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Spatial dependency and technical efficiency: an application of a Bayesian stochastic frontier model to irrigated and rainfed rice farmers in Bohol, Philippines

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Abstract

We investigated the role of spatial dependency in the technical efficiency estimates of rice farmers using panel data from the Central Visayan island of Bohol in the Philippines. Household-level data were collected from irrigated and rainfed agro-ecosystems. In each ecosystem, the geographical information on residential and farm-plot neighborhood structures was recorded to compare household-level spatial dependency among four types of neighborhoods. A Bayesian stochastic frontier approach that integrates spatial dependency was used to address the effects of neighborhood structures on farmers' performance. Incorporating the spatial dimension into the neighborhood structures allowed for identification of the relationships between spatial dependency and technical efficiency through comparison with nonspatial models. The neighborhood structure at the residence and plot levels were defined with a spatial weight matrix where cut-off distances ranged from 100 to 1,000 m. We found that spatial dependency exists at the residential and plot levels and is stronger for irrigated farms than rainfed farms. We also found that technical inefficiency levels decrease as spatial effects are more taken into account. Because the spatial effects increase with a shorter network distance, the decreasing technical inefficiency implies that the unobserved inefficiencies can be explained better by considering small networks of relatively close farmers over large networks of distant farmers.

JEL classifications: C01, C11, C23, C51, D24

Keywords: Rice farming; Spatial dependency; Bayesian approach; Efficiency

1. Introduction

Numerous attempts have been made to measure technical efficiency (TE) and other efficiency estimates in farming (Alvarez, 2004; Balde et al., 2014; Coelli and Battese, 1996; Hossain and Rahman, 2012; Idiong, 2007; Karagiannis and Tzouvelekas, 2009; Michler and Shively, 2014; Quilty et al., 2014); to this end, one of the common econometric approaches is the stochastic frontier analysis (Aigner et al., 1977; Meeusen and van den Broeck, 1977). Previous studies have contributed to the understanding of how large TE is; how different TE levels are among individual farmers; and what are the factors that underlie the differences. These studies generated useful policy implications for efficient farming, especially in developing countries where wide productivity variations have been observed. Despite the aforementioned research, spatial dependency among farmers has yet to be adequately analyzed. Farrell (1957) expressed concerns about spatial factors such as how climate and location influence efficiency. Although the concerns existed at the time, the econometric techniques required to complete such an analysis were not available during the time of Farrell's research. The importance of making use of spatial information in agricultural economics, and in particular the little attention paid to spatial autocorrelation in land use data has still been highlighted in more recent times (Bockstael, 1996).

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Recent developments in spatial econometrics have made it possible to observe the spatial effects in the stochastic frontier analysis (Anselin, 1988; Areal et al., 2012; Glass et al., 2013, 2014, 2015; Tsionas and Michaelides, 2015). Furthermore, Druska and Horrace (2004) extended the estimator presented by Kelejian and Prucha (1999) and applied it to a stochastic frontier model for the panel data of 171 Indonesian rice farmers. Another innovation in this area was the adoption of the Bayesian paradigm in the estimation procedure (Schmidt et al., 2008). With this approach, Koop and Steel (2001) and Kumbhakar and Tsionas (2005) investigated geographical variations of outputs and farm productivity for 370 municipalities in Brazil. Similarly, Areal et al. (2012) also investigated the spatial dependence of 215 dairy farms in England at a 10-km grid-square level using the Bayesian paradigm. All these studies have used a meso-level data to measure the spatial distribution of farmers.

Although these meso-level studies are valuable in recognizing the importance of spatial dependency in agriculture, important questions surrounding this topic remain unanswered. To illustrate, one unanswered question is how and through what kinds of networks the spatial dependency of TE shows up at the farm level.

The purpose of this article is to investigate the role of spatial dependency in TE, using a unique micro-level farm panel dataset from individual rice farmers in Bohol, Philippines. We aim to identify the types of networks in which spatial dependency arises in TE. The data were collected for four consecutive rice growing seasons from 2009 to 2011, coupled with detailed geographical information to capture different kinds of networks among sample farmers. This data set allowed us to compare spatial dependency among two separate neighborhood structures (residential neighborhood and farm plot neighborhood) in two different agro-ecosystem (irrigated and rainfed ecosystems). Taking advantage of the panel data structure, analyses were performed following a one-step procedure as described in Areal et al. (2012), which integrates spatial dependency into the stochastic frontier analysis with a Bayesian estimation approach. The rest of the article is organized as follows. The next section provides some background information about the major characteristics of the two rice farming systems in Bohol. Section 3 presents the empirical model used to estimate the TE and the endogenous spatial effect of rice farming TE. Section 4 describes the data set used in this study. Section 5 presents the estimation results and discussions. Section 6 concludes and derives policy implications for rice farming productivity in Philippines.

2. Rice farming in Bohol

Rice production in Bohol consists of two agro-ecosystems: irrigated and rainfed farming. The Bohol Irrigation System (BIS) started its operation in 2009, currently spans 14 villages in 3 municipalities, and is expected to service as many as 4,104 hectares in the future (JICA, 2012). The BIS works through a gravity irrigation system composed of a reservoir dam, a main canal, secondary canals and laterals, turnouts, and farm ditches. Most of the farmers in the project site converted their rainfed plots to irrigated plots as long as their plots were accessible to the irrigation facilities. Our sample famers were randomly taken from these irrigated famers. The rainfed sample farmers were randomly taken from adjacent villages that have similar cultural and climatic background (Fig. 1). Rainfed rice farming is conducted in a traditonal manner with moderate use of modern inputs and little use of machineries. The same scenario applied to the irrigated area until the start of irrigation in 2009.

Farmers in the irrigated area must form a water users group. A group consisting of 20 individual farmers on average and its members rely on the same intake gate on a canal and thus share irrigation water with each other. Since the location and the water supply capacity of each intake gate is determined by the capacity of the canal and the topography of the area, the size and composition of the water users group is basically determined exogenously. In addition, our field observation tells us that no farmer exchanged their plots in order to move to a particular water user group. This means that there is no self-selection behavior in the formation of the water user group.

Member farmers are expected to pay an irrigation service fee equivalent to 150 kg of paddy per hectare per season to the National Irriagtion Administration (NIA).[1] The members of the water users group are expected to manage local irrigation facilities collectively. Since they share irrigation water, the synchronization of farming practices is needed among them. Meanwhile, rice farming under rainfed conditions is conducted more independently. In this regard, the opportunities for networking are more frequent, and the demand for strict coordination is higher among irrigated farmers than rainfed farmers.

In the study site, rice is the dominant crop and is cultivated twice a year. The Bohol Island belongs to a climatic area characterized by even rainfall distribution throughout the year. During our survey period of four agricultural seasons in two years (2009–2011), our study site experienced two weather shocks: severe drought in the second season and flood in the fourth season. Furthermore, rainfed areas suffered directly from these variations. Meanwhile, the water supply condition among irrigated farmers was mitigated by the irrigation system, to some extent. Hence, the irrigated farmers suffered fewer water shortages in the second season than the rainfed farmers. Since the BIS has no drainage system, all the famers suffered flood in the fourth season.

A notable feature of the study site, which is important in network analyses, is that the places of residence are relatively scattered over a wide geographical area; although we

[1] With a market price of Php 14–20 per kg, the 150 kg of paddy is equivalent to about Php 2,500–3,000. As of February 2018 1USD = 51 Php (Philipino Peso).

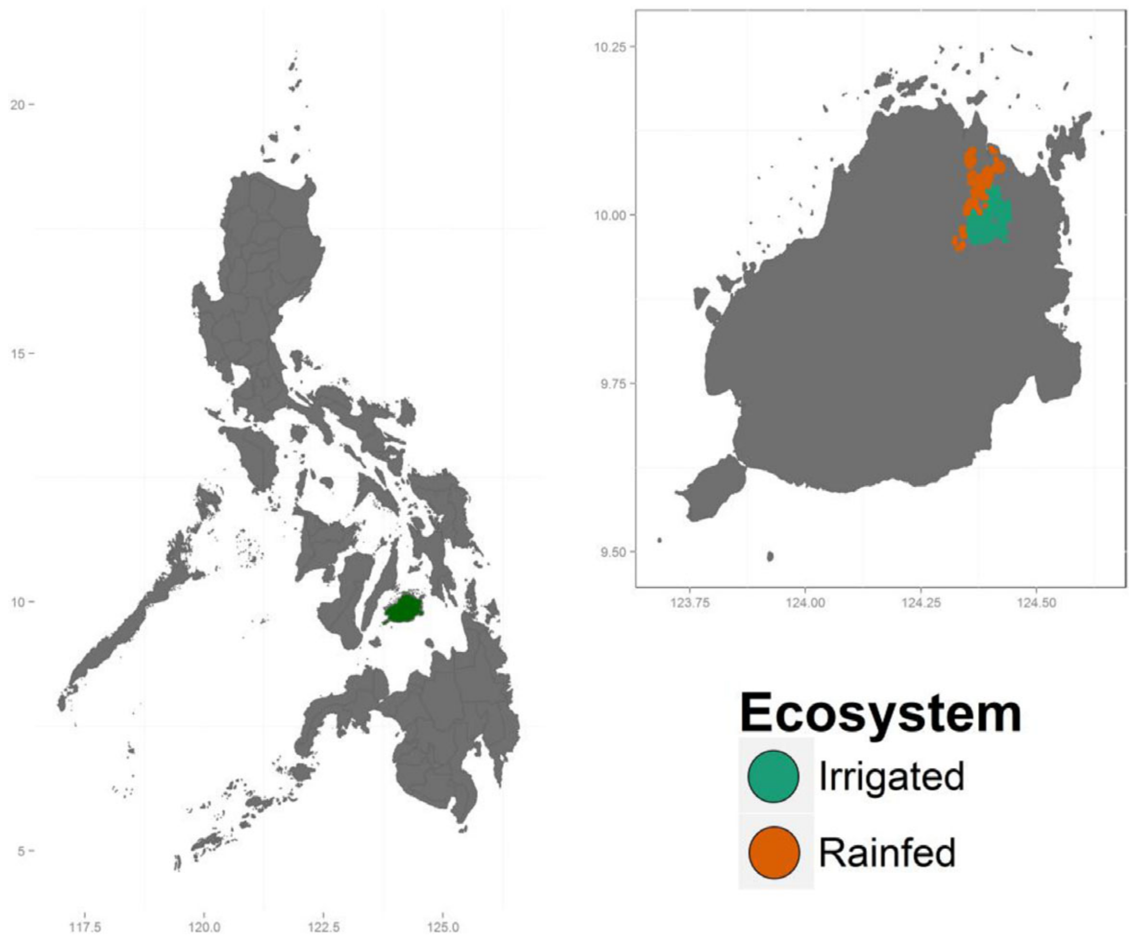

Fig. 1. Location of study sites designated by ecosystem. [Color figure can be viewed at wileyonlinelibrary.com]

can still find the center of a village where residences and small businesses are concentrated. Hence, the data presented in this study have wide geographical variations in residential networks, which is different from another type of common residential pattern in which residents are highly concentrated in a particular place.

3. Modeling

Since the seminal works of Aigner et al. (1977) and Meeusen and Van Den Broeck (1977), the stochastic frontier approach (SFA) has become the most commonly used method of modeling the production and measure efficiency of farm-level data. The SFA estimates the parametric form of a production function and recognizes the presence of two 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 of the producer's 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 Areal et al. (2012), the stochastic frontier production function for a balanced panel data assuming efficiency is constant over time[2] is defined as[3]:

$$y_{it} = x_{it}\,\beta + z_{it}\theta + p_{it}\psi + v_{it} - u_i, \tag{1}$$

where y_{it} denotes the production of farm i ($i = 1, 2, \ldots, N$) at season t ($t = 1, \ldots, T$) with $T = 4$; x_{it} represents a $(N \times T) \times k$ matrix of inputs of production; z_{it} is a $N \times m$

[2] This is not an uncommon assumption to make especially when the time series is relatively short as in this case (two years).

[3] A specification including time and its interactions was estimated but no significant time effects were found. A referee has noted that the model does not include heteroscedasticity terms. This is an area that has not been explored within this context. We have run the nonspatial model and extracted the errors and the inefficiency terms. However, there is not a prior reason to believe that allowing for heteroscedasticity would make it necessarily a better model. We have conducted a Levene's test on the errors to test whether the variance changes through the periods. We found that the variance for year 2 is actually different (P-value of < 0.05), but the standard deviations for the years are not very different in absolute values: Year 1: 0.246; year 2: 0.306; year 3: 0.230; year 4: 0.239.

matrix of nonstochastic environmental variables (farmer's level of education, household size, household head, being a female, remittance), associated with the ith farm at the tth observation (farm-specific variables); p_{it} is a $N \times (T-1)$ matrix of dummy variables for periods 2–4; β, θ, and ψ are respectively $k \times 1, (T-1) \times 1$ and $m \times 1$ vectors of unknown parameters to be estimated; v_{it} is the random error, and u_i represents the inefficiency of the ith farm. Stacking all variables into matrices we obtain:

$$y = x\beta + z\theta + p\psi + v - (u \otimes 1_T), \tag{2}$$

where the inefficiency term in the standard efficiency analysis usually assume u to follow an exponential of half-normal distribution. However, u can be made spatially dependent by defining it as:

$$u = \rho W u + \tilde{u}, \tag{3}$$

where W is a weight matrix; ρ is the spatial coefficient, which is assumed to be between 0 and 1; and u and $\tilde{u}$ are latent variables whose distributional form is unknown. In the context of farming, $\rho W u$ captures the effects of shocks spreading among neighboring farmers through similarity in socioeconomic, agroecological, and institutional backgrounds of the group defined by W.

Estimation of spatial models requires specification for the spatial structure of observation units considered in the study. As such, a distance-based weight matrix, $\boldsymbol{W}$, of a Boolean type with elements w_{ij} was defined as follows[4]:

$$w_{ij} = \exp\left(\frac{-{d_{ij}}^2}{s^2}\right), \tag{4}$$

where d_{ij} is the distance in kilometers between the residence/farm location i and the residence/farm location j; s is the distance from the residence/farm where spatial dependence may be relevant, i.e., the cut-off point of spatial dependence. Finding the appropriate cut-off distance is an empirical issue (Roe et al., 2002) that is commonly dealt with by estimating the spatial model using different cut-off distances (Areal et al., 2012; Areal and Riesgo, 2014; Bell and Bocksteal, 2000; Kim et al., 2003; Roe et al., 2002).

Therefore, we use two types of Bayesian models, one standard SFA (nonspatial) and spatial models (with cut-off distance ranging from 100 to 1,000 m), which allow for an investigation of the relationship between spatial dependency and efficiency under different farm environments. Results from the nonspatial model and the spatial model with the highest spatial dependency are compared as follows. Once the farm efficiency estimates from both models are obtained, the efficiency percentage change between the spatial and nonspatial model is calculated per household and farm environment (residential or farm plot). This allows us to explore how much accounting for spatial dependency can help in explaining efficiency. If the area used to determine the neighborhood is relatively large, we may find spatial dependence; however this may not help in explaining efficiency. The same would occur if certain spatial effects that were accounted for are not relevant in explaining inefficiency, i.e., the spatial models in this case would be underperforming compared with the nonspatial models. Having found spatial dependency, a farm with a positive percentage change in their efficiency level would indicate that such farm's efficiency level would have been underestimated under the nonspatial approach (i.e., positive aspects such as sharing information that make farms more efficient were not taken into account). We would expect this to be the case of farms that work closely and share knowledge under similar environment. On the other hand, we may expect farms that work more independently to show lower levels of spatial dependence; and no or small percentage changes in cases where the spatial model matches the performance of the nonspatial model or even negative percentage change in cases where the nonspatial model outperforms the spatial models.

A translog functional form was chosen for the stochastic frontier production analysis. To explain, the translog is a flexible functional form 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. As mentioned above, some nonstochastic environmental variables were incorporated directly into the nonstochastic component of the production frontier accounting for changes in the production level.[5]

Thus, the variable, *Education,* was included and consists of the years of formal schooling of the primary decision-maker of the household; the variable *Size*, which is the total number of people living in the household; *Gender*, a binary variable taking a value of one when the household head is female; and *Remittance* consisting 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

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

[5] There are two general approaches to incorporate nonstochastic environmental variables into technical efficiency analysis (Coelli et al., 2005). The first, the one used here, is to incorporate them in the nonstochastic part of the frontier model, whereas the second approach incorporates them into the stochastic component of the production frontier (Kumbhakar and McGukin, 1991). We have decided to use the first approach to distinguish between observed information, which is included in the production side and nonobserved information (spatial aspects) into the stochastic part of the frontier. However, following the suggestion of a reviewer we also conducted the second approach in which *Education*, *Size*, *Gender*, and *Remittance* are removed from the nonstochastic part and are used in a second stage as explanatory variables for the estimated efficiency. The coefficient estimates of the nonstochastic part are similar. Regarding the explanatory variables for efficiency, *Education* was found to be associated with higher levels of efficiency in all cases whereas *Remittance* was found to be associated with lower levels of efficiency (i.e., farmers recipients of relatively larger amounts of remittances were found to be less efficient than those receiving lower amounts of remittances). These results can be found in the Appendix.

disadvantage of female head. Educated farmers are generally assumed to have better farming capacity and access to information; therefore, they are more productive (Battese and Coelli, 1995). The amount of remittance indicates that farmers have alternative income sources other than rice farming. Hence, we hypothesize that remittance, which captures an unimportance of rice farming, has a negative effect on production levels.

The data for all inputs and outputs are normalized by their respective geometric means prior to estimation. This makes the model's parameter estimates directly interpretable as elasticities that are evaluated at the geometric mean of the data. To cope with the great number of zero observations for fertilizer inputs, the procedure proposed by Battese (1997) was followed. The original variable for fertilizer was replaced with $x_{it}^k = \max(x_{it}^k, D_{it}^k)$, where D_{it}^k is a 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:

$$\ln\ y_{it} = \alpha_0 + \sum_k \alpha_k \ln\left(x_{it}^k\right) + \frac{1}{2}\sum_k\sum_j \alpha_{kj} \ln\left(x_{it}^k\right)\ln\left(x_{it}^j\right) + \beta_k D_{it}^k + \theta_1 Education_{it} + \theta_2 HHsize_{it} + \theta_3 Gender_{it} + \theta_4 Remittance_{it} + \sum_{l=2}^{4} \psi_l p_l + V_{it} - U_i, \quad (5)$$

where y is the output, t is a time index ($t = 1, \ldots, T$), k and j are the inputs, and $\alpha_0, \alpha_k, \alpha_{kj}, \theta_1, \theta_2, \theta_3, \theta_4, \psi_l, \beta_k$ are the parameters to be estimated. The symmetry property was imposed by restricting $\alpha_{kj} = \alpha_{jk}$. The U_i are farm-specific inefficiency terms as defined above. The estimation was conducted using a Bayesian approach that integrates the latent distributions of u and $\tilde{u}$ into the estimation process as defined in Eq. (3) (Areal et al., 2012). Thus, a standard form for the conditional likelihood function was assumed in efficiency analysis with a spatial component added to:

$$p\left(y|\beta, h, \rho, \mu_u^{-1}, \tilde{u}\right) = \prod_{i=1}^{N} \frac{h^{\frac{T}{2}}}{(2\pi)^{\frac{T}{2}}} \exp\left(-h\frac{\varepsilon'\varepsilon}{2}\right). \quad (6)$$

By reparameterizing $\tilde{y} = [y + (I - \rho W)^{-1}\tilde{u} \otimes 1_T]$, $x = x + z + p$ the expression for the conditional likelihood function was obtained:

$$p\left(y|\beta,h,\rho,\mu_u^{-1},\tilde{u}\right) \propto h^{\frac{TN}{2}} \exp\left(-\frac{h}{2}(\tilde{y}-x\beta)'(\tilde{y}-x\beta)\right). \quad (7)$$

The prior distribution for the parameters $\beta, h, \mu_z^{-1}, \tilde{u}, \rho$ are an independent Normal-Gamma prior for β and h; the prior for μ_u^{-1} is assumed to be Gamma with parameters 2 and $-\ln(r^*)$, where r^* is the median of the prior distribution, and the conditional distribution for $\tilde{u}$ is:

$$p\left(\tilde{u}_i|\alpha, \mu_u^{-1}\right) = \frac{\tilde{u}_i^{\alpha-1}}{\mu_u^j \Gamma(\alpha)} \exp\left(-\mu_u^{-1}\tilde{u}_i\right), \quad (8)$$

where $\Gamma(\alpha)$ is the Gamma function with parameter $\alpha = 1$, which is commonly used in the literature. The prior for ρ is assumed to have a positive impact on the efficiency and is defined as an indicator function $I(\cdot) = 1$ if $\rho \in [0, 1]$, or otherwise $I(\cdot) = 0$.

The following conditional posteriors are obtained from the joint posterior distribution, $p(\beta, h, \rho, \mu_u^{-1}, u|y)$: the conditional posterior for β and h are a Normal distribution and Gamma distribution as in Koop (2003). The conditional posterior distribution for μ_u^{-1} is $p(\mu_u^{-1}|\beta, h, \rho, \tilde{u}, y) \sim G(m, \eta)$ where $m = \frac{N+1}{\sum_{i=1}^{N}\tilde{u}_i - \ln(r^*)}$ and $\eta = 2N + 2$. Furthermore, the conditional posterior distribution for $\tilde{u}_i$ is

$$p\left(\tilde{u}_i|\beta, h, \rho, \mu_u^{-1}, y\right) \propto \exp\left[-\frac{hT}{2}\left[z_i - \left(\bar{x}_i\beta - \bar{y}_i + \frac{\mu_u^{-1}}{Th}\right) + (\tilde{u}_i - u_i)\mu_u^{-1}\right]\right], \quad (9)$$

where $\bar{x}_i = \sum_{t-1}^{T} \frac{x_{it}}{T}$ and $\bar{y}_i = \sum_{t-1}^{T} \frac{y_{it}}{T}$ and the conditional posterior for the spatial dependence parameter ρ is $p(\rho|\beta, h, \mu_u^{-1}, \tilde{u}, y) \propto \exp(-h\frac{\varepsilon'\varepsilon}{2}) \times I(\rho \in (0, 1))$. Finally, the conditional posterior distributions for $\tilde{u}_i$ and ρ each requires a posterior Metropolis-Hastings algorithm step (Hastings, 1970; Metropolis et al., 1953).[6]

4. Data

The data for this study were collected by the International Rice Research Institute (IRRI) from 2009 to 2011 to conduct an impact assessment of the Bohol Irrigation Development Project in the Philippines. There were 496 observations per season from two different ecosystems; 205 and 291 observations from rainfed and irrigated ecosystems, respectively. Therefore, the panel used for the stochastic frontier analysis has a size of 820 and 1,164 for rainfed and irrigated, respectively. Data on household characteristics, inputs, and output for rice farming were collected with a structured questionnaire. Additionally, the data set also contains geographical coordinates at both the farm plot and farmer residences.

Descriptive statistics for the variables used in the efficiency analysis are available in Table 1. Capital is defined as the sum of the current values of agricultural machineries such as tractors, sprayers, and other farming devices. Since the level of mechanization in the area is low, the capital value is not very large

[6] We use a random walk chain Metropolis-Hastings algorithm, which takes draws proportionately in different regions of the posterior making sure that the chain moves in the appropriate direction (Koop, 2003), where a new set of $\tilde{u}_i$ is proposed using a Metropolis based on $(\tilde{u}_i|\beta, h, \rho, \mu_u^{-1}, y) \propto \exp[-\frac{hT}{2}[z_i - (\bar{x}_i\beta - \bar{y}_i + \frac{\mu_u^{-1}}{Th}) + (\tilde{u}_i - u_i)\mu_u^{-1}]]$. On the other hand, to draw ρ the Metropolis is based on $p(\rho|\beta, h, \mu_u^{-1}, \tilde{u}, y) \propto \exp(-h\frac{\varepsilon'\varepsilon}{2}) \times I(\rho \in (0, 1))$.

Table 1
Summary statistics of production inputs and socioeconomic characteristics by ecosystems

	Rainfed ($n = 820$)	Irrigated ($n = 1,164$)	Difference
Output (kg)	724.430	1364.897	640.467***
	(636.956)	(1107.032)	
Seed (kg)	30.996	37.773	6.777***
	(23.123)	(26.179)	
Fertilizer (kg)	27.674	43.023	15.349***
	(35.886)	(34.791)	
Labor (Mandays)	32.868	43.685	10.817***
	(18.363)	(25.570)	
Plot size (Ha)	0.573	0.619	0.045***
	(0.409)	(0.412)	
Capital (PHP)	1028.623	1151.318	122.695***
	(860.518)	(923.425)	
Education (Yrs.)	6.080	5.728	0.352
	(3.468)	(3.011)	
Household size	5.606	5.601	0.005
	(2.322)	(2.582)	
Female household head (%)	7.44%	4.90%	2.54%
Remittance† (%)	7.35%	4.69%	2.66%
Yield (Ton/ha)	1.436	2.352	0.916***
	(0.949)	(1.172)	

Note: ***, **, and * mean the difference is statistically significant at the 1%, 5%, and 10% levels, respectively.
†: Calculated as remittance as a portion of total income.

in either area. Notably, it is apparent from Table 1 that farmers in the irrigated areas perform more intensified rice farming (high inputs and high output), particularly with regard to the level of fertilizer and labor. For comparison's sake, we report the yield at the bottom of Table 1, which supports the notion of higher productivity in the irrigated areas. Additionally, education attainment is nearly the same for farmers from the two ecosystems. Moreover, socioeconomic characteristics such as household size, female-led households, and remittances as a percent of total income were not found to be significantly different between rainfed and irrigated systems.

5. Results

We estimated both spatial and nonspatial models for each ecosystem (rainfed and irrigated) by considering residential and plot neighborhood structures. We also estimated the spatial models by considering various definitions of the weight matrix based on 10 cut-off distances from 100 to 1,000 m by 100 m.[7] We found no significant differences in the estimated coefficients of the nonspatial models in comparison to the spatial counterparts. Coefficient estimates associated with production inputs were consistent with what we would expect, which was that inputs have a positive relationship with outputs.

Table 2 shows the summary results obtained for the spatial dependence parameter rho (ρ) with cut-off distance (100–1,000 m). The spatial dependence parameter rapidly decreases as the cut-off distance increases, reaching its highest average value at a 100-m cut-off distance. This is an expected finding that means nonobservables explain efficiency at distances equal or below 100 m. Moreover, this finding is also in accordance with Tobler's First Law of Geography which says that near things tend to be more related than distant things. Another interesting result is that spatial dependence was stronger for irrigated farms than for rainfed farms (Table 2). Thus, for the 100-m model, the probability that the spatial dependence parameter is greater in irrigated farms than rainfed farms is 63% and 78%, respectively, for the plot and residence neighborhoods.[8] For irrigated farms, the probability that the spatial effect is greater under the plot neighborhood structure than under the residential neighborhood structure is 54%, whereas for the rainfed farms this probability is 71%.

Lastly, as the spatial dependence increases with shorter distances, the mean efficiency also increases, suggesting that the more unobservable aspects (e.g., cooperation, information sharing) are explained with the spatial models the more "inefficiency" from the nonspatial models is controlled for. Thus, the estimated mean efficiency for the irrigated farms models with plot spatial dependence at 100, 400, 700, and 1,000 m are 0.91, 0.90, 0.88, and 0.87, respectively. Additionally, the estimated mean efficiency for the rainfed farms models with plot spatial dependence at 100, 400, 700, and 1,000 m are 0.88, 0.87, 0.86, and 0.86, respectively. As for the residence spatial dependence, the results are consistent with what we found in the plot spatial models. The estimated mean efficiency for the irrigated farms models with residence spatial dependence at 100, 400, 700, and 1,000 m are 0.91, 0.90, 0.89, and 0.88, respectively. The estimated mean efficiency for the rainfed farms models with plot spatial dependence at 100, 400, 700, and 1,000 m are 0.88, 0.87, 0.86, and 0.86, respectively. However, although spatial dependency increases with shorter distances, this does not mean that spatial models always explain efficiency better than a nonspatial model. The use of nonspatial models may be able to explain efficiency as well as or even better than spatial models when cut-off distances are relatively large. Notably, the average efficiency levels of non-spatial models for irrigated and rainfed farms is 0.89 and 0.85, respectively, for both plot and residence coordinates models, which suggests that for irrigated farms, only spatial models with cut-off distances at 100 and 400 m explain efficiency better than the nonspatial model. For the case of rainfed farms all spatial models outperform the nonspatial

[7] We find no significant differences among 10 different cut-off distance models in the coefficients associated to the production inputs and the environmental factors. Estimated parameters for spatial (all distance cut-off) and nonspatial models are available upon request from the authors.

[8] These were obtained comparing the conditional posterior distributions obtained for ρ for rainfed farms for residence and plot neighborhoods after 25,000 draws from the conditional distributions with 5,000 draws discarded and 20,000 retained. The comparison was done between each of the 20,000 values of the conditional posterior distributions for ρ. When the spatial dependence of on type of farm (1) is greater than another (2) a value of 1 is given, and 0 otherwise.

Table 2
Spatial dependence at different cut-off distances

Distance (m)	Spatial parameter rho							
	Plot				Residence			
	Irrigated		Rainfed		Irrigated		Rainfed	
100	0.218	(0.014, 0.565)	0.153	(0.010, 0.375)	0.195	(0.015, 0.478)	0.086	(0.006, 0.209)
200	0.095	(0.006, 0.237)	0.067	(0.004, 0.160)	0.076	(0.004, 0.185)	0.055	(0.003, 0.130)
300	0.057	(0.003, 0.134)	0.041	(0.002, 0.099)	0.045	(0.002, 0.107)	0.041	(0.002, 0.097)
400	0.042	(0.003, 0.096)	0.026	(0.001, 0.065)	0.032	(0.001, 0.076)	0.029	(0.006, 0.209)
500	0.033	(0.002, 0.071)	0.019	(0.009, 0.381)	0.026	(0.001, 0.060)	0.023	(0.001, 0.057)
600	0.028	(0.002, 0.058)	0.014	(0.001, 0.036)	0.022	(0.015, 0.048)	0.018	(0.001, 0.045)
700	0.022	(0.002, 0.047)	0.012	(0.001, 0.032)	0.018	(0.001, 0.040)	0.015	(0.001, 0.037)
800	0.020	(0.002, 0.039)	0.010	(0.001, 0.027)	0.016	(0.001, 0.035)	0.012	(0.001, 0.031)
900	0.016	(0.001, 0.033)	0.009	(0.001, 0.022)	0.014	(0.001, 0.030)	0.011	(4E-4, 0.027)
1,000	0.015	(0.002, 0.028)	0.008	(5E-4, 0.019)	0.012	(0.001, 0.026)	0.009	(4E-4, 0.022)

Note: The interpretation of the Bayesian 95% coverage posterior (a, b) is that according to our data and model the parameter is between a and b with a 0.95 probability.

model. This result suggests that spatial effects at relatively small distances (<400 m) (e.g., sharing information, use of common resources) are important determinants for irrigated rice production. For data sets that cover relatively large areas, accounting for spatial dependency in this way helps control for some of the unobserved heterogeneity in the sample, e.g., climatic and topographical conditions. However, the source and processes behind the spatial dependence cannot be explained due to the variety of heterogeneous possible reasons. In this study, the fact that the sample is relatively homogeneous works as an advantage in explaining such spatial dependence. Since the observed spatial dependence exists at such small cut-off distances (100 m), it cannot be a result of any climatic condition.

Fig. 2(a) shows the distribution of efficiency for irrigated and rainfed farms using non-spatial model and spatial models (at 100, 400, 700, and 1,000 m) in the case of plot neighborhood. Interestingly, in all four scenarios, the distribution is skewed toward the right and has a relatively long left tale. Very few farmers have efficiency levels less than 0.5. The distribution of efficiency varies not only by ecosystem, but also by type of neighborhood. In every case, the distribution of the nonspatial model is very distinct from the spatial models. This finding exposes the biases in efficiency levels that arise when spatial considerations are ignored, i.e., cases where the efficiency distribution from spatial models is located to the right of the nonspatial efficiency distribution. More specifically, for the case using plot neighborhood, models for irrigated farms where spatial effects were found to be relatively high (100 and 400 m) have a narrow distribution to the right of the nonspatial efficiency distribution. This suggests that part of the farm inefficiency not captured under the nonspatial model can be explained by these spatial models. Also, the fact that the distribution shape is narrower indicates that differences between farm efficiency levels have been reduced once spatial effects have been taken into account.

Hence, although we find that the shorter the distance, the greater the spatial dependence in both cases of irrigated and rainfed, we can see in Fig. 2(a) (bottom) that for rainfed farms the effect of such increase in spatial dependence with distance is relatively small in explaining efficiency (efficiency distributions are closer to each other than for Fig. 2a (top)). Additionally, considering the nonspatial efficiency distribution as a reference, we found that the efficiency distribution using the spatial model for irrigated farms (100 m, 400 m) and rainfed farms (all distances) is situated to the right of the nonspatial case (Fig. 2a). This means that for irrigated farms, spatial dependence may help explaining inefficiency, i.e., irrigated farmers working more closely. However, for rainfed farms, which work more independently but are more affected by climatic conditions, spatial dependence contributes relatively more to explaining efficiency than irrigated farms (i.e. taking the non-spatial distribution as reference the gap to the 100 m distribution to the right is greater for rainfed farms than for irrigated farms).

For irrigated farms, information sharing about technology among plot neighbors may determine production levels. This may not be the case for rainfed farms whose practices may be determined more independently, and the level of production may be more dependent on the plot's location, i.e., specific agronomic conditions rather than sharing knowledge. When examining spatial models that use large neighborhood areas and their contributions to explaining inefficiency, e.g., comparing efficiency distributions using the spatial dependence model (cut-off distance 1,000 m) versus nonspatial dependence model (cut-off distance 100 m) for irrigated farms, we found small spatial dependence in our longer distance spatial model.

Fig. 2(b) shows the distribution of efficiency for irrigated (top) and rainfed (bottom) farms, using a nonspatial model and spatial models (at 100, 400, 700, and 1,000 m) in the case of residential neighborhood structure. For the models on irrigated farms, the same findings were produced as in the case of plot neighborhood, suggesting that both natural conditions of the spatial area and communication between farmers with neighbor residence plays a role in explaining part of

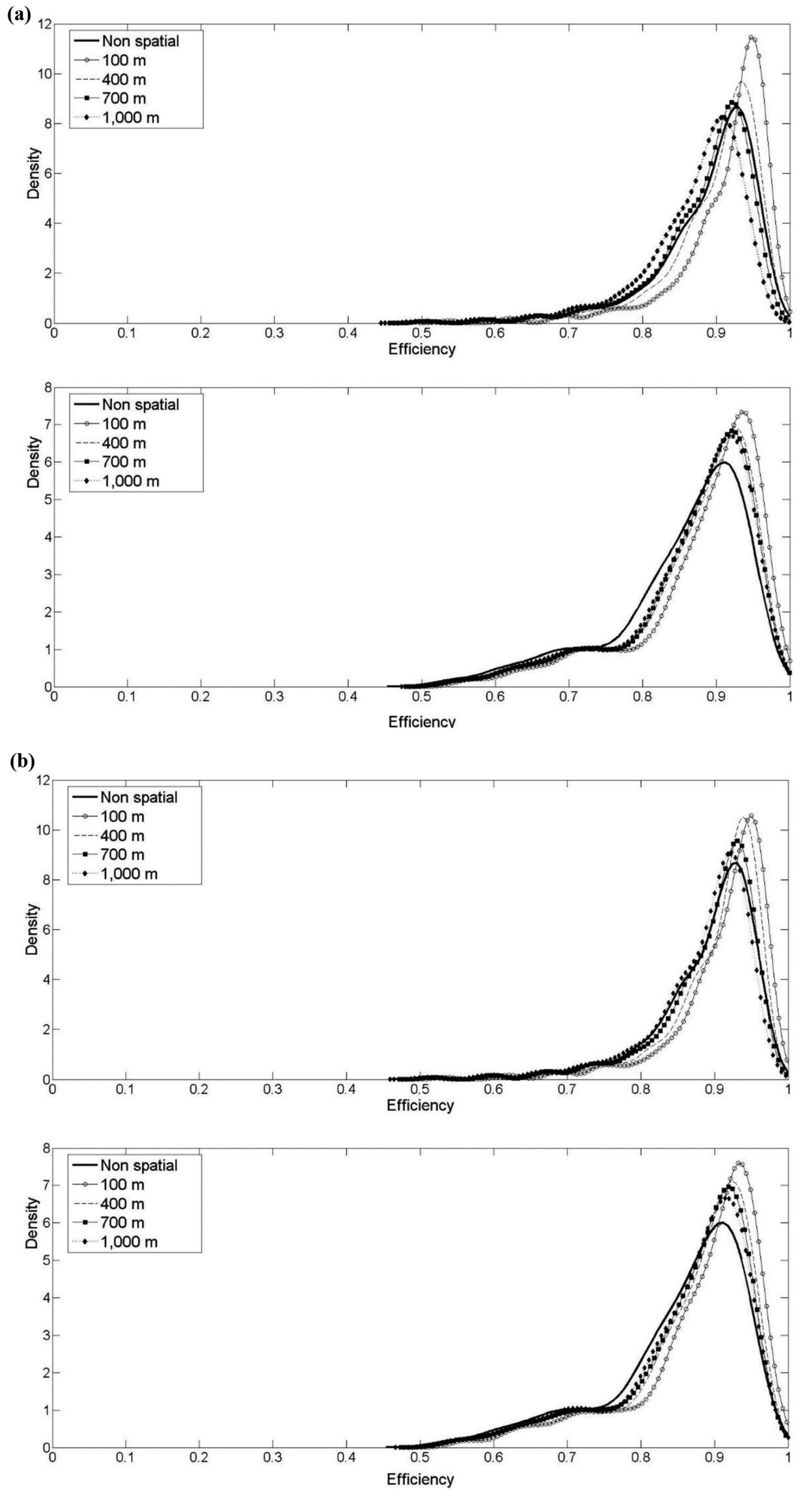

Fig. 2. (a) Distribution of efficiency in irrigated farms (top) and rainfed farms (bottom) using plot coordinates. (b) Distribution of efficiency in irrigated farms (top) and rainfed farms (bottom) using residence coordinates.

the inefficiency detected by the nonspatial models. As in the plot coordinates case, the efficiency distribution for rainfed farms when spatial effects are taken into account are different from the efficiency distribution obtained by the nonspatial model.

This aforementioned finding suggests that natural conditions are likely playing a role in explaining the estimated inefficiency levels gathered by the nonspatial model.

Spatial dependence can explain why the level of connectedness, i.e., working together and sharing information, is

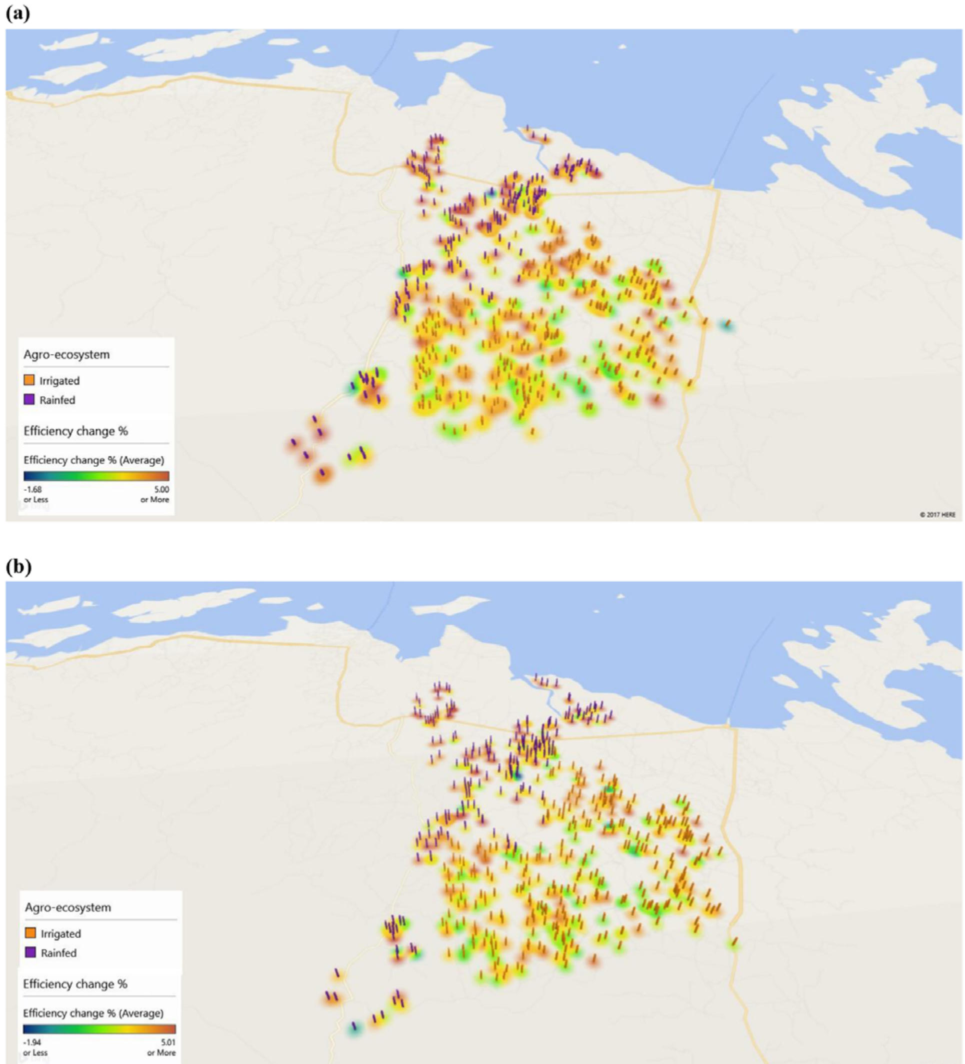

Fig. 3. (a) Percentage change in efficiency score between spatial model (100 m) and nonspatial (plot coordinates). (b) Percentage change in efficiency score between spatial model (100 m) and nonspatial (residence coordinates). [Color figure can be viewed at wileyonlinelibrary.com]

important in explaining efficiency levels. We found that different neighborhood (residential and plot) explain similar spatial processes, and there are two types of processes that are captured by residential neighborhood and plot neighborhood. Both social and environmental conditions are captured for farmers' residence and plot location. Using plot neighborhood, Fig. 3(a) shows the map of percentage change in farm efficiency levels for both irrigated and rainfed farms in this study area. Rainfed farms tend to have greater increases in efficiency levels once the spatial dependency is incorporated into the analysis. Irrigated farms have relatively less increase in efficiency levels once spatial dependency is incorporated.

The finding above needs some clarification because we found stronger spatial dependency in irrigated area. Irrigated farms being more spatially dependent means that the efficiency levels of neighboring irrigated farms are more similar between them than the efficiency levels of neighboring rainfed farms. This is possibly due to conditions and practices under irrigation being more similar between neighboring irrigated farms than the conditions and practices under rainfed between neighboring rainfed farms. The fact that we can capture this with the spatial models helps us identify better farm efficiency levels (i.e., avoiding attributing unobservable environmental conditions to inefficiency). The nature of the spatial dependency is what determines its effect of spatial dependency on the farm efficiency estimation. Thus, for irrigated farms the nature of spatial dependency may come from similar environmental conditions and practices (e.g., through sharing information), whereas for rainfed farms it may come from more variable conditions (e.g., climatic and topographical conditions). Being able to capture unobservable variable conditions was found to be relatively more important in explaining efficiency levels for rainfed farms than capturing unobservable environmental conditions and practices for explaining farm efficiency levels for irrigated farms (i.e., accounting for more variable conditions such as weather conditions are more determinant than more "controlled" conditions in explaining efficiency levels).

Fig. 3(b) shows the map of percentage change in farm efficiency levels for both irrigated and rainfed farms in the study area using residence neighborhood. In this case, we found similar results as in the plot neighborhood. We found a higher efficiency increase on the rainfed area than on the irrigated area. Again, we expected this result since natural conditions are expected to be more important in explaining efficiency for rainfed farms than for irrigated farms. Still, we find increase in efficiency levels for irrigated farms. This finding may be a result of the residence neighborhood, or it may be a result of partially capturing the social aspect.

The percentage average increase in efficiency is, on average, higher for rainfed farms (3.4% and 3.3% for plot and residential neighborhood) than for irrigated farms (2.9% and 2.6% for plot and residential neighborhood), in light of the average efficiency levels mentioned above for the spatial model using the 100-m cut-off distance for irrigated and rainfed farm (0.91 and 0.88), and the efficiency levels obtained from the equivalent nonspatial models (0.89 and 0.85). Hence, we found that although the spatial dependence parameter (ρ) tells us the strength of the spatial dependence, which is generally greater for irrigated than for rainfed farms, such strength, i.e., incorporating spatial dependency into the analysis, follows a nonlinear relationship with how well the spatial model performs compared with the nonspatial model in terms of percentage change in efficiency between spatial and nonspatial models. To explain, using the plot neighborhood structure, the spatial dependence parameter at 100 m for irrigated and rainfed farms is 0.195 and 0.086, respectively, and the percent efficiency increase is 2.6% and 3.3% for irrigated and rainfed farms, respectively.

The estimated models also show noteworthy results. *Education* has a positive and significant effect in irrigated as well as rainfed environments. Even though the rainfed farmers are more educated by about 0.4 years than irrigated farmers, there was no significant difference in means between the two ecosystems (see Table 1). In the irrigated area, the rice farming is more modernized in the sense that farmers use new and improved varieties and chemical inputs, as well as following standardized agronomic practices under controlled irrigation. Formal education for literacy as well as basic scientific knowledge is important to understand these types of practices. The fact that education significantly contributed to improve output in the rainfed environment also makes sense because even though farming is less intensified in the rainfed environment; formal education is still useful to the rainfed farmers. In fact, the results in Table 2 show the largest educational impact in the rainfed farmers' plot neighbor model (0.013). Additionally, *Household size* was found to be insignificant in all estimated models. This finding was expected because more farmers reach out to hired labor for farm operations. Finally, regarding the dummy variables for the studied periods we found that results corroborate the expected effects where rice production in periods 2 and 4 levels was lower than the first period (i.e., the benchmark period) due to the severe drought in the second season and flood in the fourth season mentioned above.

6. Conclusions and policy implications

This article investigates the role of spatial dependency in TE for different ecosystems and neighborhood structures focusing on rice farmers in Bohol, Philippines. A spatial econometrics Bayesian approach was used to estimate the stochastic production parameters, as well as the spatial dependency parameters. The results were compared with nonspatial Bayesian SFA. We found that spatial dependency exists at the residential and plot levels, maintaining more strength for irrigated than rainfed farms. We also found that technical inefficiency levels decrease as spatial effects are more taken into account. Since the spatial effects increases with a shorter network distance, the decreasing technical inefficiency means that the unobserved inefficiencies can be explained better by considering small networks of relatively close farmers over large networks of distant farmers, reflecting the location-specific nature of farming.

Two policy implications can be drawn from this study. First, a stronger spatial dependency in the irrigated area indicates the existence of stronger externalities; a positive shock on one farmer's TE improves the TE of the nearby farmers. The existence of externalities may justify public interventions. However, it is important to note that we also found that the size of the spatially dependent network is small. Hence, such an externality may be easily internalized through collective actions within the small group. In irrigated area, the water users group may serve as an appropriate unit for this purpose. Although this is an important practical issue, it is beyond the scope of this article and requires future study. Additionally, since the rainfed farming is more individualistic, policies which are targeted to individual farmers are relatively more important, in comparison to the case of irrigated area. Having observed a strong impact of schooling years, educational support or extension may work effectively in improving rainfed farmers' TE, which is currently lower than the irrigated farmers.

Although our analysis focuses on TE for rice production technology change and scale effect are also relevant aspects to be considered in long-term studies. Our data cover only two years which did not allow for TFP growth and technological progress estimation as done in studies like Coelli et al. (2005) Nin et al. (2003), Singbo and Larue (2016) and Umetsu et al. (2003). In addition, evidence of spatial dependency in technological progress has been largely demonstrated in the economic literature. The role of spatial dependence in technological progress has mainly been stressed in the context of regional productivity (see Benhabib and Spiegel, 1994; Griffith et al., 2004; Nelson and Phelps, 1966). Similar to the endogenous growth theory in economic literature, technological progress varies across farmers and it depends on farmers' ability to innovate or use the improved technologies. As we highlighted above, farmers use the technology differently with human capital or the level of education being commonly cited as drivers of technological progress. In addition, farmers located below the frontier require sufficient social capabilities to allow them to successfully exploiting the technologies employed by the most efficient farmers.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix A1: Spatial model with cut-off distance of 100 m.
Appendix A2: Non-spatial model
supporting information