I test is significant, then spatial interaction is present in data samples, suggesting the need to quantify and model the nature of the spatial dependence in more detail and implying that the use of standard OLS is likely to be problematic. This study used Moran's I to identify the critical cut-off distance for neighborhood structure in the form of a spatial correlogram. A spatial correlogram is a set of plots showing how spatial autocorrelation varies as a function of distance between neighbors (Oden 1984). Standardized or $z$ value of Moran's I is used to identify if spatial autocorrelation is significant in each cut-off distance and is given by:

$$z_I = \frac{I - E(I)}{SD(I)} \quad (17)$$

The common significant highest peak among the technical efficiencies for each location would be the threshold distance of the neighborhood, which was used in the succeeding spatial analysis. Moran's I test and spatial correlogram were done using ArcGIS V2.1.

**Specification of Spatial Regression Model**

Assuming that Moran's I statistic suggests spatial dependence in the data set, the next step was to select the appropriate form of spatial model to be estimated. The candidate specifications can be a spatial lag model or autoregressive model (Eq. 9), spatial error model (Eq. 10), ARAR model (Eq. 11), or cross regressive model (Eq. 12). To determine the most appropriate model for technical efficiency in each season and neighborhood location, a set of Lagrange multiplier tests was performed. The Lagrange multiplier tests $LM_\lambda$ and $LM_\rho$ are unidirectional tests with the spatial error and the spatial lag model as their respective alternative hypotheses (Florax and Nijkamp 2003). The LM error test is identical to a scaled Moran coefficient (for row-standardized weights) and reads as:

$$LM_\lambda = \frac{1}{T}\left(\frac{u'Wu}{s^2}\right)^2 \quad (18)$$

where $s^2$ is the maximum likelihood variance $u'u/n$, $T$ is a scalar computed as the trace of a quadratic expression in the weight matrix, $T = tr\,(W'W + W^2)$, and the test asymptotically follows a $\chi^2$ distribution with 1 degree of freedom.

The LM-lag test has the same asymptotic distribution with the following formula:

$$LM_\rho = \frac{1}{nJ_{\rho.\beta}}\left(\frac{u'Wy}{s^2}\right)^2 \quad (19)$$

where:

$J_{\rho\beta} = [(WXb)'M(WXb)+Ts^2]/ns^2$ is a part of the estimated information matrix;

$b$ is the OLS estimated parameter vector; and

$M$ is the projection matrix $I-X(X'X)^{-1}X'$.

The multidirectional test (SARMA)[1] such as the test against ARAR is similar to the sum of the error and the lag test:

$$LM_{\rho\lambda} = \frac{(u'Wy/s^2-u'Wu/s^2)^2}{RJ_{\rho.\beta}-T} + \frac{(u'Wu/s^2)^2}{T} \tag{20}$$

and follows a $\chi^2_{(2)}$ distribution.

Robust tests for spatial dependence were also performed to account for the potential presence of a spatial lag or spatially correlated errors when testing for the presence of spatially correlated errors or a spatial lag, respectively (Anselin et al. 1996; Florax, Folmer, and Rey 2003). The formula for a spatial error process robust to the local presence of a spatial lag is given by:

$$LM_{\lambda}^{*} = \frac{1}{T-T^2(nJ_{\rho.\beta})^{-1}}\left(\frac{u'Wu}{s^2}-T(NJ_{\rho.\beta})^{-1}\frac{u'Wy}{s^2}\right)^2 \tag{21}$$

The test for a spatial lag process robust to the local presence of spatial error is given by:

$$LM_{\rho}^{*} = \frac{1}{nJ_{\rho.\beta}-T}\left(\frac{u'Wy}{s^2}-\frac{u'Wu}{s^2}\right)^2 \tag{22}$$

Both tests asymptotically follow a $\chi^2_{(1)}$ distribution.

This study followed the hybrid specification strategy outlined by Florax, Folmer, and Rey (2003), which was initially introduced in Anselin et al. (1996). Figure 1 shows the flow chart of the spatial model diagnostic procedure. First, estimate the initial model by means of OLS. Then, test the hypothesis of no spatial dependence due to an omitted spatial lag or due to spatially autoregressive errors, using $LM_\rho$ and $LM_\lambda$, respectively. If both tests are not significant, then run the cross-regressive model. If one or more spatially lagged regressors are significant, then use the cross-regressive model. Otherwise, the initial estimates (OLS model) is the final specification. If both $LM_\rho$ and $LM_\lambda$ tests are significant, look at the results of the robust tests. If neither of the robust tests is significant, examine the magnitude of $LM_\rho$ and $LM_\lambda$. If the value of $LM_\rho$ is higher than $LM_\lambda$ then use the spatial lag model; otherwise, use the spatial error model. If only one of the robust tests is significant, then estimate the specification that pointed to the significance of the two robust tests. If $LM_\rho$ is significant but $LM_\lambda$ is not, then use the spatial lag model. Otherwise, use the spatial error model. If both $LM_\rho$ and $LM_\lambda$ are significant and both of their robust tests are significant, it follows that the SARMA test is also significant. In this case, the ARMA[2] model (the combination of spatial lag and spatial error model) is the most appropriate specification. The series of Langrange multiplier tests was performed using R Version 3.1.0 with "spdep" package.

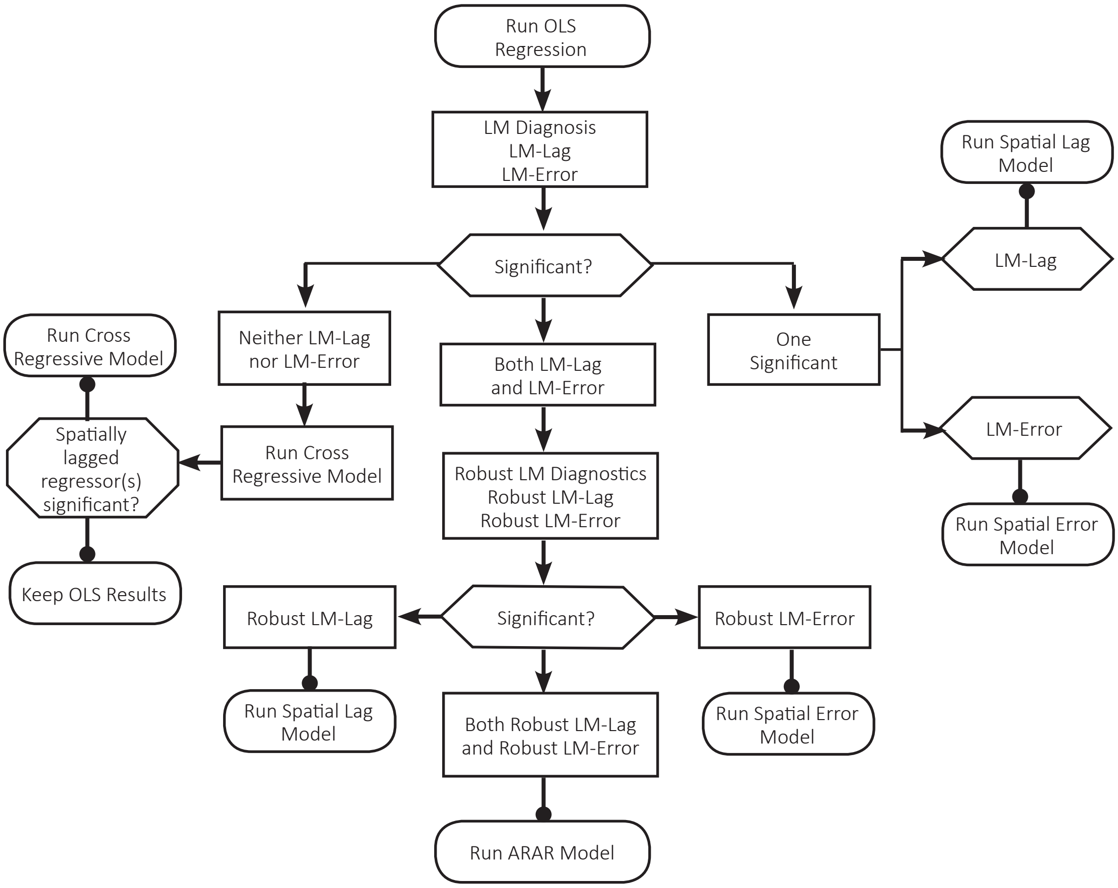
## DATA

Data used in this study were collected in Guimba, Nueva Ecija, northern Philippines as shown in Figure 2. Nueva Ecija is referred to

1 Spatial autoregressive moving average

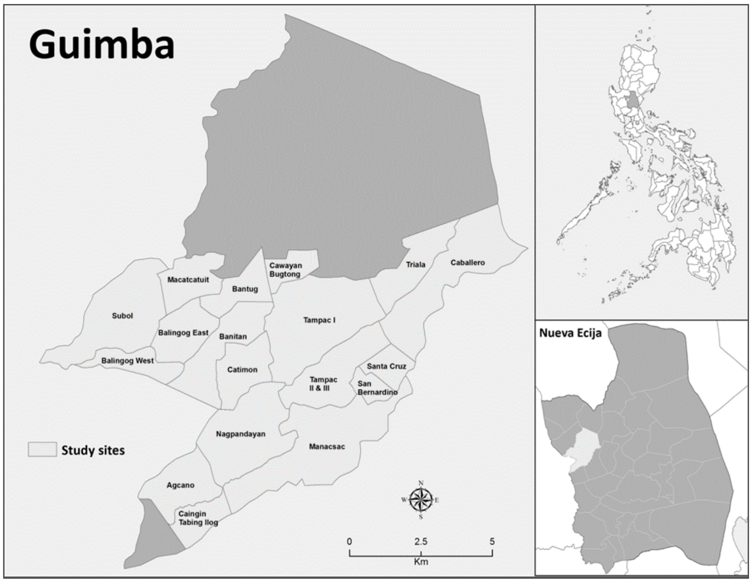
2 Autoregressive moving average

**Figure 1. Diagnostics of the specification of the appropriate spatial model**




Note: Adopted from Anselin et al. (1996)

**Figure 2. Geographical location of the study site**




Source: Geographic Information Systems (GIS) laboratory of the International Rice Research Institute (IRRI) as the rice granary of the Philippines because of its large area devoted to rice farming. Of all the municipalities of Nueva Ecija, Guimba has the largest rice area and the most number of rice farmers. A total of 270 households were proportionally allocated to 18 purposively selected irrigated neighboring or contiguous villages; the respondents were identified using systematic random sampling for each village. This was done by starting at a main landmark (such as barangay hall, school, or church) and then choosing every fifth rice farming household going to the right as respondent until the number of sample households in the village was satisfied.

The main decision maker of the household's rice farm was interviewed using structured and pretested survey questionnaires. Information on the household's socio-economic and farm characteristics and rice production data of dry and wet seasons of 2013 were collected. The coordinates of the respondent's residence and his/her farm (best parcel) were obtained through global positioning system (GPS) using Garmin® GPS receivers. They were recorded at the main entrance of the respondent's residence and in the middle of his/her best parcel plot.

**Table 1. Descriptive statistics of variables included in the frontier production function across seasons**

| VARIABLE | | UNIT | MIN | MAX | MEAN | STD. DEV. |
|---|---|---|---|---|---|---|
| Name | Description | | | | | |
| Dry season | | | | | | |
| YIELD | Yield | kg/ha | 3,189 | 11,200 | 6,651 | 1,423 |
| SEEDQTY | Seed quantity | kg/ha | 12 | 174 | 83 | 41 |
| NITROQTY | Nitrogen quantity | kg/ha | 23 | 332 | 117 | 45 |
| PESTCOST | Pesticide cost | PHP/ha | 0 | 5,040 | 1,169 | 869 |
| IRRCOST | Irrigation cost | PHP/ha | 800 | 6,000 | 2,504 | 719 |
| MACHCOST | Machine rental and fuel cost | PHP/ha | 788 | 13,527 | 5,812 | 2,312 |
| LABOR | Labor input | person-day/ha | 22 | 119 | 58 | 21 |
| HYBRID | Hybrid rice | dummy | 0.00 | 1.00 | 0.20 | 0.40 |
| Wet season | | | | | | |
| YIELD | Yield | kg/ha | 1,200 | 7,650 | 4,568 | 1,142 |
| SEEDQTY | Seed quantity | kg/ha | 15 | 200 | 94 | 33 |
| NITROQTY | Nitrogen quantity | kg/ha | 22 | 282 | 91 | 39 |
| PESTCOST | Pesticide cost | PHP/ha | 0 | 5,400 | 1,080 | 882 |
| IRRCOST | Irrigation cost | PHP/ha | 780 | 4,400 | 1,926 | 592 |
| MACHCOST | Machine rental and fuel cost | PHP/ha | 631 | 12,972 | 4,877 | 2,146 |
| LABOR | Labor input | person-day/ha | 17 | 131 | 57 | 22 |
| TYPHOON | Affected by typhoon | dummy | 0.00 | 1.00 | 0.30 | 0.46 |

USD 1 = PHP 43.80

**Table 2. Likelihood ratio test results between Cobb-Douglas and translog frontier production functions across seasons**

| SEASON | PRODUCTION FUNCTION | LOG-LIKELIHOOD | LR TEST | P-VALUE |
|---|---|---|---|---|
| Dry | Cobb-Douglas | 71.0983 | 47.31 | 0.001 |
| | Translog | 94.7515 | | |
| Wet | Cobb-Douglas | -3.7800 | 58.99 | 0.000 |
| | Translog | 25.7145 | | |

**Table 3. Results of the translog frontier production function across seasons**

| VARIABLE | DRY SEASON | | WET SEASON | |
|---|---|---|---|---|
| | Coefficient | Std. Err. | Coefficient | Std. Err. |
| Stochastic frontier | | | | |
| CONSTANT | 6.3545 *** | 0.4142 | 6.2398 *** | 0.3750 |
| ln SEEDQTY | 0.0084 | 0.0341 | 0.0422 | 0.0395 |
| ln NITROQTY | 0.0557 * | 0.0306 | -0.0102 | 0.0313 |
| ln PESTCOST | 0.0109 | 0.0140 | 0.0184 | 0.0141 |
| ln IRRCOST | 0.0831 ** | 0.0394 | 0.0878 * | 0.0450 |
| ln MACHCOST | 0.2008 *** | 0.0289 | 0.1558 *** | 0.0334 |
| ln LABOR | -0.0523 * | 0.0315 | 0.0586 * | 0.0338 |
| HYBRID | 0.2347 *** | 0.0698 | | |
| TYPHOON | | | -0.1373 *** | 0.0263 |
| ln SEEDQTY • ln SEEDQTY | -0.0157 | 0.0294 | 0.1649 *** | 0.0443 |
| ln NITROQTY • ln NITROQTY | 0.0757 * | 0.0449 | 0.1744 *** | 0.0650 |
| ln PESTCOST • ln PESTCOST | 0.0016 | 0.0027 | 0.0018 | 0.0028 |
| ln IRRCOST • ln IRRCOST | -0.0464 | 0.0847 | -0.0472 | 0.0831 |
| ln MACHCOST • ln MACHCOST | 0.1320 *** | 0.0279 | 0.1401 *** | 0.0355 |
| ln LABOR • ln LABOR | 0.0249 | 0.0750 | -0.2186 ** | 0.0927 |
| ln SEEDQTY • ln NITROQTY | 0.0088 | 0.0500 | -0.2077 ** | 0.0919 |
| ln SEEDQTY • ln PESTCOST | 0.0050 | 0.0084 | 0.0002 | 0.0168 |
| ln SEEDQTY • ln IRRCOST | 0.0018 | 0.0562 | -0.0740 | 0.1259 |
| ln SEEDQTY • ln MACHCOST | 0.0620 * | 0.0319 | 0.0522 | 0.0802 |
| ln SEEDQTY • ln LABOR | -0.1223 ** | 0.0532 | -0.0999 | 0.0861 |
| ln NITROQTY • ln PESTCOST | -0.0031 | 0.0126 | -0.0053 | 0.0147 |
| ln NITROQTY • ln IRRCOST | 0.0030 | 0.0953 | -0.0215 | 0.0779 |
| ln NITROQTY • ln MACHCOST | -0.0522 | 0.0505 | -0.1654 ** | 0.0647 |
| ln NITROQTY • ln LABOR | -0.0423 | 0.0931 | -0.0820 | 0.0694 |
| ln PESTCOST • ln IRRCOST | -0.0015 | 0.0212 | -0.0271 | 0.0212 |
| ln PESTCOST • ln MACHCOST | 0.0102 | 0.0098 | 0.0154 | 0.0109 |
| ln PESTCOST • ln LABOR | -0.0061 | 0.0139 | 0.0114 | 0.0165 |
| ln IRRCOST • ln MACHCOST | 0.1447 | 0.0880 | -0.0422 | 0.0794 |
| ln IRRCOST • ln LABOR | 0.0956 | 0.1168 | 0.0410 | 0.0913 |
| ln MACHCOST • ln LABOR | 0.0129 | 0.0707 | 0.2191 *** | 0.0660 |
| Variance parameters | | | | |
| $\sigma^2$ | 0.0635 *** | 0.0103 | 0.1646 | 0.0190 |
| $\lambda$ | 2.1422 *** | 0.0431 | 8.7079 | 0.0399 |
| Log-likelihood | 94.7515 | | 25.7145 | |

Dependent variable: LN yield in kg/ha
***p < 0.01, ** p < 0.05, * p < 0.10

## RESULTS AND DISCUSSION

### Production Function and Technical Efficiency

Table 1 shows the descriptive statistics of the variables included in the production frontier analysis for the 2013 dry and wet seasons. All continuous variables are expressed in per hectare (/ha) values, where yield is the dependent variable and the rest are independent variables. There are also dummy variables pertaining to types of soil and whether or not the farm was affected by typhoon (wet season only). Translog and Cobb-Douglas stochastic production functions were estimated using the maximum likelihood method. Based on the results of likelihood ratio tests (Table 2), the translog stochastic production function was more appropriate for the data set in both dry and wet seasons because the LR test results were significant.

Table 3 shows the maximum likelihood estimates for the parameters of the translog stochastic production function of the dry and wet seasons. The estimates of parameters of the stochastic production function for the dry season indicate that amount of nitrogen, irrigation cost, and machine and fuel cost positively and significantly affected yield, a finding consistent with economic theories. The dummy variable for planting hybrid varieties is also positive and significant, which means that farmers who plant hybrid varieties tend to have higher yield compared with those who plant inbred varieties. On the other hand, the number of labor days/ha is negative but also significant. However, after computing the partial derivative of the translog frontier production function with respect to labor and plugging in the coefficients and mean values of the inputs, the result is positive. This means that the overall effect of labor to output is positive. During the wet season, irrigation cost, machine and fuel cost, and labor input had positive and significant effects on yield, indicating that higher application of these inputs, according to economic theory, will tend to increase yield. The dummy variable pertaining to whether or not the rice field was affected by typhoons is negative and significant. This implies that rice fields affected by typhoons have lower yield due to lodging and flooding.

Table 4 shows the distribution of farmers' technical efficiencies during the wet and dry seasons. The average technical efficiency in the dry season was 0.84, higher than the wet season's 0.75. Moreover, about 75 percent of the farmers had technical efficiency of more than 80 percent during the dry season, compared with only around 43 percent

**Table 4. Distribution of farmer's technical efficiency across seasons**

| TECHNICAL EFFICIENCY | DRY SEASON | | WET SEASON | |
|---|---|---|---|---|
| | Count | Percent | Count | Percent |
| 0.50 and below | 1 | 0.4 | 22 | 8.1 |
| 0.51 - 0.60 | 4 | 1.5 | 24 | 8.9 |
| 0.61 - 0.70 | 14 | 5.2 | 48 | 17.8 |
| 0.71 - 0.80 | 51 | 18.9 | 62 | 23.0 |
| 0.81 - 0.90 | 120 | 44.4 | 54 | 20.0 |
| More than 0.90 | 80 | 29.6 | 60 | 22.2 |
| Total | 270 | 100.0 | 270 | 100.0 |
| Min, max | 0.49, 0.96 | | 0.24, 0.98 | |
| Mean | 0.84 | | 0.75 | |

**Figure 3. Histogram of farmer's technical efficiency with normal distribution curve, dry season, 2013**

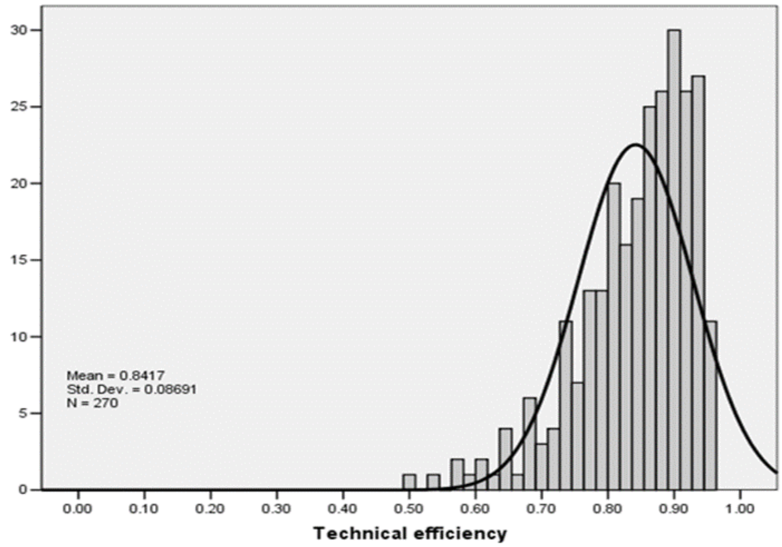
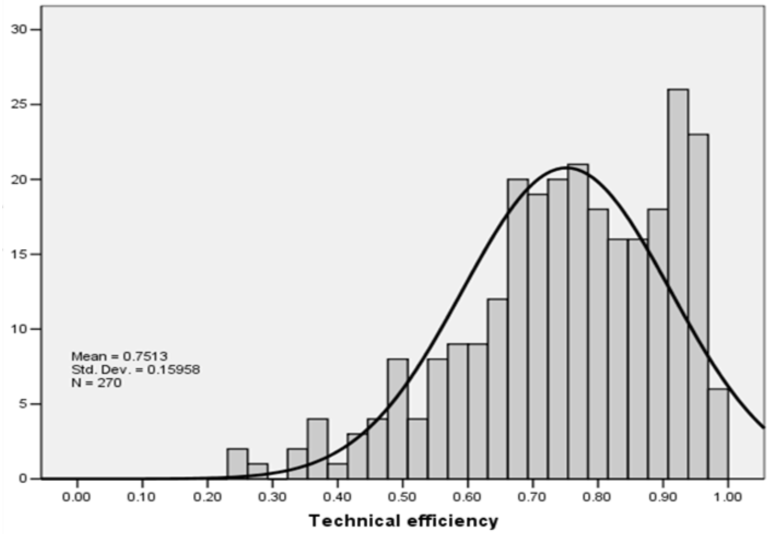
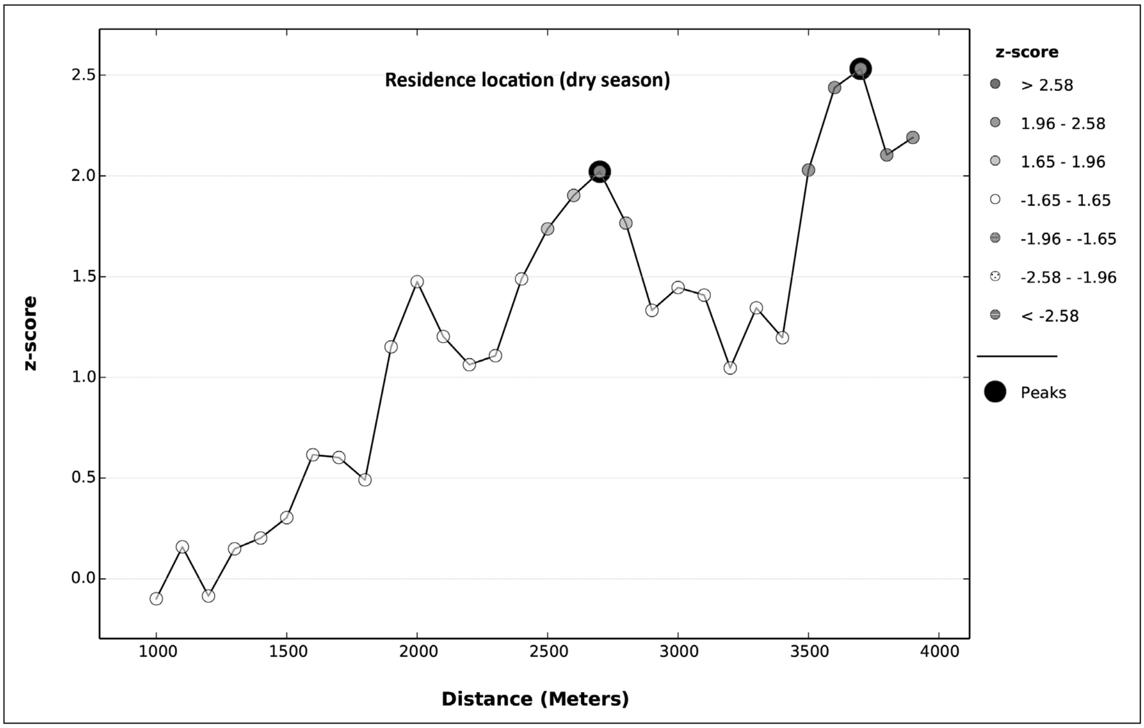


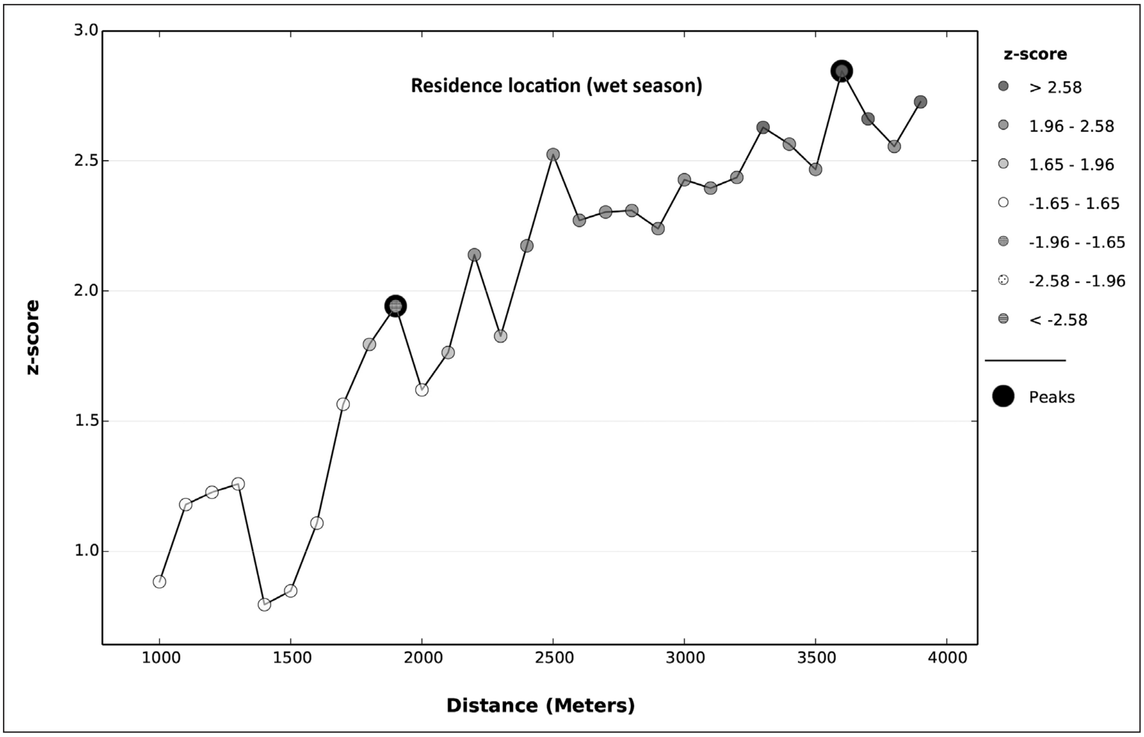

**Figure 4. Histogram of farmer's technical efficiency with normal distribution curve, wet season, 2013**

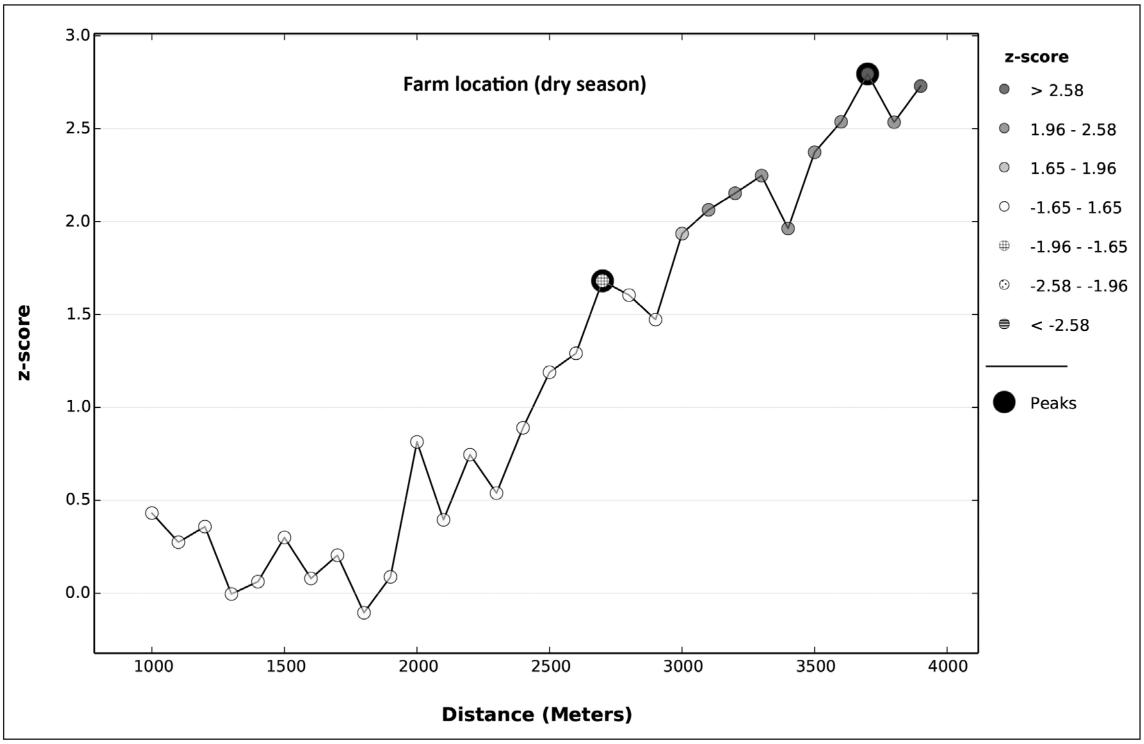


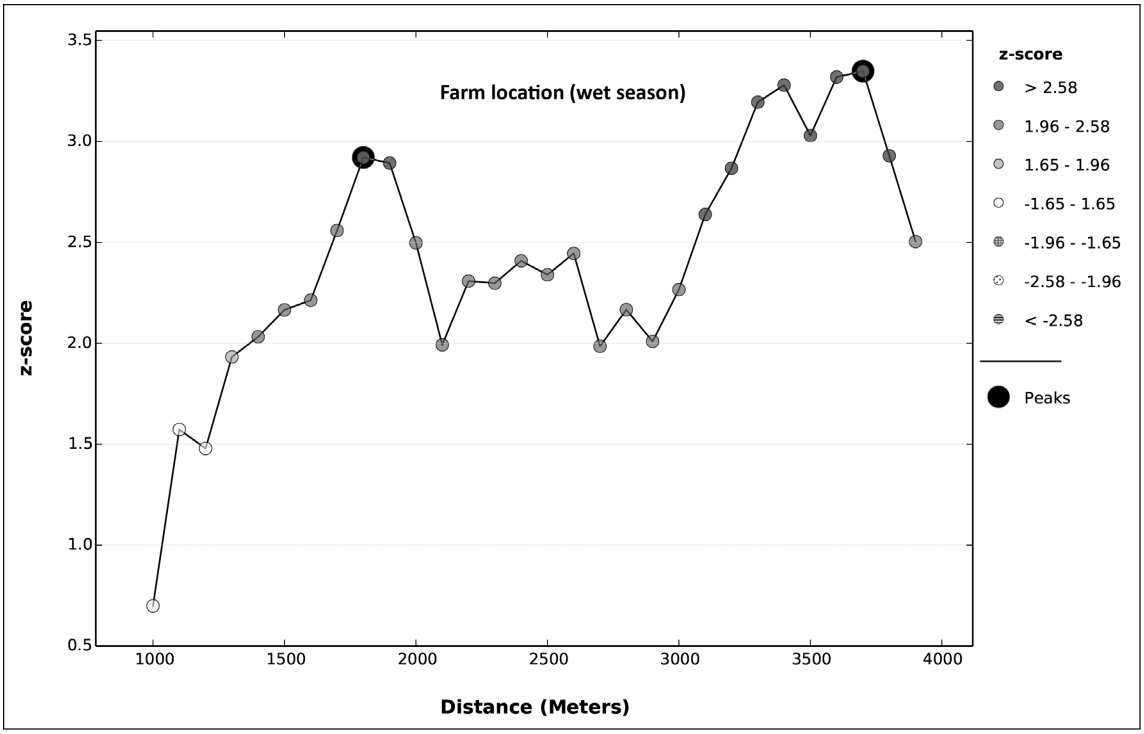

of farmers during the wet season. As Figures 3 and 4 show, the normal distribution curve of technical efficiency in the dry season is more skewed to the left compared with that in the wet season, implying that the farmers were more technically efficient during the dry season. Farmers in irrigated areas had higher technical efficiency during the dry season because of a more favorable environment and less weather disturbance. In tropical Asia, irrigated lowlands are more favorable for rice production in the dry season than in the wet season because of the higher solar radiation in the dry season (Peng and Senadhira 1998). In addition, some farmers opt to cultivate hybrid rice for higher production during the dry season.

**Figure 5. Spatial correlogram of farmer's technical efficiency locations and seasons**




Farm location (dry season)
z-score
Distance (Meters)
z-score
> 2.58
1.96 - 2.58
1.65 - 1.96
-1.65 - 1.65
-1.96 - -1.65
-2.58 - -1.96
< -2.58
Peaks


Farm location (wet season)
z-score
Distance (Meters)
z-score
> 2.58
1.96 - 2.58
1.65 - 1.96
-1.65 - 1.65
-1.96 - -1.65
-2.58 - -1.96
< -2.58
Peaks

**Moran's I and Spatial Correlogram**

Moran's I tests were done to determine the rational distance among farmers where spatial autocorrelation on technical efficiency is significant. Figure 5 shows the spatial correlograms of the technical efficiency for the dry and wet seasons across locations. As mentioned, a spatial correlogram is a plot of points where the standardized or z-score associated with Moran's I is a function of distance. The significant and highest peaks of the segment of each graph are highlighted by a blue outline, which corresponds to the distance where spatial dependence is stronger. The distances with high peaks were all candidates for the fixed neighborhood distance that was used as basis for identifying if farmers were neighbors or not. Of the identified distances, the longest distance for each location was selected so that it can cover all other identified distances. Based on this criterion, a distance of 2.7 km was selected as the fixed neighborhood distance for both the residence and farm location. Neighbors in this study were then defined as those located no farther than 2.7 km from each other. This definition was used for both farmers' residence and farm locations.

**Spatial Models of Farmer's Technical Efficiency**

Table 5 shows the basic descriptive statistics of all the factors included in the spatial econometric models of farmers' technical efficiency. The youngest household head was 22 years old; the oldest was 85. On the average, the respondents were 53 years old and had 9 years of formal education. Most of the households were nuclear, which means only the immediate members of the family

**Table 5. Descriptive statistics of variables included in the spatial econometric models**

| VARIABLE | | UNIT | MIN | MAX | MEAN | STD. DEV. |
|---|---|---|---|---|---|---|
| Name | Description | | | | | |
| AGEHEAD | Age of household head | year | 22 | 85 | 53 | 12 |
| EDUCHEAD | Education of household head | year | 2 | 20 | 9 | 3 |
| TENURE | Tenure status | dummy 1-owned, 0-otherwise | 0 | 1 | 0.74 | 0.44 |
| HHLDTYP | Type of household | dummy 1-nuclear 0-extended | 0 | 1 | 0.64 | 0.48 |
| FARMSIZE | Farm size | ha | 0.10 | 16.00 | 1.32 | 1.48 |
| LOAMY | Loamy soil | dummy 1-loamy 0-otherwise | 0 | 1 | 0.15 | 0.36 |
| CLAYEY | Clayey soil | dummy 1-clayey 0-otherwise | 0 | 1 | 0.61 | 0.49 |
| INCOME | Household income | PhP/year | 12,600 | 1,975,500 | 224,430 | 220,131 |
| CONTTECH | Frequency of contact with technician in a year | count/year | 0 | 36 | 2 | 4 |
| SOCNET | Size of social network | count | 3 | 320 | 34 | 43 |
| TYPHOON | Affected by typhoon (wet season) | dummy 1-yes, 0-no | 0 | 1 | 0.30 | 0.46 |

USD 1 = PhP 43.80

**Table 6. Spatial regression models on farmer's technical efficiency for farm locations across seasons**

| VARIABLE | DRY SEASON[a] | | WET SEASON[b] | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| CONSTANT | 0.7242 *** | 0.0436 | 1.3530 ** | 0.5317 |
| AGEHEAD | -0.0006 | 0.0004 | -0.0001 | 0.0008 |
| EDUCHEAD | 0.0015 | 0.0018 | 0.0009 | 0.0031 |
| TENURE | 0.0015 | 0.0120 | 0.0629 ** | 0.0193 |
| HHLDTYP | 0.0117 | 0.0110 | 0.0338 | 0.0212 |
| FARMSIZE | -0.0117 *** | 0.0044 | -0.0161 ** | 0.0076 |
| LOAMY | 0.0173 | 0.0168 | 0.0602 ** | 0.0295 |
| CLAYEY | 0.0008 | 0.0127 | -0.0273 | 0.0225 |
| LN INCOME | 0.0314 *** | 0.0074 | 0.0507 *** | 0.0130 |
| CONTTECH | 0.0032 *** | 0.0012 | 0.0035 | 0.0022 |
| SOCNET | 5.76E-05 | 1.23E-04 | 4.84E-05 | 2.14E-04 |
| TYPHOON | | | -0.0160 | 0.0198 |
| ρ | | | -0.8411 | 0.493 |
| γ | 0.3630 * | 0.2068 | 0.8098 *** | 0.1354 |
| Moran's I (error) | 0.0194 *** | | 0.0348 *** | |
| LM Lag | 2.2403 | | 5.6557 ** | |
| Robust LM Lag | 1.1891 | | 6.1156 ** | |
| LM Error | 2.8315 * | | 9.1198 *** | |
| Robust LM Error | 1.7803 | | 9.5797 *** | |
| SARMA | 4.0206 | | 15.2354 *** | |

Neighborhood structure: Standardized distance (2,700 m)
[a]Spatial error model
[b]ARAR model
***$p < 0.01$, ** $p < 0.05$, * $p < 0.10$

were living in their house. On the average, a household was cultivating 1.32 ha of land and earning around PHP 225,000 annually. About 75 percent of the total household income was from farm income and around 25 percent was from off-farm income. Most of the cultivated land was owned by the farmers; the soil type was mostly clayey. Farmers contacted agricultural technicians at an average of twice a year. Respondents regularly talked to at least three people to consult on agriculture-related topics. The most number of people approached by respondents was 320, and the average was 34. Around 30 percent of the respondent's rice area was affected by typhoon during the wet season.

The specification strategy of the spatial regression model (discussed in the methodology section) was employed to select the final model in each season and location. Tables 6 and 7 show the summary of the selected spatial models for farmer's technical efficiency across locations and seasons. The ρ coefficient in the model indicates the magnitude and significance of the effect of the neighbors' technical efficiency on that of the farmer's. It is not significant in the ARAR model during the wet season. On the other hand, γ coefficients in the spatial error and ARAR models are all significant, suggesting that spatial dependency is present in the error term of the model. This means that spatial dependency is caused by unobserved characteristics that

**Table 7. Spatial regression models on farmer's technical efficiency for residence locations across seasons**

| VARIABLE | DRY SEASON[a] | | WET SEASON[b] | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| CONSTANT | 0.7276 *** | 0.0437 | 0.9562 | 0.6366 |
| AGEHEAD | -0.0006 | 0.0004 | -0.0003 | 0.0008 |
| EDUCHEAD | 0.0016 | 0.0018 | 0.0008 | 0.0031 |
| TENURE | 0.0015 | 0.0120 | 0.0619 *** | 0.0196 |
| HHLDTYP | 0.0118 | 0.0110 | 0.0337 | 0.0214 |
| FARMSIZE | -0.0115 *** | 0.0043 | -0.0167 ** | 0.0077 |
| LOAMY | 0.0175 | 0.0167 | 0.0620 ** | 0.0298 |
| CLAYEY | 0.0013 | 0.0126 | -0.0249 | 0.0225 |
| LN INCOME | 0.0310 *** | 0.0074 | 0.0527 *** | 0.0131 |
| CONTTECH | 0.0032 ** | 0.0012 | 0.0034 | 0.0022 |
| SOCNET | 5.83E-05 | 1.21E-04 | 6.61E-05 | 2.14E-04 |
| TYPHOON | | | -0.0163 | 0.0198 |
| ρ | | | -0.6581 | 0.838 |
| γ | 0.4118 * | 0.2112 | 0.6994 *** | 0.2478 |
| Moran's I (error) | 0.0233 *** | | 0.0365 *** | |
| LM Lag | 3.4155 * | | 5.6560 ** | |
| Robust LM Lag | 0.3758 | | 5.2710 ** | |
| LM Error | 3.8542 ** | | 9.4739 *** | |
| Robust LM Error | 0.8145 | | 9.0889 *** | |
| SARMA | 4.2300 | | 14.7449 *** | |

Neighborhood structure: Standardized distance (2,700 m)
[a]Spatial error model
[b]ARAR model
***$p < 0.01$, ** $p < 0.05$, * $p < 0.10$

were not captured by the model but just the same influenced their technical efficiency; these were beyond the control of the estimation of the model. In other words, farmers in the same neighborhood were under the influence of the same factors, which were unknown as far as this study was concerned. These factors may include rainfall and soil condition, as well as the institutional and political environment, which were similar at the neighborhood level and therefore could induce some elements that may simultaneously affect all the neighbors. If spatial dependency is present in the error term and still runs the OLS model, then the OLS estimates are inefficient. In this case, inefficiency can be avoided by using appropriate spatial models (spatial error or ARAR model) to capture the spatial dependency in the error term.

Farm size and household income significantly influenced farmer's technical efficiency across locations and seasons, a finding consistent with what Koirala, Mishra, and Mohanty (2013); and Villano and Fleming (2004) found in the Philippines. The negative sign of the coefficient of farm size implies that small and marginal farmers tend to have higher technical efficiency than large farmers. On the other hand, household income positively influenced farmer’s technical efficiency, which means that farmers with higher income tend to have higher technical efficiency. However, the effect of income on technical efficiency should be interpreted with caution due to possible endogeneity.

Frequency of contact with agricultural technicians had a positive effect on farmer's technical efficiency and is statistically significant during the dry season. Farmers who interact more with agricultural technicians can probably acquire more knowledge and learn more techniques that enable them to maximize their efficiency in rice production.

The coefficients of tenure status and loamy type of soil are positive for both seasons, but not statistically significant during the dry season. This means farmers who are owner-cultivators tend to have higher technical efficiencies than those under share-cropping and lease arrangements. This is consistent with the results obtained by Koirala, Mishra, and Mohanty (2016) in Central Luzon, Philippines, who found that farmers who lease their land tend to have higher technical inefficiency. In terms of soil type, farmers who cultivate rice fields with loamy soil had higher technical efficiency than those who work on clayey and sandy soil. Loam soil is ideal for agricultural use because it contains (and can retain) more nutrients, moisture, and humus than other soil types.

Though not significant, the education level of the household head, who mostly was also the main farmer of the family, positively affected technical efficiency. Thus, the more number of years spent in schooling, the greater the tendency to increase technical efficiency. The age of the household head, which reflects his/her experience in rice farming, is negative and also not statistically significant. Villano and Fleming (2004), Gomez and Neyra (2010), and Luis et al. (2010) also found that education and age had positive and negative effects, respectively, on technical efficiency of rice farmers in the Philippines. However, these effects were statistically significant. The statistically insignificant coefficients of education and age in the current study may be due to the limited variability in the data set.

The magnitude of the coefficient of the size of farmer's social capital in rice farming is negligible and not significant. This implies that the number of people inside and outside the village whom the farmer regularly (at least once a month) talks to and personally approaches regarding agricultural topics, including rice farming, does not matter in terms of rice productivity. Probably, what matters most to farmers are the quality and suitability of information they acquire from other people.

## CONCLUSIONS AND RECOMMENDATIONS

The levels of technical efficiency of farmers in irrigated areas in Guimba, Nueva Ecija, northern Philippines still need improvement, especially during the wet season. Improving the farmers' technical efficiency will increase their rice production and profit. Furthermore, technical efficiency was found to be a spatial phenomenon. Spatial dependence on the error term was detected in all spatial regression models across seasons and locations to identify factors affecting a farmer's technical efficiency. This means that there were factors that were not captured by this study and were beyond the control of the estimation of the model, which affected their technical efficiencies just the same.

Small and marginal farmers tend to have higher technical efficiency than large farmers. Household income positively influences farmer's technical efficiency, meaning farmers with higher income tend to have higher technical efficiency. Moreover, the skills and knowledge of rice production gained by a farmer through regular contact and consultation with agricultural technicians contribute to the high level of technical efficiency. Farmers who are owner-cultivators have higher technical efficiency than sharecroppers. Loamy soil, which contains more nutrients, moisture, and humus than other soil types, also contributes to farmers' high level of technical efficiency. On the other hand, age, education, and size of social capital of the household head do not significantly influence his/her technical efficiency.

The findings of this study can help guide the local government of Guimba in formulating agricultural policies and in implementing essential interventions to improve the technical efficiency of rice farmers in the municipality. Given that institutional and political environment may be one of the driving forces that exert a similar influence on farmers' technical efficiency, policies aimed at promoting or enhancing cooperation among farmers may be promulgated to improve their technical efficiency. Furthermore, since the frequency of contact with agricultural extension workers positively influences farmers' technical efficiency, the government could enhance such interaction and provision of support services to rice farmers. Household income is also a significant factor of technical efficiency of farmers. With higher income, farmers can meet the optimal input demand of rice farming and reach the target level of production. Hence, the government could provide livelihood programs to serve as a secondary income source for farmers. Additional household earnings from these programs can be added to the farm capital.

Further research could be conducted to identify and fully understand the reasons behind the factors that significantly affect farmers' technical efficiency in the spatial regression models. Moreover, future research on farmers' technical efficiency could use the "one-step" instead of the "two-step" estimation procedure, which must also incorporate spatial analysis. If possible, complete enumeration of farmers in the study site could be done to better capture the presence of spatial dependence on technical efficiency among neighboring farmers. Finally, this study recommends considering spatial econometric techniques in other research areas that involve space and time dimensions. Spatial econometric analysis can be applied not only in cross-sectional data sets but also in longitudinal or panel data sets.

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